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PREDICTIVE MAINTENANCE BASED ON UNBALANCE SEVERITY ANALYSIS OF ROTATING MACHINES

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Abstract. *This paper presents a classification method for unbalancing fault severity in rotating machines based on the force created by the mass of unbalancing. The unbalancing severity was broken down into 3 discrete levels which are H (High), M (Medium) and L (Low). Test results verification led to the use of Random Forest algorithm as a classifier for the unbalancing severity defect, reaching a global accuracy of 93.73%, with average standard deviation of 2.15% and total computational cost of 12.5 hours.*

Keywords: *random forest, unbalancing, predictive maintenance*

1. INTRODUCTION

The rotating machines are very important components in the industrial processes. From the production, transportation and storage of chemical and petrochemical products to the separation of air and the generation of energy, rotating machines play very important role in the processes. In the oil, gas and petrochemical market about two thousand new compressors and five thousand new pumps are installed every year (Pareschi *et al.*, 2012). Once compressing and pumping processes are expensive and so crucial, reliability is an issue to be reached in those processes.

The growing automation of the industrial production processes permitted the development of efficient monitoring systems, and consequently, made possible the implementation of predictive maintenance procedures. Such procedures include the measurement of several different parameters of the machinery allowing fault prediction and better maintenance planning, in terms of a more cost-efficient production plant stop schedules, and spare parts inventory planning. In other words, these procedures lead to manufacturing costs reduction and have been considered as an evolution of the maintenance procedures. According to Chow (2000), the prognostic system comes, not only to recognize the machine operating status, but also to estimate its remaining life-time.

Excessive machine vibration leads to defects, shortened machinery life, emergency shutdowns, production shortage and higher maintenance costs, in terms of labor and parts. Possible vibration causes generated inside the machine (not originated outside) are 1) Imbalance; 2) Misalignment; 3) Worn or defective parts (bearings in special); and 4) Loose parts or connections.

More specifically, imbalance vibrations at rotating machines can be caused by:

- Corrosions or erosion of rotors.
- Uneven mass distribution in electrical windings (poor winding process) for electric motors.
- Deposit of dirt on rotors.
- Manufacturing defects.
- Material imperfections due to cavities, bubbles, foreign materials, etc.
- Eccentric rotors.

- Cracked/damaged fans.
- Incorrect key hole.
- Machining errors.

An example of machine affected by imbalance is the centrifugal pump as presented in Taneja (2013) for which the unbalanced rotor may lead to cracks and ruptures in the rotor shaft as described by Serra (1995), damage to the seals and consequent leakage. There are many examples of pump's shaft cracks found in nuclear power plants caused by unbalanced rotors, also there are some examples of corroded impellers causing vibration amplitude increase, due to no compliant impeller coat specification according to Precision Balancing (2017).

The research made by Kim *et al.* (2012) studied the health state probability estimation and was conducted applying the Support Vector Machine (SVM) algorithm. The machine prognostics was generated based on the probability distributions of each health states. In order to demonstrate the viability of the proposed model, bearing fault cases of High Pressure-Liquefied Natural Gas (HPLNG) pumps were examined to observe the failure degradation process. The choice of appropriated features for the classification of the bearing degradation degree, the distance evaluation procedure was employed. Many health states were scrutinized to determine the optimal number of degradation stages for accurate estimation of machine remnant life. The results demonstrate that the proposed prognosis model divided in five degradation stages has the potential to be applied as an estimation tool in real life industrial applications.

The study published by Hu *et al.* (2012) proposes an ensemble approach that uses the k-fold cross validation (CV) to estimate the accuracy of a given ensemble and proposes three weighting schemes to find the weight values. The results achieved from a-three-case-study proposes that the ensemble approach with any weighting scheme gives more accurate Remaining Useful Life (RUL) predictions compared to a unique algorithm when member algorithms producing diverse RUL predictions have comparable prediction accuracy and that the optimization-based weighting scheme results a good performance.

