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Asset Management of Electrical Machines PS2

Paper 11138

Anomaly Detection in Regulation Ring from Bulb Turbines using Deep Learning

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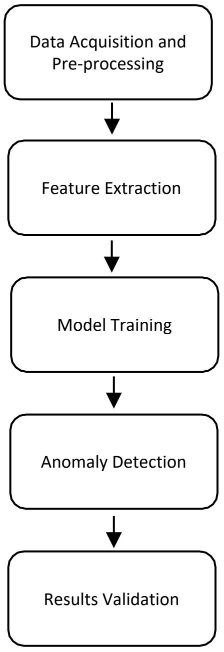
Motivation

- 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 are 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 regulation ring is part of a system that moves the guide vanes from the wicket gate. With the movement of the regulation ring, more or less water passes through the turbine. 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.
- To contribute to the solution of this problem, Deep Learning approach is proposed.
- 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, and in the electric sector, its use in practice for fault diagnosis has also been advancing.
- The proposed deep learning model can automatically capture useful signal information and detect anomalies in the regulation ring of Bulb-type turbines.

Figure 1 – Regulation ring

Method/Approach



Data acquisition

- In this study, data was used from the signal registers of the regulation ring from the Generating Unit (GU) 38 in Santo Antônio HPP located in Porto Velho, RO, Brazil.
- The database has records collected between 2020 and 2021. In total, around 1400 samples were acquired.
- The regulation ring has 2 proximeters attached at 120° (DAR-120) and 240° (DAR-240) that measure displacement, sampled at 20kHz.

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Feature Extraction

- For each vibration signal, the feature extraction is performed.
- Thirty-four features were extracted for each vibration signal.

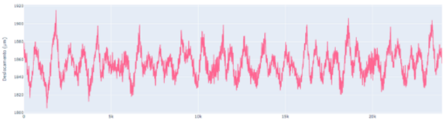

Figure 2 – Example vibration signal

N - Features	Features
1	Zero Crossing Rate
2	Energy
3	Entropy of Energy
4	Spectral Centroid
5	Spectral Spread
6	Spectral Entropy
7	Spectral Flux
8	Spectral Rolloff
9–21	MFCCs
22–33	Chroma Vector
34	Chroma Deviation

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.
- 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.

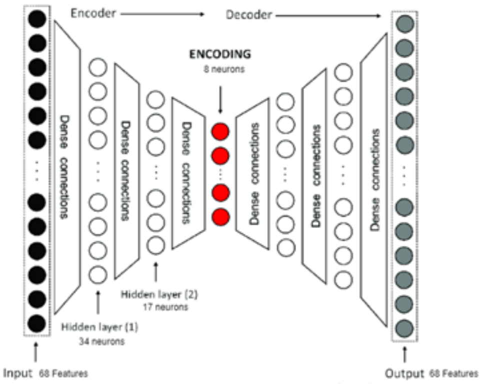

Figure 3 – Model Deep Autoencoder

Evaluation

- 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.

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

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

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Results and Discussion

- The first step of the results was to analyze the learning curve throughout the training of the model. Figure 5 shows the learning curve in the training data and in the validation data.
- 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 loss train and validation learning curves.
- For a better visualization, a sum of the anomalies over time (accumulation) was performed to compare with data obtained from the plant technicians. The model's response in relation to the anomaly detection can be seen in Figure 7.
- Based on the equations that assess the quality of the model in detecting anomalies, it can be observed that the model obtained **87% accuracy** and **92% precision** in detecting anomalies, which can be considered good values.

Conclusion

- The results of the detection performed by the model were validated with the technical field team, thus being able to say that the model was able to detect the anomalies in the regulation ring (for the specific generating unit).
- Based on the results obtained and metrics for detecting and accumulating anomalies over time, we can say that the model would be a 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 of possible preventive maintenance on the regulation ring.
- It is good to point out these are the results of initial studies, for the generalization to other generating units have not been tested yet.

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".

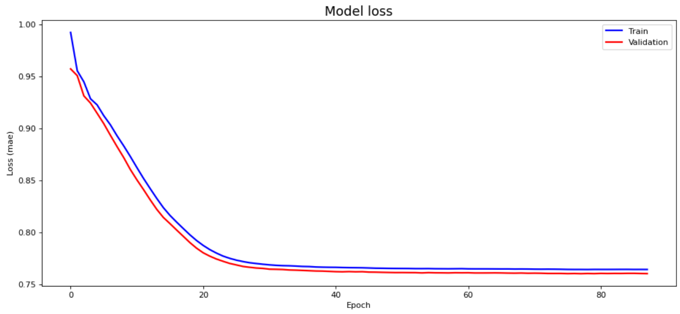

Figure 4 – Model learning curve (Train and Validation).

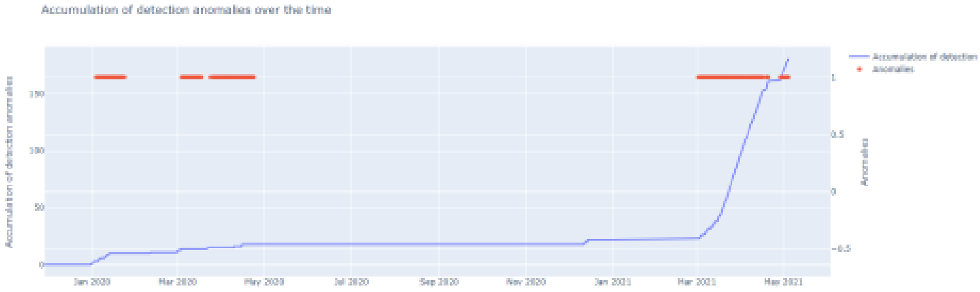

Figure 5 – A sum of the anomalies over time (accumulation)

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