11138 Session 2022
A1 – Rotating Electrical Machines
PS2 – Asset Management of Electrical Machines

Anomaly Detection in Regulation Ring from Bulb Turbines using Deep Learning

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SUMMARY

The large demand in the energy market requires that the Operation and Maintenance (O&M) in hydroelectric plants often take place under extreme conditions, as a consequence, it is common for several types of failures to occur. One way to increase the productivity of a hydroelectric plant is to ensure that it is fully operational. The occurrence of failures can lead to downtime and cause financial losses to the company that operates the plant. It is therefore in the interest of energy companies to find a way to avoid these types of failures and replace corrective and preventive maintenance with predictive maintenance. Since hydroelectric energy is acquired through the conversion of hydraulic energy supplied by a flow of water into electrical energy, the flow's contact with the turbine generates unwanted loads and vibrations throughout the generating unit, resulting in fatigue and anomalies. The distributor actuation is made by hydraulic pistons that transmit the movement to the regulating ring and with time they can present defects or anomalous behavior. Using a generator unit database containing vibration signals from sensors located in the regulation ring, features were extracted for mapping normal and anomalous behavior. These features are provided to a model based on an unsupervised machine learning approach, more specifically Deep Learning. A Deep Autoencoder was used to develop a proposed approach, this type of model consists of two symmetrical artificial neural networks. Anomaly detection was done using the reconstruction error of the signals obtained by the Deep Autoencoder. The results show that the proposed method based on Deep Learning is effective and robust in detecting anomalies in the control rings of bulb turbines, using unlabeled vibration data.

KEYWORDS

Regulation Ring; Bulb Turbines; Anomaly Detection; Deep Learning.

INTRODUCTION

Hydroelectric power is a renewable source that is ancient and widespread throughout the world. Recently, the high demand in the energy market creates, in the context of Operation and Maintenance (O&M), extreme regimes in hydroelectric plants and, therefore, the concern with downtime avoidance and early detection of faults is constant. One way to increase the productivity of a hydroelectric plant, aiming at the aforementioned aspects, is to ensure that it is fully operable through optimized predictive maintenance practices.

The occurrence of failures can result in downtime and bring financial, material, and even human losses to the company that operates the plant. So finding a way to avoid these types of failures, by replacing corrective and preventive maintenance with predictive maintenance is in the interest of energy companies.

Concerning the turbines of interest in this study, Bulb-type generating units usually comprise mainly composed of buried parts, generators, water guides, main shafts, bearings, runners, and concrete components. All working parts are on the same axis, which is a horizontal-shaft turbine.

The distributor actuation is made by hydraulic pistons that transmit the movement to the regulation ring, which is coupled to a lever system that controls the position of the guiding vanes. As hydroelectric energy is acquired through the conversion of hydraulic energy provided by a flow of water into electric power, the contact of the flow with the turbine generates unwanted loads and vibrations of the whole generating unit, thus causing fatigue and anomalies [1].

Through vibration monitoring of machines with adequate systems to perform it, it is possible to verify if there are anomalies in the vibration spectrum correlated with this failure mode within the machine. With proper analysis, valuable information can be obtained about the machine's health conditions.

Finally, Deep Learning is part of a wide family of learning methods (Machine Learning) based on data representation and has been quite successful in advancing the state of the art in several areas [2], and in the electric sector its use in practice for fault diagnosis has also been advancing.

Studies involving supervised learning methods require labeled data of the failure modes that one wants to monitor, that is, the data samples are previously identified as healthy or failures so that the models can be trained. As most hydroelectric power plants operate continuously and uninterruptedly, it is not trivial to collect data under all machine conditions, that is, normal and faulty conditions.

To contribute to the solution of this problem, in this work an unsupervised Deep Learning approach is proposed. The proposed deep learning model can automatically capture useful signal information and detect anomalies in the regulation ring of Bulb-type turbines.

METHODOLOGY

As illustrated in the diagram in Figure 1, the functioning of the proposed methodology is divided into four stages: data acquisition and processing, feature extraction, model training, anomaly detection and results in validation.