In the work performed by Lima *et al.* (2013), a study was made to analyze the failure diagnosis of a continue current electric motor. This analysis was made using vibrations signals measured by piezoelectric accelerometers with a sample rate of 800 Hz. The signals recorded were obtained from the experimental bench Alignment/Balance Vibration Trainer (ABVT) of Spectra Quest. The failure scenarios analyzed in this work were: normal (no fault), unbalance and misalignment with a total of 606 scenarios analyzed. The features used in this research were extracted in the frequency domain generating a feature vector dimension of 10. The algorithm used to perform the pattern recognition in this work was the multilayer perceptron neural network reaching a hit percentage of 93.5%.

Pestana *et al.* (2016) developed a study, which also made use of the experimental bench ABVT of the Spectra Quest. The failure scenarios analyzed in this work were: fail in the outer track, in the rolling element, in the cage, unbalance and misalignment. The total of failure scenarios analyzed were 1951. The features used in this research were extracted by the kurtosis and entropy calculation and the feature vector dimension was 19. The algorithm used to evaluate the system performance was also the multilayer perceptron neural network that reached 99.1% of precision.

The research made by Martins *et al.* (2016) shows the classification of 9 types of faults in the experimental bench ABVT (defect in the cage, in the roller and in the outer track of non inverter bearing; defect in the cage, in the roller and in the outer track of inverter bearing; unbalance; horizontal parallel misalignment; and vertical parallel misalignment), for which the separation of train and test sets was made by the k-fold method. The algorithm used to perform the classification was the random forest, which reached an accuracy of 97.48%.

In the paper of Martins *et al.* (2016) was presented a system to estimate the fault severity in rotating machines. After diagnosing the failure in a machine, the degree of failure might be measured in order to properly plan the next action to recover the machine and mitigate the halt and maintenance costs. The work addressed unbalance, misalignment and bearing faults quantifying them in 3 levels of fault severity namely L (low), M (intermediate), H (high) without considering a mathematical expression or the mechanical background of the topic. The tests assessed the performance of the severity quantifiers applying random forest and artificial neural networks, concluding that a combination of these techniques achieves a higher overall performance of 91.42% with average standard deviation of 4.31% and average computational cost of 24.04 hours.

In the paper of Cerrada *et al.* (2016) was proposed a study of feature selection for a diagnostic system performed by using genetic algorithms and a classifier based on random forest, in a supervised environment. The main purpose of this paper was to develop a robust system for the multi-class fault diagnosis in spur gears, by choosing the best set of condition parameters. This method uses frequency and time domain features extracted from the vibration signals. Applying genetic algorithms the original condition parameters was reduced to approximately 66% regarding the initial size, and the classification precision of method reached 97%.

After presenting in Section 1 a brief introduction of failure classification in rotating machine, some motivation and related work already published in the area, the rest of the paper is divided as follows: In Section 2 is presented an overview of the random forest classification technique, which is a supervised machine learning approach for pattern recognition. Section 3 details the database recording setup and its characteristics specifying the amount of data signals

for each unbalancing mass. It also explains unbalancing force related to the recorded signals and the whole planning for the experimental evaluation in estimating the unbalancing fault severity levels. Several different ranges for unbalancing fault severity levels with respect to the unbalancing force are assessed and discussed in Section 4. Finally the Section 5 summarizes the paper achievements, showing the most consistent experimental performances and validating the efficiency of the proposed system in the context of machine failure prognosis.

2. RANDOM FOREST

The random forest classifier is an ensemble machine learning technique based on decision trees constructed during the training step, whose the output class is given by the mode of the classes output by individual trees. The technique combines the bootstrap with the random feature selection strategies building decision trees. It is a supervised classification algorithm, i.e., the training sample must have the class identification to the algorithm be able to recognize the patterns of data set. The decision trees are naive classifiers, in other words small variations in the training set can cause significant changes in the classifier. In order to overcome this problem, the bagging method is used. Acuna and Rojas (2001) states that this method presents good results when applied to naive classifiers, where multiple classifiers can compensate the bias of a single classifier. The objective of using multiple trees to make a forest is to overcome the problem of the bias caused by an unique tree.

