DINAME 2023 - Proceedings of the XIX International Symposium on Dynamic Problems of Mechanics,
A.S. De Paula, A.T. Fabro and M.R. Machado (Editors), ABCM.
Pirenópolis, Go, Brazil, February 26th to March 3rd, 2023

Machine Learning Based Fault Detection on Belt Conveyor Idlers

João L. L. Soares [1], Thiago B. Costa [1], Lis S. Moura[1], Walter S. Sousa[1], Alexandre L. A. Mesquita[1], André L. A. Mesquita[1], Danilo S. Braga[2]

[1] Federal University of Pará, Av. Brasília, s/n - Vila Permanente, Tucuruí - PA, 68.455-901.

[2] Dynamox, Rd. SC 401, 600, St. Parque Tecnológico Alfa, Florianópolis - SC, 88.030-909.

Abstract: Belt conveyors are used extensively in mining industry. Faults in their components can compromise the entire plant production. Machine learning-based techniques have been applied successfully for condition monitoring and fault diagnosis of industrial equipment. Therefore, in this paper a machine learning based method is presented for the diagnosis of faults in belt conveyor idlers. The method consists in applying wavelet transform to the measured vibration signals, extracting features from the processed signals and applying the Gradient Boosting method to classify the state of the idlers. Finally, with dimensionality reduction (PCA), the model achieved accuracy of 100% for two different failure modes.

Keywords: Machine learning, GBDT, Wavelet packet, Belt conveyor idler, Fault Detection.

INTRODUCTION

Belt Conveyors are equipment with a function to materials transport, and consist of the following basic components conveyor belt, drive system, gearbox, couplings and head pulley. Furthermore, it includes set of idlers, which support the loads in belt region of the equipment (ABNT NBR 6177, 2016).

These components that make up the conveyor may present dangerous zones while the equipment is in operation, including the risk of accidents. Situations such as the belt slipping over the idlers can cause overheating on the surface of the components, causing a risk of burns to workers or even the beginning of fire, if close to flammable materials. As such, idler bearing failure and excessive friction between the idler surface and the belt are listed among the root causes for these hazardous situations, accounting for 20 to 40 percent of events (Martin Engineering, 2016)

Also, according to Li et al. (2013), failures as slipping, deviation, and belt tearing occur, frequently, in belt conveyors due to faulty idlers. When a fault is detected in early stage, breakdowns can be avoided and, consequently, it is possible to reduce economic losses. However, accidents on belt conveyors are common, due to the difficulty of detection of potential failures at real time, resulting in late maintenance (Li et al., 2020).

In this context, the predictive analysis becomes a solution to monitor conditions and physical parameters of the equipment, as an alternative for maintenance planning (Pinto and Xavier, 2003). One of parameters is the vibration signal that provides information about failure modes in rotating components (Guilherme, 2016). Currently, an alternative is applying the machine learning to detect idler faults considering the possibility of problems solving by algorithms with signal processing techniques (Sharma, Umapathy and Krishnan, 2019). This paper proposes to apply the methodology Gradient Boosting Decision Tree to classify idlers conditions (normal or faulty) using the energy wavelet extracted of vibration signals, with the aid of PCA for dimensionality reduction.

THEORETICAL FOUNDATIONS

Idlers Failure Mode

The idler can be described as a roll assembly with the function of supporting the conveyor belt. It usually consists of three rolls: two rolls inclined in sideways and one centered roll horizontally (IPCD, 2022). Two of main failures mode are bearings faults and shell cover wear. The first one occurs in the following incorrect conditions: material, manufacture, handling, design, mounting, operation condition and lubricant (ISO 15243, 2004). About the shell cover wear, when a bearing fails and, consequently, an idler stop rotating, the component heats up by friction with the belt (Vásic, Stojanović and Blagojević, 2020). Figure 1 illustrates some kinds of failures idlers.