Figure 1 - Diagram of the proposed methodology.

Data acquisition

In this study, data was used from the signal registers of the regulation ring of the distributor of the Generating Unit (GU) 38 at the Santo Antônio HPP located in Porto Velho, RO, Brazil. The adjustment ring has 2 proximeters, radial at 120° (DAR-120) and 240° (DAR-240) that measure displacement, sampled at 20kHz. The database has records collected between 2020 and 2021. Figure 2 shows the example turbine with the regulation ring where the sensors are located.

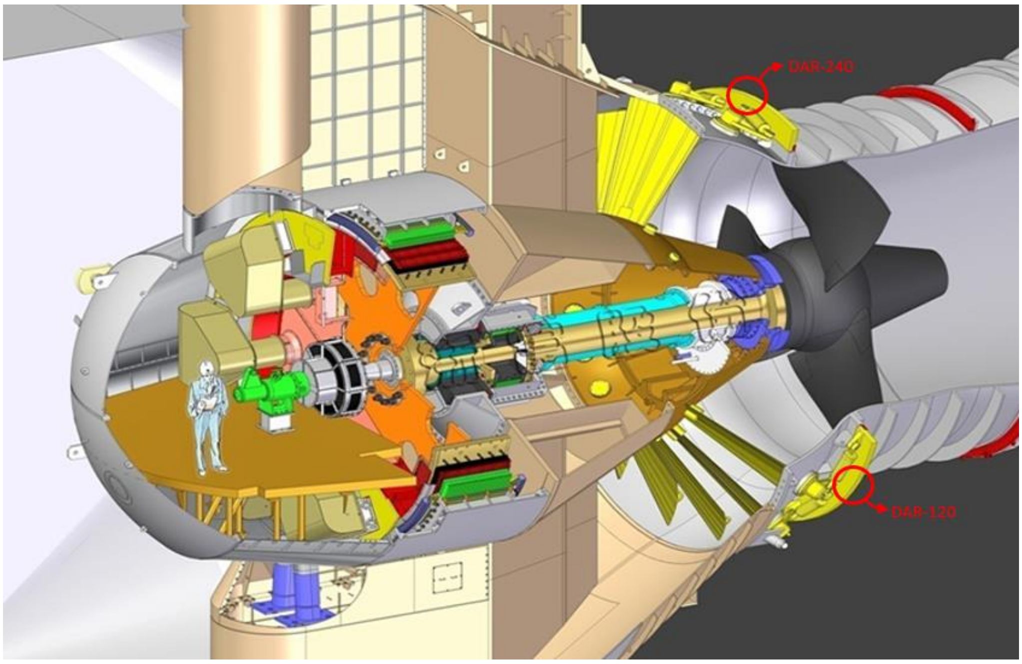

Figure 2 – Generating unit. Source: [3], modified by author

In Figure 3, an example of the displacement signal of the DAR-120 and DAR-240 sensors can be seen. In total, around 1400 signals were acquired.