A random forest is a classifier constituted of a set of tree structured classifiers where the trees are independent identically distributed random vectors and each tree casts a unit vote for the most popular class for a given input vector as proposed by Breiman (2001). The ensemble model consists in preparing different data models corresponding to different decision trees, whose result is given by a “voting” procedure along the tree models. The diagram shown in Fig. 1 describes the steps for implementing a random forest approach. As mentioned, the whole training data is divided into subsets similarly to the statistical approach known as bootstrap. However, this step is allegedly not crucial to the efficiency of the random forest technique. For each data subset several decision trees are evaluated for different dimensions of feature vectors, i.e., from the whole set of feature dimensions $\{f_1, \dots, f_n\}$, one is removed, for instance, f_i , making that dimension null, \emptyset_i , thus the reduced dimensionality vector is represented by $\{f_1, \dots, \emptyset_i, \dots, f_n\}$. The classification is achieved by applying a test feature data to all decision trees, and the final classification is obtained by the voting process.

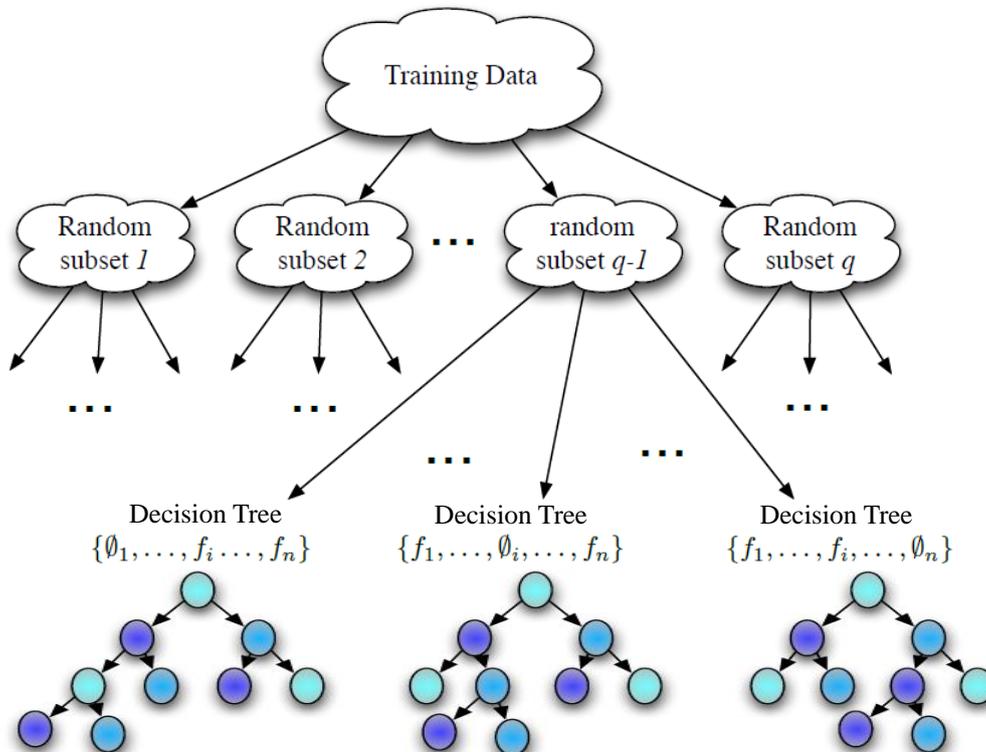


Figure 1. Diagram of random forest algorithm

3. EXPERIMENTAL WORKBENCH

A dataset recorded by using an electric motor based machine running under different defect condition was used to evaluate the performance of the random forest classifier for the fault prognostic. The project used the experimental

workbench ABVT, Alignment/Balance Vibration Trainer manufactured by Spectra Quest Inc. The research used the vibration analysis method described in the work proposed by Martins *et al.* (2016). Figure 2 exemplifies the recording setup for mass imbalance data acquisition, where can be observed the experimental workbench ABVT (rotorkit) with the inertial discs and the two roller bearings, the accelerometers assembled close to the bearing, the tachometer sensor, the data acquisition board and the computer to control and record the mass imbalance fault simulation signals.

