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ASSET PREDICTIVE MAINTENANCE IN HYDROELECTRIC POWER STATION BASED ON CONVOLUTIONAL AUTOENCODER AND NOVELTY DETECTION TECHNIQUES.

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Abstract. Traditionally, maintenance of hydroelectric generation assets is carried out within preventive programs, gradually adjusting to current operating conditions and situations that lead to corrective maintenance, resulting in high maintenance costs for hydroelectric plants. Therefore, predictive maintenance is crucial in the electric power generation sector. This study contributes to this challenge by providing a methodology for detecting faults in assets associated with the Esmeralda Hydroelectric Power Station of the company Central Hidroeléctrica de Caldas EPM Group (CHEC). To this purpose, the data obtained by the Supervisory Control and Data Acquisition (SCADA) system is averaged over 10 minutes, and then, a convolutional autoencoder acts like a data descriptor. Several advantages of the proposed methodology include: (i) The model training uses only data of the healthy asset to address the data imbalance problem; (ii) The proposed methodology has been validated using CHEC SCADA data, demonstrating its robustness under actual operating conditions; (iii) Reliable predictions are achieved based on continuous monitoring of variables, where the mean squared error metric and the analysis of the weighted fault trend consider the asset's criticality; (iv) And finally, early alerts are provided with enough time, enabling the identification of the assets with potential fault condition and allowing to take the proper maintenance decisions. This methodology significantly enhances the maintenance practices for hydroelectric power generation, leading to increased efficiency, reduced costs, and improved asset reliability.

1 INTRODUCTION

With the growth of Industry 4.0, companies have begun to incorporate data-based technologies to support different processes, such as maintenance, changing from preventive maintenance to predictive maintenance [1]. The data provided by a Supervisory Control and Data Acquisition (SCADA) system offers valuable information for developing effective maintenance strategies to extend the useful life of assets, reduce unexpected stops, reduce costs, increase plant safety, and increase the reliability and availability of assets, among others. However, having data is not enough if it is not accompanied by inference or artificial intelligence models that perform appropriate analysis and increase the speed of analysis and reporting of timely information [2, 3]. In the traditional field, artificial intelligence systems involve distinguishing various classes or types of failures. However, in an industrial environment, most data corresponds to a state without machine failures [4]. In this scenario, the machine learning techniques are focused on describing the normal operating condition of the machine as best as possible, such that it can detect atypical behaviors associated with potential failure indicators.

Several projects present the combination of data acquisition systems and artificial intelligence to perform fault detection in industry. Yet, an important aspect relies upon appropriately including these technologies in the industrial process. In [3] proposes to combine an artificial neural network (ANN) with data mining (DM) techniques, such as association rule mining (AR), to improve asset performance and energy efficiency. However, it is mentioned that data availability and quality are critical aspects for successfully implementing this approach. Additionally, monitoring asset performance can become complex in operational situations where operating conditions are diverse or when it is not feasible to monitor the condition of assets. Meanwhile, [5] proposes a novel health monitoring approach for wind turbines based on SCADA data and uses an optimized deep belief network model to improve fault detection. Thus, the proposed approach is based on SCADA data, which may limit its applicability in cases where this data type is unavailable. Furthermore, it is highlighted that the performance of the proposed model may depend on the selection of parameters, which may require a certain level of tuning and optimization [6]. In [7], it is presented an analysis of the strengths and weaknesses of big data and real-time data processing technologies for predictive maintenance cases in Industry 4.0. However, it primarily focuses on analyzing open-source technologies, which may limit its applicability to environments that rely on proprietary commercial solutions. For [8], the integration of Industry 4.0 technologies in Total Productive Maintenance (TPM) practices in large manufacturing companies in Brazil shows that this integration entails benefits and barriers related to the attributes of the Theory of Diffusion of Innovation. [9] develops a reference architecture for an intelligent maintenance management system that meets the visions and requirements of Industry 4.0, focusing on the oil and gas sector. Likewise, it is based on a specific case study, which limits its generalization to other industrial contexts. It also points out that there are challenges to overcome, such as the need for a standardized reference architecture and a solid business model in the context of Industry 4.0.[10] proposes a complete methodology to guarantee the maintenance of industrial models based on data, addressing the problem of conceptual changes (concept drift) and optimizing costs and restrictions. Limitations of this article include the need for more research on the identification of conceptual differences and the relationship between the characteristics of those changes and their detection, as well as the need for an optimal methodology for implementing the proposed solutions.