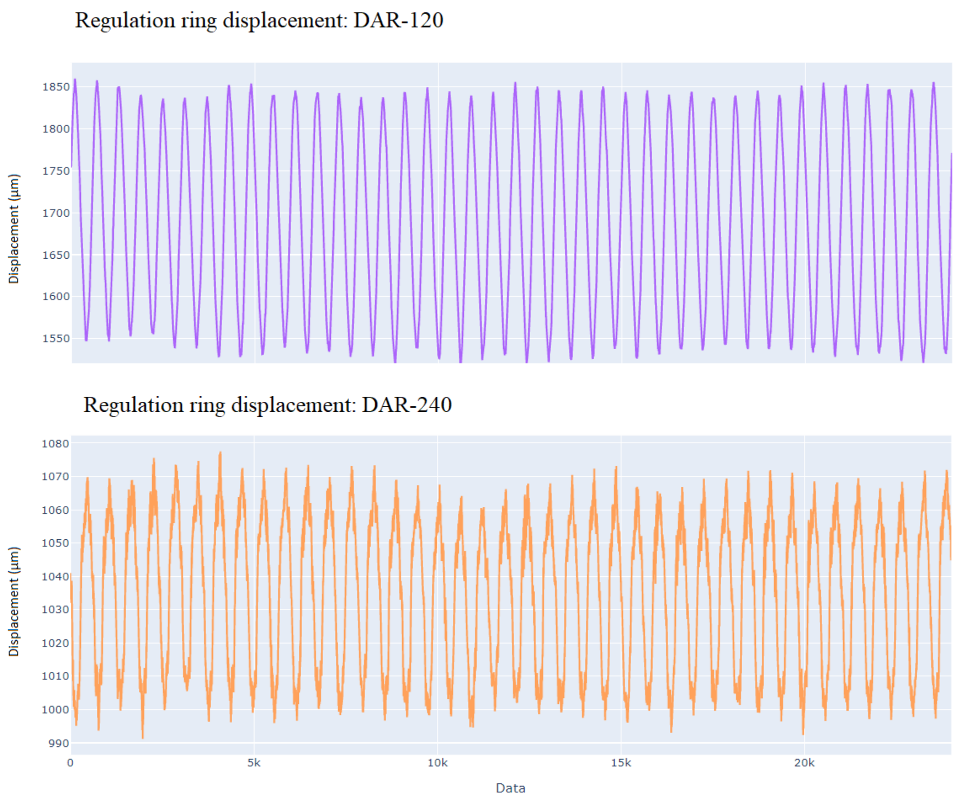

Figure 3 - Example of a signal for DAR-120 and DAR-240 sensors.

Feature Extraction

According to [4], given a large initial set of physical variables, the feature extraction process consists of generating a new set of variables with better discrimination capacity and smaller size than the initial set. Another important factor to be highlighted is that generally this new generated set ends up losing its physical meaning. As presented in [5], feature extraction has a very important role in the field of digital signal processing, given that it provides a more succinct numerical representation of the signal as it is built up and, consequently, the characterization of it in the context of machine learning becomes viable.

The features are extracted in two domains : time and frequency, due to the information contained in both domains. The 34 extracted characteristics are presented below.

Feature Extraction – Time Domain

Let $x_i(n)$, n = 1, ... ,N be the sequence of samples contained in the analysis i-signal.

Zero-Crossing Rate (ZCR): it can be defined as the zero crossing rate of a sampled frame, that is, the rate of change of the signal. It is defined by the number of times the numerical changes from positive to negative and vice versa, divided by the frame length. Equation 1 presents the expression that determines the ZCR:

$$Z[x_i(n)] = \frac{1}{2N}\sum_{n=1}^{N}|sgn[x_i(n)] - sgn[x_i(n-1)]| \qquad (1)$$

where $sgn()$ is defined by the function presented in Equation 2.

$$sgn[x_i(n)] = \begin{cases} 1, & if\ x_i(n) \geq 0 \\ -1, & if\ x_i(n) < 0 \end{cases} \qquad (2)$$

Energy: this feature provides information about the intensity and activity of the signal., its energy can be obtained by Equation 3.

$$E[x_i(n)] = \sum_{n=1}^{N}|x_i(n)|^2 \qquad (3)$$

Entropy: it is a term with many meanings, but in the area of information theory it usually refers to the average uncertainty ratio that a process produces, which is measured by the well-known discrete equation (Equation 4) of Shannon entropy.

$$H[x_i(n)] = \sum_{n=1}^{N} x_i(n) \log_a x_i(n), \qquad (4)$$

where a is the base of the logarithm.

Feature Extraction – Frequency Domain

To extract spectral features, the Discrete Fourier Transform (DFT) is first applied to x(n), resulting in sequence called X(f).

Spectral centroid: it is a measure that identifies the center of energy of a signal. The equation for the spectral centroid can be seen in Equation 5.

$$Centroid = \frac{\sum_{k=1}^{N} kX(k)}{\sum_{n=1}^{N} X(k)} \qquad (5)$$

The result of this operation informs the average DFT index in which the largest portion of the spectrum's energy is contained.