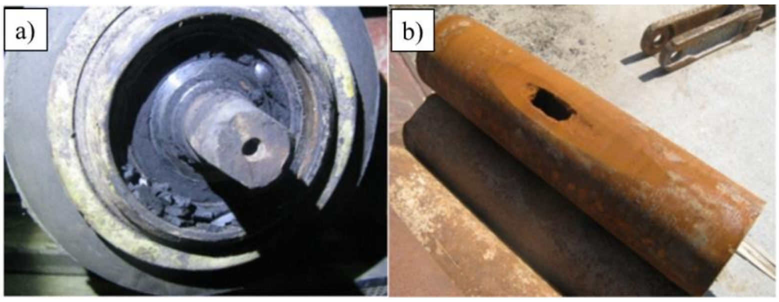

Figure 1 – Failure modes a) Bearing faults; b) Shell cover wear (Vásic et al, 2020)

Wavelet Packet Decomposition

Wavelet analysis was created in a revolutionary way by presenting a different view of the time-frequency spectrum together, in addition to being able to analyze data from non-stationary signals. With this, it was possible to change paradigms created on signal processing and mathematical models. Consequently, the Wavelet Transform (WT) uses non-stationary signals to extract information from the frequency variations of these signals and to detect their temporally and/or spatially located structures (Oishi et al., 2012).

The WT is a signal processing created as an alternative to substitute the Fourier Transform when is necessary to analyze periodicity of events at different scales of the temporal variability with no stationary series, as illustrated in Fig. 2. The analysis consists in extract information about amplitude variation in timeline (Santos, Freire and Torrence, 2013). Similarly, the WT uses the wavelet basis as the Fourier Transform uses the trigonometric basis. The big difference is that trigonometric bases use sinusoidal and unlimited functions with non-finite energy and constant amplitudes. On the other hand, wavelet bases are periodic of short duration and with zero value outside the domain (Silva, 2019).

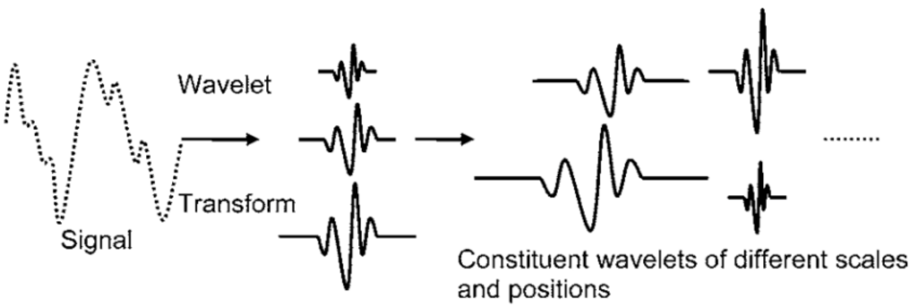

Figure 2 – Wavelet Transform (Sygouni, Tsakiroglou and Payatakes, 2006)

Due to the difficulty in identifying Wavelet functions, Multi-Resolution Analysis (MRA) was created in the 90's, which made it possible to create Wavelet functions under desired conditions of local regularity. From the MRA, families of wavelet functions were created, such as the Daubechies families, expressed in Fig. 3. Unlike most other Wavelet bases, the Daubechies family does not have an analytic expression, having functions expressed from iterative methods with scale relations (Oishi et al., 2012).

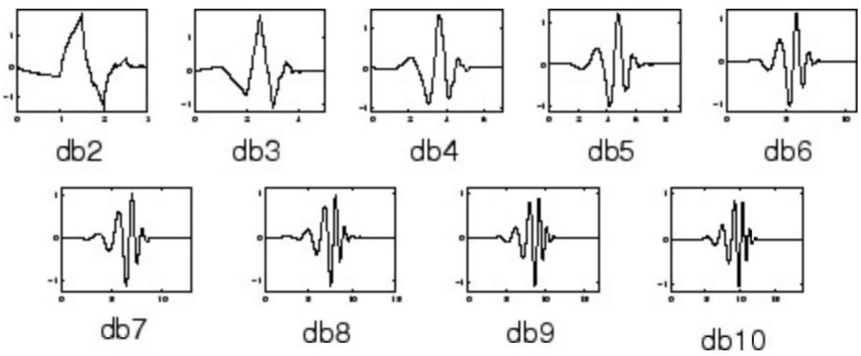

Figure 3 – Daubechies Families (Silva, 2019)

One of the wavelet analyses used, by WT, is the WPD (Wavelet Packet Decomposition) method, to which the signal decomposes into multiple bands from low to high frequency. Thus, for each band a corresponding energy is extracted from the spectrum (Li et al., 2013).