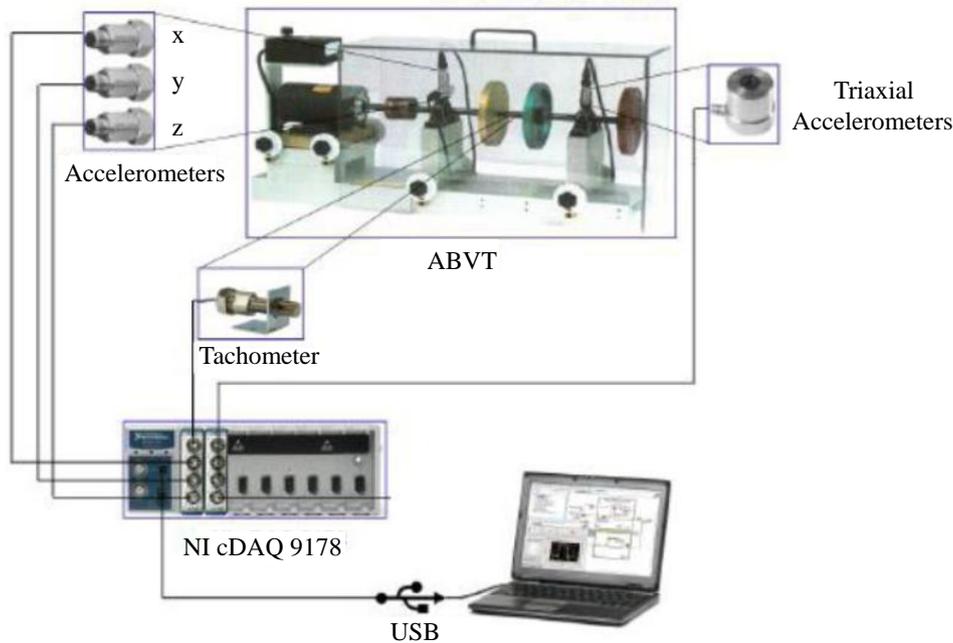


Figure 2. Recording setup of the experimental workbench ABVT.

4. COMPUTATIONAL PROCEDURE

The defect was analyzed by collecting and recording 333 different fault scenarios along with different rotating speeds. These scenarios had 7 different levels obtained with 7 different unbalancing masses: 6 g (49 fault scenarios), 10 g (48 scenarios), 15 g (48 scenarios), 20 g (49 scenarios), 25 g (47 scenarios), 30 g (47 scenarios), 35 g (45 scenarios).

The resulting unbalancing fault severity effects were divided into 3 discrete levels: H (High), M (Medium) and L (Low), thus forming the output classes of the classifier following similar reasoning as Hussein and Irina (2016) and Gan *et al.* (2016). This classes separation was based on the magnitude of the unbalancing force represented by Eq. (1), in which m is the unbalancing mass, r is the mass distance from the spin axis in the center of the inertial disk, and w is the angular velocity.

$$F_c = m.r.w^2 \quad (1)$$

The experiments were conducted in order to evaluate the most appropriate range of the three discrete levels of unbalancing fault severity, which can be decided by the standard deviation values of the classes accuracy. It is desirable a certain balance among the classes accuracies and standard deviations, because a larger difference in these metric brings a higher uncertainty in the accuracy value and classifiers that performs better to one specific class to the detriment of other classes. Furthermore, the validation of the combination between the unbalancing force and random forest techniques to estimate the unbalancing fault severity is also one of the targets of the experiment. Figure 3 shows how the recorded database signals according to the unbalancing masses are related to the unbalancing forces, which depend not only from the mass, but also from the motor angular velocity presenting in details the unbalancing force range for each unbalancing mass and varying the rotating frequency of the motor.

The vibration signals were collected from piezoelectric accelerometers, and then processed to obtain the extraction of 31 features of each fault scenario, to be further used to train the classifier. The features extraction process uses calculation of Fourier Transform, Kurtosis and Entropy of the collected signals. The resulting features dataset was then divided into Training dataset and Test dataset using k-fold cross-validation method. As commented before, the classification algorithm used was Random Forest, which in turn is an ensemble of several elementary decision trees. The different results of each tree of the ensemble pass through a vote process. The most voted result indicates the classified severity level. The model is then used to classify a new sample not previously recorded in the initial dataset. The configuration parameter used by this algorithm is the number of tree in the ensemble. The research tested a variation of the trees quantity from 1 to