Spectrum entropy:according to [6], the spectral entropy can be calculated similarly to the signal entropy, but this time in frequency domain.

Spectral Flux: can be understood as a measure of the spectral shift that occurs between two successive frames and can be calculated as the difference quadratic between two consecutive windows.

$$F_t = \sum_{k=1}^{L} (X_t(k) - X_{t-1}(k))^2 \quad (6)$$

where X_t(k) t is the L-length normalized magnitude of the Fourier transform at the current frame t.

Spectral Rolloff: was extracted from the vibration signals. It refers to frequency under which a certain percentage (cutoff) of the distribution of magnitude of the spectrum is contained [6].

Mel-Frequency Cepstral Coefficients (MFCC): they are a type of cepstral representation of a given signal. The MFCCs are very popular and widely used in systems where it is necessary to interpret information contained in signs. In this work, 13 filters were applied to extract the MFCC, thus, totalling 13 extracted features.

Chroma vector: is a representation of the spectral energy of the signal made through a vector of 12 elements [8]. In this work, the 12 elements for each signal were extracted.

Anomaly Detection - Deep Autoencoder

Detecting anomalies is a crucial task in implementing machine learning models. Anomaly detection refers to the identification of patterns that are not in accordance with the expected normal behavior [9]. Anomaly detection in unsupervised models tries to find anomalies in the data without using any type of label.

To develop the proposed approach, we used a deep autoencoder (Deep Auto Encoder - DAE), which has the task of reconstructing/synthesizing the input data in the output. A deep autoencoder is composed of two symmetrical artificial neural networks, where one represents encoding and the other decoding.

The first network, after learning, encodes the input variables in a set called the latent space, with a representation of lesser dimensionality, which forces the network to learn the most salient characteristics of the training data. Meanwhile, the second decodes/reconstructs into synthesized equivalent variables. Learning the dataset leads the autoencoder to reconstruct the input variables approximating them to the probability distribution of the feature space [10].

From this, the reconstruction error is used as a metric to measure the degree of normality or anomaly of the data, as they are proportional quantities. Anomalies are detected by analysing the error in the reconstruction of vibration signals, that is, the difference between the acquired signals and those reconstructed by the neural network.

The encoder can be represented by coding Equation 7.

$$h = f(x) \quad (7)$$

The decoder can be represented by decoding Equation 8.

$$r = g(h) \quad (8)$$

The autoencoder in general can be described by Equation 9, where you want r as close as the original input x.

$$g(f(x)) = r \tag{9}$$

Figure 4 presents the architecture of the deep autoencoder proposed in this work.