Energies from different frequency bands of a vibration signal can be used as features to enable fault identification using an intelligent classifier algorithm. The following Equations 1, 2 and 3 represent the function of Wavelet Packet, Wavelet Packet Coefficients and energy of band, respectively. The *n* represents the decomposition level, *j* is the scale factor, *k* is the translation factor and *f(t)* is the signal in time domain.

$$W_{j,k}^{n}(t) = 2^{\frac{j}{2}} W^{n}(2^{j}t - k) \tag{1}$$

$$w_{j,k}^{n} = \int_{-\infty}^{\infty} f(t) W_{j,k}^{n} dt \tag{2}$$

$$E(J,i) = \left\| w_{j,k}^{n} \right\|^{2} \tag{3}$$

Gradient Boosting Decision Tree

Gradient Boosting Decision Tree (GBDT) is a machine learning model used to regression and classification. In Decision Tree is created a 'root' of data samples where develops two branches to divide a feature in two groups to stablish a threshold value. The 'branch' will divide in another 'branches' until creation of exclusive collections or reduce the groups to few samples. The last 'branches', also, are named as 'leaves. With the Gradient Boosting is possible to optimize of Decision Trees accuracy with classification rules that minimize learning error (Liu et al, 2020).

According to Liu et al. (2021), a weak learner is found, in which a classification tree model is readjusted to the residuals of a predecessor model in order to minimize error between output values and true values. Thus, the final predictive model is obtained from the sum of the results of all models from the previous iteration.

The GBDT process consists of finding optimized parameters α and β through Eq. 4, where $F_m(x_i)$ is the prediction function obtained in the *mth* iteration. Initially, an initial weak classifier F_0 (Eq. 5) must be defined, starting from the constant β to reach the minimum value of the loss function $L(y, F_m(x))$ (Li et al., 2020).

$$(\alpha_m, \beta_m) = \arg\min_{\alpha,\beta} \sum_{i=1}^{N} (L(y_i, F_m(x_i)) + \beta h(x_i;\alpha)) \tag{4}$$

$$F_0 = \arg\min_{\beta} \sum_{i=1}^{N} (L(y_i, \beta) \tag{5}$$

In order to reduce the loss function, the *mth* classifier ($\beta_m h(x; \alpha m)$) is constructed in the gradient descent direction in Eq. 6. The sample data are fitted from the basic classifiers to obtain an initial model and the parameter α_m and the fit of $h(x; \alpha)$ in Eq. 7. With α_m calculated it is possible to calculate Eq. 8 with the current model weight. With the parameters established, the prediction function (Eq. 9) is calculated, being updated after each iteration until the convergence condition (Li et al., 2020).

$$-g_m(x_i) = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right], F(x_i) = F_{m-1}(x_i), i = 1, \dots, N \tag{6}$$

$$\alpha_m = \arg\min_{\alpha,\beta} \sum_{i=1}^{N} [-g_m(x_i) - \beta h(x_i;\alpha)]^2 \tag{7}$$

$$\beta_m = \arg\min_{\alpha,\beta} \sum_{i=1}^{N} L([y_i, F_{m-1}(x) + \beta h(x_i;\alpha_m)]^2) \tag{8}$$

$$F_m(x) = F_m(x) + \beta_m h(x_i;\alpha_m) \tag{9}$$

About a loss function, when applied in computational methods, it is customary to use a log-loss function, whether for binary or multi-class classifications and iterative procedure depends on the number of estimators defined to initial setup. In addition, the maximum depth of the tree must be evaluated to limit the number of nodes evaluated, according to the input variables (Scikit Learn, 2022).