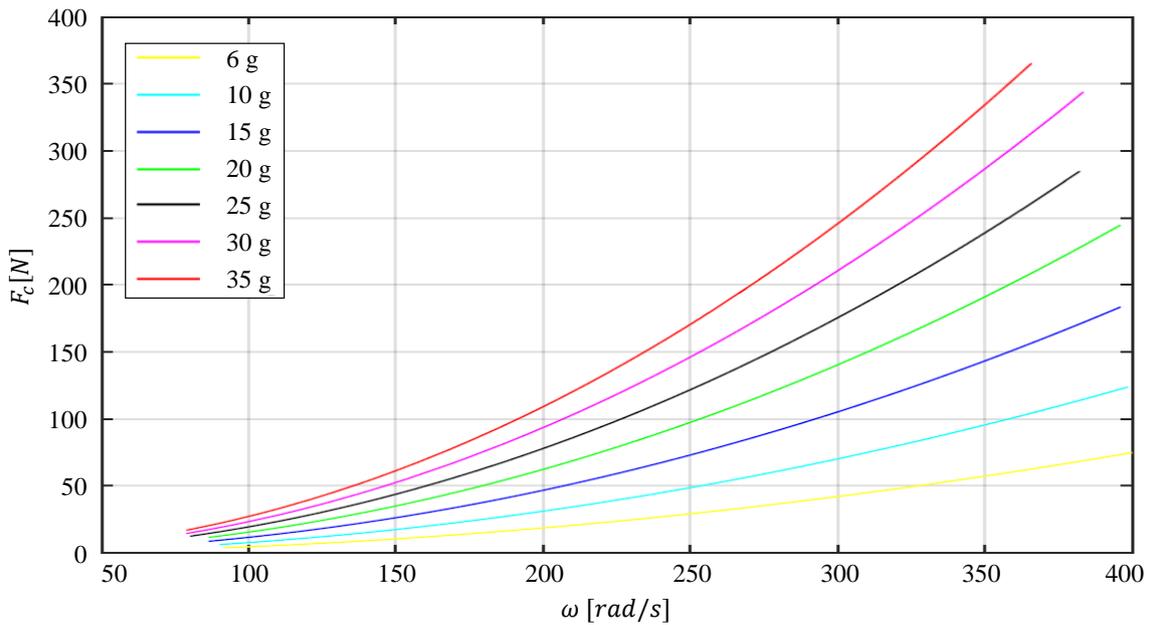


Figure 3. Graphic of unbalancing force versus angular velocity for all unbalancing masses separately.

100, equivalently to Martins *et al.* (2016), and concluded that this range was enough to find out the minimum quantity of trees which would still obtain a high quantity of hits. The k-fold cross-validation generated 120 combinations of training datasets, which were used to train the 100 trees in the ensemble. This means the algorithm had to be run 12,000 times. This high quantity of running cycles required the algorithm to be run in a cluster of computers with 3.5 GHz of processor clock and 32 Gb of RAM, and not in a regular personal computer.

5. RESULTS AND DISCUSSION

The experiments done with the unbalancing signals provided the observation of the random forest capability to quantify the unbalancing severity level. The greater the unbalancing level, the greater the probability of machine malfunctioning and production shortage. The experiments were divided into 4 evaluations with different ranges of the unbalancing force for the 3 discrete level of fault severity to observe the influence of the range boundaries in the system accuracy and uncertainty.

5.1 EXPERIMENT 1

In the first experiment the classes were separated as follows:

- L - Unbalancing force $[0; 118.4[$ N;
- M - Unbalancing force $[118.4; 136.8[$ N;
- H - Unbalancing force $[136.8; \infty[$ N.

Table 1 presents the range separation among the 3 discrete level of severity and how it is related to the signals of the recorded database. The data distribution among the classes were 0.68%, 0.23% and 0.09% for the levels L, M and H, respectively. Although the data amount of the classes is not balanced, it is not required to the random forest classification technique to perform appropriately. However it could affect the system efficiency due to the characteristics of the problem under analysis.

Table 2 shows the results obtained when classifying the unbalancing severity level using a 38 trees random forest. The average accuracy achieved was $91.45\% \pm 4.12\%$ with a total processing time of 12.27 hours. The class H obtained the smallest accuracy of the 85.56% with standard deviation of 12.58%, which suggests that this range separation could be rearranged to improve the system efficiency.