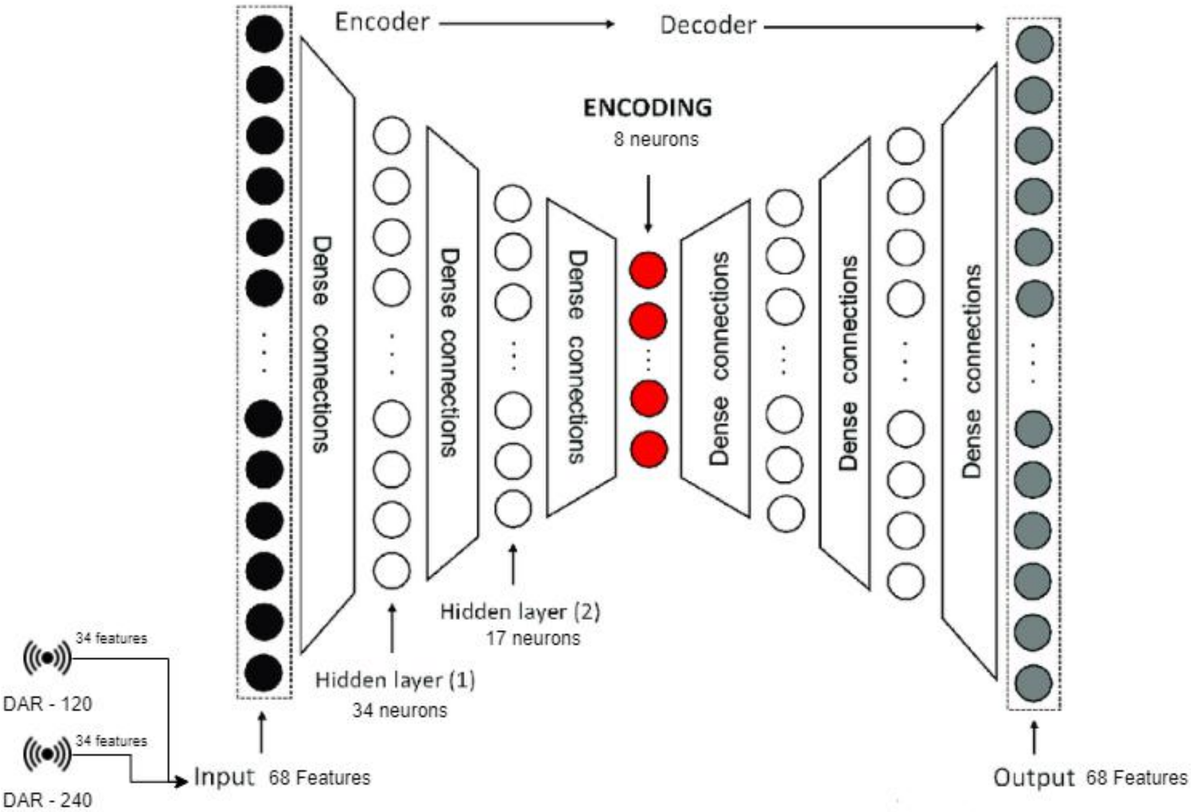

Figure 4 - Architecture of the proposed deep autoencoder model. Source: [11], modified by author

Evaluation metrics

To assess the quality of the proposed approach in detecting anomalies, evaluation metrics such as accuracy and precision were used. In this classification concept, we have some metrics that indicate the errors and successes of a model, compared to the expected result.

- True Positives (TP): correct classification of the positive class;
- False Negatives (FN): error in which the model predicted the negative class when the real value was positive class;
- False Positives (FP): error in which the model predicted the positive class when the real value was negative class;
- True Negatives (TN): correct classification of class negative.

Equation 10 shows how the accuracy metric is calculated, this metric indicates an overall performance of the model. Among all the rankings, how many did the model correctly classify.

$$\text{accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{10}$$

Equation 11 presents the precision metric, this metric indicates among all the classifications of the positive class that the model made, how many are correct.

$$\text{precision} = \frac{TP}{TP + FP} \tag{11}$$

RESULTS

The first step of the results was to analyze the learning curve throughout the training of the model. A learning curve is a graph of the model's learning performance over experience or time. Figure 5 shows the learning curve in the training data in the validation data.