Principal Component Analysis

Principal Component Analysis (PCA) is the best-known algorithm applied for dimensionality reduction. Dimensionality reduction is used to solve problems with greater agility by minimizing the number of features addressed, without significantly compromising the information analyzed, that is, preserving the degree of significance of the information. PCA projects the dataset onto the hyperplane (Fig. 4) with the closest identified proximity and that preserves a greater amount of variance between the data (Géron, 2019).

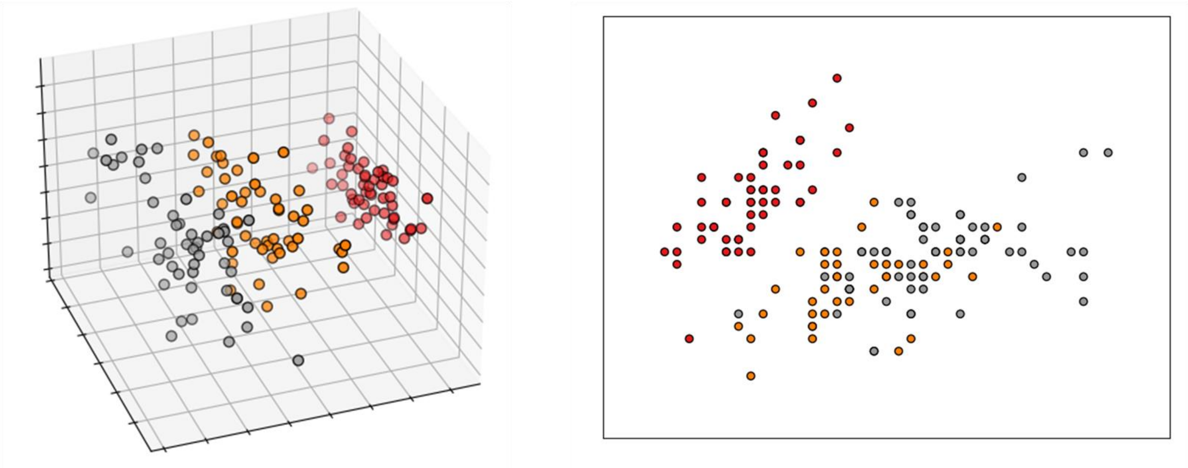

Figure 4 – Hyperplane projection (Scikit Learn, 2022)

EXPERIMENTAL AND COMPUTATIONAL PROCEDURE

Vibration signals were collected from a belt conveyor with components characteristics described in Table 1. The measurement points were distributed on the sides of the three idlers frames as illustrated in Fig. 5. 180 vibration measurement data were acquired under normal and faulty conditions of the unloaded belt conveyor (i.e. without material). The signals were processed to compose 720 data samples for the classifier algorithm. In faulty condition, it was introduced one defective roller in the same side of the measurements. Also, it was introduced two different failure modes: bearing faults and surface wear (Fig. 6).

Table 1 – Technical specifications of belt conveyor drive system

Item	Manufacturer	Frequency (r/min)	Reduction
Engine (1 hp)	WEG®	1620	-
Gearbox	Pierine®	108	1:15
Pulley	Imepel®	108	-
Idler	Imepel®	930	-

Figure 5 – Experimental test

Vibration data were collected by an accelerometer Teknikao®: model NK 30. They were recorded in the SDAV software, also from Teknikao®, with frequency range of 1 Hz – 2 kHz and test time per sample of 6,55 s (8192 points). After tests, the data was upload to an algorithm created in Python 3.7® where the following libraries were imported: Scikit-learn (Machine Learning), NumPy (Mathematical functions), Pandas (Data analysis), PyWavelets (WPD) and Matplotlib (Visual resources).