5.2 EXPERIMENT 2

In this second experiment, it was evaluated different range separation towards a more balance among the classes data amount dividing them as follows:

Table 1. Experiment 1 - Unbalancing severity level mapping data distribution using imbalance force levels $L = [0; 118.4[$ N, $M = [118.4; 136.8[$ N and $H = [136.8; \infty[$ N.

Unbalancing Mass	Mass Severity (Signals)			Total
	L	M	H	
6 g	49	0	0	49
10 g	46	2	0	48
15 g	35	13	0	48
20 g	30	17	2	49
25 g	26	17	5	47
30 g	23	14	10	47
35 g	20	14	11	45
Total	229	77	28	333

Table 2. Experiment 1 - Confusion Matrix of the Unbalancing Severity Analysis with corresponding unbalancing force levels $L = [0; 118.4[$ N, $M = [118.4; 136.8[$ N and $H = [136.8; \infty[$ N.

Output	Target Classes (%)		
	L	M	H
L	97.48 ± 1.80	5.29 ± 4.94	0 ± 0
M	2.52 ± 1.80	91.44 ± 5.94	14.42 ± 12.58
H	0 ± 0	3.27 ± 4.17	85.56 ± 12.58

- L - Unbalancing force $[0; 78.95[$ N;
- M - Unbalancing force $[78.95; 157.9[$ N;
- H - Unbalancing force $[157.9; \infty[$ N.

The data distribution among the classes were 0.55%, 0.23% and 0.22% for the levels L, M and H, respectively, as can be observed in Tab. 3, which compared to the experiment 1 presents a more balanced data distribution.

Table 3. Experiment 2 - Unbalancing severity level mapping data distribution using imbalance force levels $L = [0; 78.95[$ N, $M = [78.95; 157.9[$ N and $H = [157.9; \infty[$ N.

Unbalancing Mass	Mass Severity (Signals)			Total
	L	M	H	
6 g	49	0	0	49
10 g	35	13	0	48
15 g	26	16	6	48
20 g	22	14	13	49
25 g	19	14	14	47
30 g	16	12	19	47
35 g	15	10	20	45
Total	182	79	72	333

The results presented in Tab. 4 were obtained using the random forest approach with 31 trees. The average accuracy achieved was $94.13\% \pm 2.33\%$ with a total processing time of 12.33 hours. In this experiment there is still the M class with efficiency lower than 90% and with uncertainty of about 6% showing some capacity for improvement.

5.3 EXPERIMENT 3

The experiment 3 takes one more step towards the balance of the data amount for each class under study and to accomplish it the classes were partitioned as:

- L - Unbalancing force $[0; 59.21[$ N;

Table 4. Experiment 2 - Confusion Matrix of the Unbalancing Severity Analysis with corresponding unbalancing force levels $L = [0; 78.95[$ N, $M = [78.95; 157.9[$ N and $H = [157.9; \infty[$ N.

Output	Target Classes (%)		
	L	M	H
L	99.04 ± 1.22	5.37 ± 4.50	0 ± 0
M	0.96 ± 1.22	89.62 ± 5.80	6.26 ± 4.50
H	0 ± 0	5.01 ± 5.40	93.74 ± 4.50

- M - Unbalancing force [59.21; 138.17[N;
- H - Unbalancing force [138.17; ∞[N.

Compared to the experiment 2, the Tab. 5 shows the classes amount of data even more balanced with percentages for the levels L, M and H of 0.44%, 0.29% and 0.27%, respectively.

Table 5. Experiment 3 - Unbalancing severity level mapping data distribution using imbalance force levels $L = [0; 59.21[$ N, $M = [59.21; 138.17[$ N and $H = [138.17; \infty[$ N.

Unbalancing Mass	Mass Severity (Signals)			Total
	L	M	H	
6 g	42	7	0	49
10 g	29	19	0	48
15 g	21	18	9	48
20 g	17	16	16	49
25 g	15	14	18	47
30 g	13	12	22	47
35 g	11	12	22	45
Total	148	98	87	333

Table 6 represents the test performance obtained using a 41 trees random forest, which is the minimum number of trees associated with the higher accuracy obtained for the training data in the classification algorithm learning step. It reached 93.41% ± 2.28% of average accuracy in 12.31 hours of processing time. This experiment also presents the class M with accuracy below 90% and standard deviation of around 6%, still suggesting improvement capability.