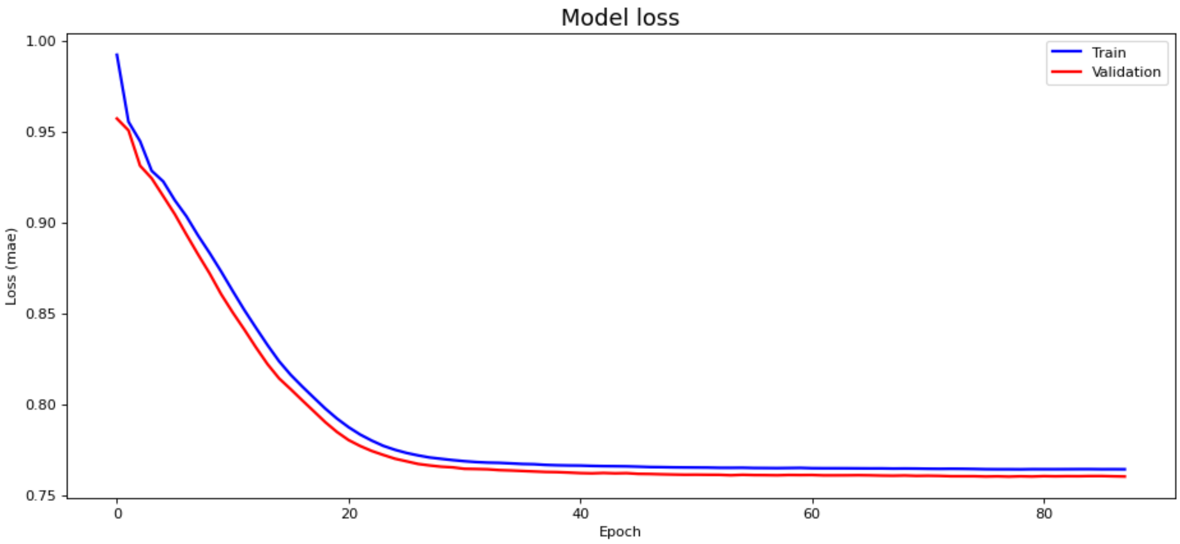

Figure 5 - Model learning curve (Train and Validation).

In it we can observe a good fit, where identified by a loss of training and validation that decreases to a point of stability with a minimum gap between the two final loss values. Model loss will almost always be less in the training dataset than in the validation dataset. This means that we should expect some gap between the lost train and validation learning curves.

According to information collected from technicians responsible for the maintenance of the generating unit, points of anomalies were registered over time. Anomalies can be seen in Figure 6.

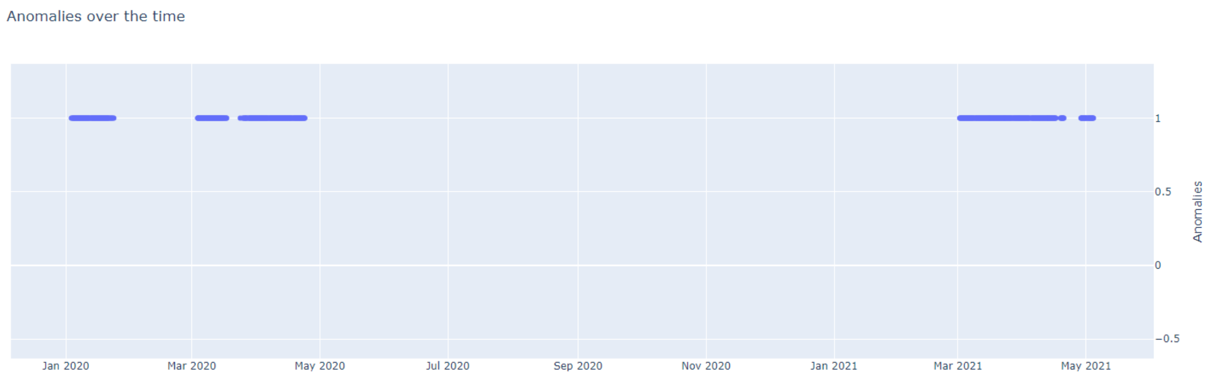

Figure 6 - Anomalies detected by field technicians.

The model's response in relation to the anomaly detection can be seen in Figure 7. For a better visualization, a sum of the anomalies over time (accumulation) was performed to compare with data obtained from the plant technicians.