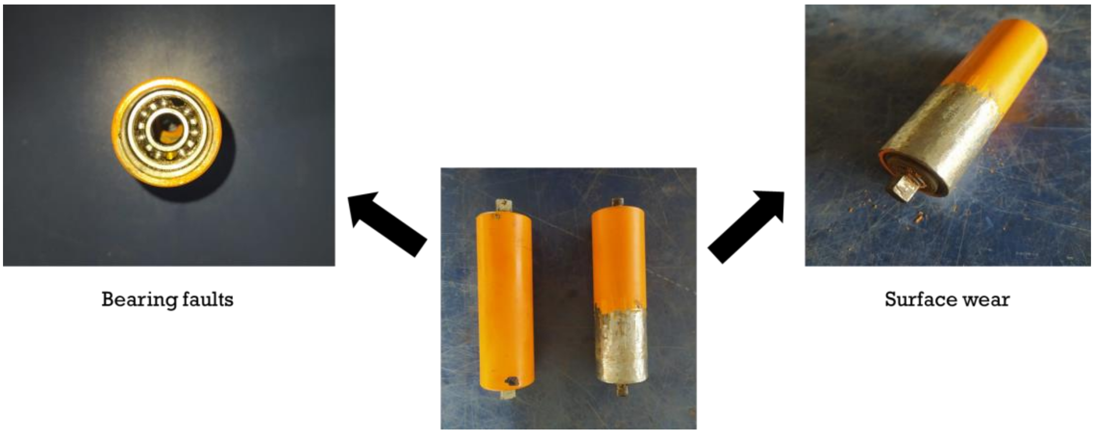

Figure 6 – Idler failure mode

The features were extracted by calculation of normalized quantization energy wavelet in 16 different frequency bands with wavelet family Daubechies 8 (db8). In this application, it was used the energy percentage of each frequency band. To find the most relevant features, it was applied the Principal Components Analysis (PCA) for dimensionality reduction (Brunton and Kutz, 2019). Finally, it was introduced a machine learning by GBDT, where was tested different numbers of estimators, to classify the idler faults and determine the accuracy, that was maximized by cross validation divided in 5 folds. The procedure is represented by Fig. 7. It was applied depth 2 to visualize the decision tree.

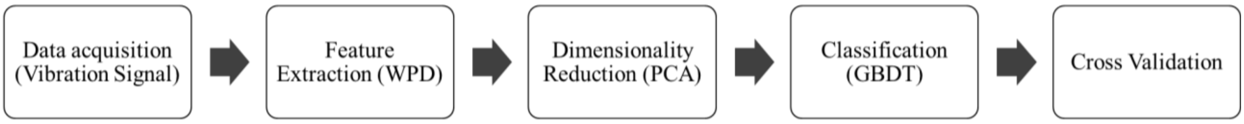

Figure 7 – Analysis methodology

RESULTS AND DISCUSSIONS

With the PCA application in wavelet energy percentage features, we observe that the highest degree of significance in the first two features for both failure modes are noticeable. Figure 8 demonstrates that in both failure modes, just, first frequency band represents above 99% of significance in relation to all features.