Table 6. Experiment 3 - Confusion Matrix of the Unbalancing Severity Analysis with corresponding unbalancing force levels $L = [0; 59.21[$ N, $M = [59.21; 138.17[$ N and $H = [138.17; \infty[$ N.

Output	Target Classes (%)		
	L	M	H
L	95.74 ± 2.63	8.41 ± 5.12	0 ± 0
M	4.25 ± 2.63	88.65 ± 5.97	4.15 ± 4.79
H	0 ± 0	2.94 ± 3.45	95.85 ± 4.79

5.4 EXPERIMENT 4

Finally, in the experiment 4 the classes severity ranges were established as being:

- L - Unbalancing force [0; 39.47[N;
- M - Unbalancing force [39.47; 118.43[N;
- H - Unbalancing force [118.43; ∞[N.

Table 7 presents the most balanced data distribution among the classes of all experiments performed and analyzed in this work. The data distribution was 0.31%, 0.38% and 0.31% for the levels L, M and H, respectively.

Table 7. Experiment 4 - Unbalancing severity level mapping data distribution using imbalance force levels $L = [0; 39.47[$ N, $M = [39.47; 118.43[$ N and $H = [118.43; \infty[$ N.

Unbalancing Mass	Mass Severity (Signals)			Total
	L	M	H	
6 g	32	17	0	49
10 g	22	24	2	48
15 g	15	20	13	48
20 g	11	19	19	49
25 g	10	16	21	47
30 g	8	15	24	47
35 g	6	14	25	45
Total	104	125	104	333

Table 8 shows the results obtained when classifying the unbalancing severity level using a 36 trees random forest. The average accuracy achieved was $93.73\% \pm 2.15\%$ with a total processing time of 12.50 hours. Compared to all three previous experiments, it is possible to verify that the method reached more than 92% accuracy in all classes with low and similar value of standard deviation for all classes. Although the classes separation of this experiment was not the one that reached the highest average accuracy among the 4 experiments, it has achieved the most consistent performance considering the classes hit rates and standard deviations individually. It suggests that the range separation adopted in the experiment 4 was the most appropriated to nature of the problem under analysis.

Table 8. Experiment 4 - Confusion Matrix of the Unbalancing Severity Analysis with corresponding unbalancing force levels $L = [0; 39.47[$ N, $M = [39.47; 118.43[$ N and $H = [118.43; \infty[$ N.

Output	Target Classes (%)		
	L	M	H
L	93.32 ± 4.85	4.84 ± 3.54	0 ± 0
M	6.68 ± 4.85	92.05 ± 3.40	4.18 ± 3.89
H	0 ± 0	3.11 ± 2.62	95.83 ± 3.89

6. CONCLUSIONS

This work evaluated the capacity to quantify the severity of the unbalancing fault of a rotating machine considering the angular velocity, differing to previous works, which the objective was the severity quantification, not considering the angular velocity, which may increase classification errors.

The experimental results observed the system classification performance varying the ranges of the 3 discrete levels of unbalancing fault severity over a well-established supervised machine learning technique known as random forest. The most consistent performance was obtained in the experiment 4, where the unbalancing force was divided into $[0; 39.47[$ N for low, $[39.47; 118.43[$ N for medium, and $[118.43; \infty[$ N for high fault severity levels. The system achieved the average performance of $93.73\% \pm 2.15\%$, with no class scoring below 92% accuracy, and the amount of data and standard deviation of the classes were relatively balanced with no value discrepancy, indicating that unbalancing force ranges chosen fit satisfactorily to the problem proposed in this work.

Although the proposed approach has shown to be efficient to solve the problem under analysis, it could be not confirmed whether the performance profile observed in the experiments was due to physics/mechanical nature of the problem or due to the intrinsic characteristics of the adopted classifiers. An investigation about this issue should be performed in future works.

The fault severity identification provides a method to identify how long a given machine part can be kept installed and working before it completely breaks down and stops. Thus this method characterizes an application for predictive maintenance.

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8. RESPONSIBILITY NOTICE

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