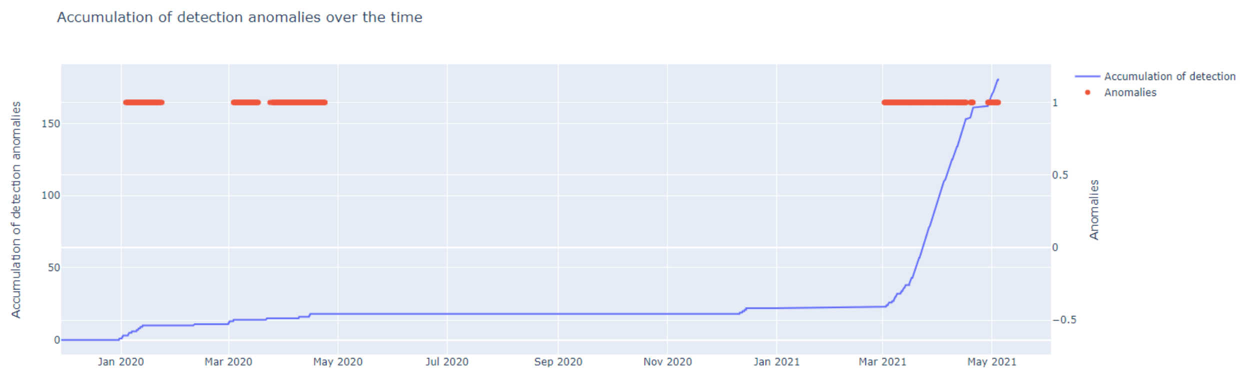

Figure 7 - Accumulation of anomalies over time.

Based on the equations that assess the quality of the model in detecting anomalies, it can be observed that the model obtained 92% precision and 87% accuracy in detecting anomalies, which can be considered good values.

It is evident that the results of the detection carried out by the model were validated with field tests, thus being able to say that the model was able to detect the anomalies in the regulation ring. Based on the results obtained and metrics for detecting and accumulating anomalies over time, we can say that the model would be a great tool to help those responsible for maintaining the regulation ring. Considering that the accumulation of anomalies can point out high loads and unwanted vibrations in the generating unit, mainly in the regulation ring, causing fatigue and defect. These accumulations can be indicative for possible preventive maintenance on the regulation ring.

CONCLUSION

The results confirm that the proposed approach based on deep machine learning is effective and robust in detecting anomalies in the regulating ring of bulb type turbines using the deep autencoder method with unlabeled vibration data.

In addition, the proposed approach could be used as a tool to assist maintenance teams with the objective of replacing corrective maintenance with preventive maintenance, considering that the accumulation of anomalies indicates something out of normality in the regulation ring. This approach can contribute to predictive maintenance in the Brazilian electricity sector.

ACKNOWLEDGMENT

This work is an integral part of the R&D project ANEEL PD-06683-0220/2020 entitled “Machine Learning System for analysis and diagnosis of failures in hydroelectric plants based on process, vibration and acoustic data”.

BIBLIOGRAPHY

[1] Cutrim, Túlio Humberto Pinheiro, and Rhaicon Ramos Lourenço. "Análise de fadiga de pinos de cisalhamento do anel de regulação de unidades hidrogeradoras." (2011).
[2] Zhou, Chong, and Randy C. Paffenroth. "Anomaly detection with robust deep autoencoders." Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining. 2017.
[3] Bulb hydro turbine for Hydropower Project. Available in: http://www.huahydro.com/product/bulb-hydro-turbine/. Accessed on: 17 Dec. of 2021.
[4] Cardoso, João Francisco de Sousa. "Predição da qualidade na indústria de fundição injectada." (2001).
[5] Rao, Preeti. "Audio signal processing." Speech, Audio, Image and Biomedical Signal Processing using Neural Networks. Springer, Berlin, Heidelberg, 2008. 169-189.
[6] Misra, Hemant, et al. "Spectral entropy based feature for robust ASR." 2004 IEEE International Conference on Acoustics, Speech, and Signal Processing. Vol. 1. IEEE, 2004.
[7] Peeters, Geoffroy. "A large set of audio features for sound description (similarity and classification) in the project." Ist Project Report 54.0 (2004): 1-25.
[8] Bartsch, Mark A., and Gregory H. Wakefield. "Audio thumbnailing of popular music using chroma-based representations." IEEE Transactions on multimedia 7.1 (2005): 96-104.
[9] Chandola, Varun, Arindam Banerjee, and Vipin Kumar. "Anomaly detection: A survey." ACM computing surveys (CSUR) 41.3 (2009): 1-58.
[10] Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016.
[11] Jiménez, Manuel, et al. "Galaxy image classification based on citizen science data: a comparative study." IEEE Access 8 (2020): 47232-47246.