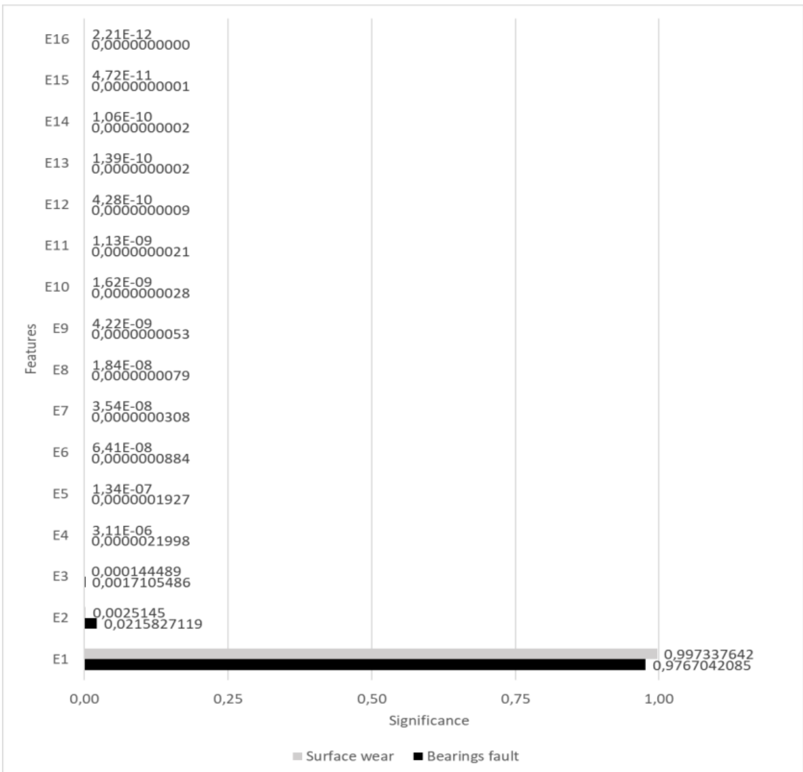

Figure 8 – Significance per feature (PCA)

So, to speed up response time for machine learning, it was selected the three most significant energy bands as features to GBDT algorithm. Between 10 and 200 estimators were evaluated for the GBDT process, where the accuracy remained above 70% as illustrated in Fig. 9. The classification of bearing defects obtained an accuracy of 100% from approximately 120 estimators, while the diagnosis for surface wear only showed an accuracy of 100% from 140, demonstrating that bearing defaults requires greater learning resources to be effective. Both defects had 90% accuracy from 60 estimators.

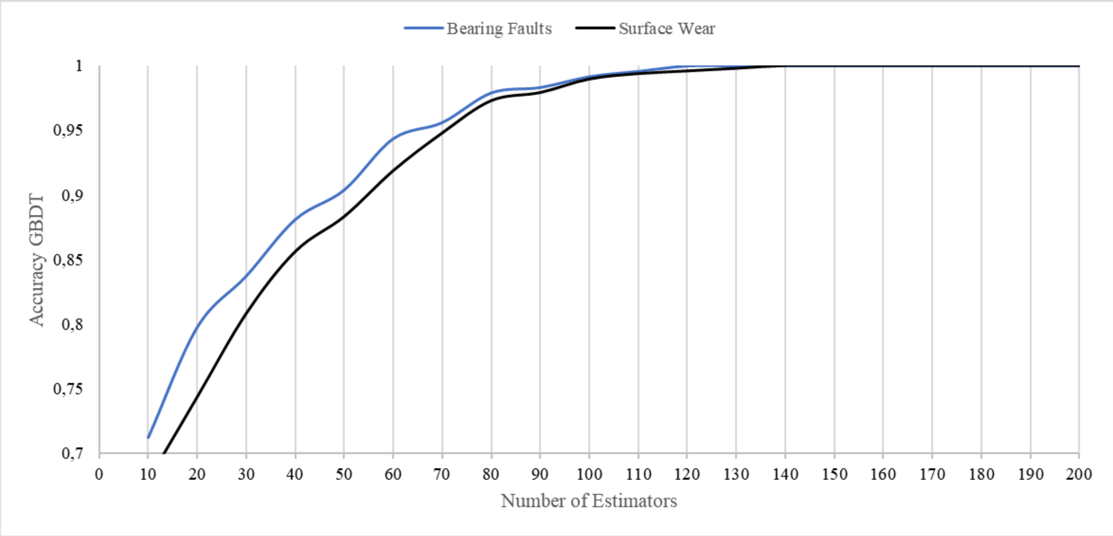

Figure 9 – Accuracy GBDT

As a result of the learning of the idler failure detection system, through the Gradient Boosting Decision Trees technique, 100% accuracies were found, as shown in Table 2. With this result, it is expected to detect if there is failure in the idler where the accelerometer is positioned.

Table 2 – Fault Diagnosis Score to 140 estimators

Failure mode	Bearing fault	Surface wear
Accuracy (%)	100,0	100,0

A confusion matrix was created to best understanding about the system classification of idlers conditions. Figure 10 illustrates the tool where, ‘0’ represents ‘Normal Conditions’ and ‘1’ represents ‘Faulty Conditions’. Furthermore, it was demonstrated that machine learning created a model, based on GBDT, without error in the secondary diagonal as false prediction, while revealing the success in correct diagnosis of the presence or absence of defects in the rollers, through the main diagonal. Despite the cross-validation, the application of test data is undoubted to verify the effectiveness of the algorithm. Thus, it avoids the generalization of the model for exclusive prediction of the training data.

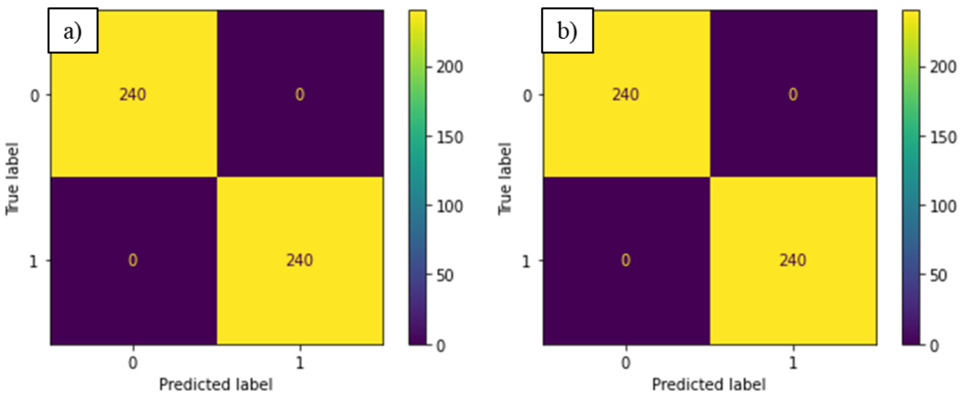

Figure 10 – Confusion matrix: a) Bearing faults; b) Surface wear

By maximum depth, it is possible to visualize the behavior of the trees, as the loss function is minimized. Figure 11 represents the last decision tree, with parameters already optimized by GBDT, for classifying both defects.

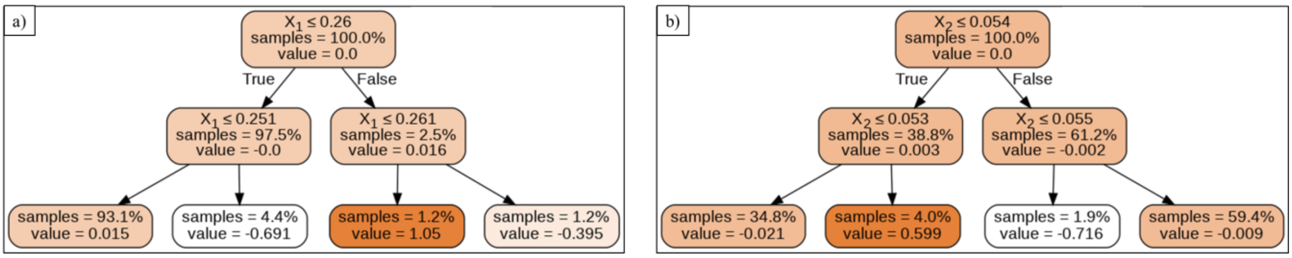

Figure 11 – Decision Tree: a) Bearing faults; b) Surface wear

CONCLUSIONS

The proposed fault detection method using the GBDT technique with characteristics extracted from wavelet energy reached an accuracy of 100% from 140 estimators. During dimensionality reduction, it was noted that three of the sixteen frequency bands have significance above 99%.

For bearing failures and hull surface wear, the machine learning model achieved 100% performance for both defects. Despite similar accuracies, the bearing defect appeared to need a smaller number of estimators, in relation to the wear defect, indicating greater ease of diagnosing the failure with less computational resources. Therefore, the system proved to be effective in detecting faults in rollers in the vicinity of the vibration collection. For future work, it is recommended to increase the database to expand the classification of defects, according to the direction, and perform the measurements with the belt conveyor loaded with particulate material.

ACKNOWLEDGMENTS

This paper was supported by Dynamox S.A.

REFERENCES

ABNT NBR 6177, 2016. Transportadores contínuos – Transportadores de correia – Terminologia.

Brunton, S. L. and Kutz, J. N., 2019. "Data-driven science and engineering: machine learning, dynamical systems, and control". Câmara Brasileira do Livro, Rio de Janeiro, 209-224 p.

Géron, A., 2019. "Mãos à Obra: Aprendizado de Máquina com Scikit-Learn & TensorFlow". Cambridge University Press, Cambridge, 21-25 p.

Guilherme, J., 2016. "Análise de Vibração – Tipos de Sinais, Transformada de Fourier e PSD". http://ensus.com.br/analise-de-vibracao-tipos-de-sinaistransformada-de-fourier-e-psd/.

IPCD, 2022. White paper: "Belt Conveyor Idler Life: Factors and Conditions".

ISO 15243, 2017. "Rolling bearings — Damage and failures — Terms, characteristics and causes".

Li, G. et al, 2020. "Tool wear state recognition based on gradient boosting decision tree and hybrid classification RBM". The International Journal of Advanced Manufacturing Technology, Vol. 110. pp. 511-522.

Li, W. et al, 2013. "Design of Online Monitoring and Fault Diagnosis System for Belt Conveyors Based on Wavelet Packet Decomposition and Support Vector Machine". Advances in Mechanical Engineering, Vol. 5. https://journals.sagepub.com/doi/10.1155/2013/797183.

Li, X. et al, 2020. "Fault Diagnosis of Belt Conveyor Based on Support Vector Machine and Grey Wolf Optimization". Mathematical Problems in Engineering. https://www.hindawi.com/journals/mpe/2020/1367078/.

Liu, X et al, 2020. "Acoustic signal-based fault detection on belt conveyor idlers using machine learning". https://www.sciencedirect.com/science/article/abs/pii/S0921883120301898?via%3Dihub.

Liu, Y et al, 2021. "Research on the fault analysis method of belt conveyor idlers based on sound and thermal infrared image features". https://www.hindawi.com/journals/complexity/2021/3734560/.

Martin Engineering. "Foundations for Conveyor Safety: The Global Best Practices Resource for Safer Bulk Material Handling". Illinois, 2016

Oishi, C. M. et al., 2012. "Introdução ao Mundo das Wavelets". Sociedade Brasileira de Matemática Aplicada e Computacional, Vol. 62, pp. 144.

Pinto, A. K. and Xavier, J. A. N., 2003. "Manutenção: função estratégica". Ed. Qualitymark, Rio de Janeiro.

Santos, C. A. G., Freire, P. K. M. M. and Torrence, C., 2013. "A Transformada Wavelet e sua Aplicação na Análise de Séries Hidrológicas". Revista Brasileira de Recursos Hídricos, Vol. 18, No. 3, pp. 271-280.

Sharma, G., Umapathy, K. and Krishnan, S., 2020. "Trends in audio signal feature extraction methods". Applied Acoustics, Vol. 158. https://www.sciencedirect.com/science/article/abs/pii/S0003682X19308795?via%3Dihub.

Silva, P. C. L., 2019. "Aplicação das Wavelets de Daubechies em Conjunto com o Método de Propagação Vetorial de Feixes na Análise de Estruturas Fotônicas". PhD, UFRN, Brazil/RN.

Scikit Learning, 2022, “sklearn.decomposition.PCA”, https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

Scikit Learning, 2022, “sklearn.decomposition.PCA”, https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html

Sygouni, V., Tsakiroglou, C. D. and Payatakes, A. C., 2006. “Capillary pressure spectrometry: Toward a new method for the measurement of the fractional wettability of porous media”. Physic of Fluids, Vol. 18. https://www.researchgate.net/publication/200029482_Capillary_pressure_spectrometry_Toward_a_new_method_for_the_measurement_of_the_fractional_wettability_of_porous_media.

Vásic, M., Stojanović, B. and Blagojević, M., 2020. “Failure analysis of idler roller bearings in belt conveyors”. Engineering Failure Analysis, Vol. 117. https://www.sciencedirect.com/science/article/abs/pii/S1350630720314229?via%3Dihub.

RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.