The Central Hidroeléctrica de Caldas CHEC Grupo EPM (located in Colombia) is a company dedicated to the generation, transmission, and distribution of electrical energy, with hydroelectric generation being one of its most significant sources of income, since an unexpected stoppage results in loss money. Therefore, the company has decided since 2019 to install a SCADA system to monitor the generation units of the Esmeralda plant. In this sense, there is currently a large amount of data that can be used to make correct decisions regarding maintenance. This work addresses the cleaning, organization, and analysis of data, as well as the classification of anomalies that occur in the plant. The proposed methodology is described in the following steps: i) Data cleaning and imputation were conducted to ensure no missing data or outliers were present. ii) Data normalization was performed using the Min-Max strategy to account for variations in data magnitudes. iii) Four statistical measures were calculated, and those retaining the highest variability were selected to represent the signals. iv) A convolutional autoencoder network was designed and rigorously tested. As a result of this applied process, it is possible to detect the occurrence of a failure early and identify the assets that generate it. This identification allows the maintenance team to act promptly and precisely, improving the company's competitiveness and guaranteeing the availability of electrical energy for the citizens it supplies.

2 METHODS

2.1 Convolutional autoencoder model

Convolutional Neural Networks (CNNs) are hierarchical models where convolutional layers alternate with subsampling layers, and they have hidden properties that preserve connections between neighboring and spatial inputs. Each group of layers within a CNN has specific functions. For instance, the initial layers learn to detect edges and curves, and subsequent layers combine them to recognize geometric shapes, culminating in identifying the image [11]. In general, due to the complexity and capacity of CNNs, they are spatially invariant, meaning that CNNs learn to recognize image features in any image.

An auto-encoder (AE) gets the input to be encoded in a low-dimensional space and then decodes it to reconstruct the original input [12]. In that sense, we define the input $\boldsymbol{x}(t) \in \mathcal{L}^2(T)$ be a signal set, lasting $T \in \mathbf{R}$ measured from M sensors, and compute its latent representation by $h = f_{(W,b)}(x) = \sigma(Wx + b)$. From this mapping, the auto-encoder principle is used to reconstruct the input by calculating $y = f_{(W^T,b')}(h) = \sigma(W^T h + b')$. Therefore, we reconstruct y_i for each of the inputs x_i using the mapping h_i and optimizing the weights in such a way as to minimize the cost function.

The combination of an autoencoder principle with CNNs is named a convolutional autoencoder (CAE) model. In such a way that CNNs allow us to locate relevant features in the input. Thus, CAEs preserve spatial localization by sharing their weights among all input locations [13]. To estimate the feature map of an input channel x_j we use the following equation:

$$h_j = \sigma(x * W_j + b_j) \tag{1}$$

where σ is the hyperbolic tangent activation function, $*$ represents the 2D convolution and b_j is distributed to the whole map. Each filter is designed to specialize in features of the entire input, so the reconstruction of the latent representation uses a single bias. Thus, the reconstruction is estimated by:

$$y = \sigma(\sum_{j \in H} h_j * \hat{W}_j + d) \tag{2}$$

where the latent feature map is represented by H, the flip operation is defined by $\hat{W}$ and d is the bias per input channel. Finally, we minimize the error of the cost function $J(\theta)$ using the mean squared error as shown is as follow:

$$J(\theta) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{3}$$

where θ are the learned parameter values or weights $(\theta_1, \theta_2, \ldots, \theta_k)$, n is the number of training samples, $\hat{y}_i$ is the prediction for the ith training sample using the parameters θ, and y_i is the class label for the ith training sample. As mentioned before, CNNs try to reconstruct the spatial patterns of the input in the output, and hence, the model is trained with images that do not contain faults. In fact, since we are seeking to achieve early fault detection, the model output will have a low error if the input image does not contain fault. Conversely, the output will have a high error if the input image contains any faults.

2.2 IMSE Metric

It is commonly understood that a matrix of pixel values can represent an image, and there are numerous approaches to dissimilarity assessment between them. Therefore, this study employs the image mean square error (IMSE) to measure the difference between the input and output images generated by the CAE. In (4), provides a detailed explanation of the IMSE:

$$IMSE = \sum_{i=1}^{N}\frac{(a_i - b_i)}{N} \tag{4}$$

where a_i and b_i are the values of the ith pixel of two images, A and B, respectively, while N is the total number of pixels in the matrix. When the IMSE is used to establish a threshold, a high amount of false positives may be generated, resulting in decreased methodology effectiveness. To address this issue, the exponentially weighted moving average (EWMA) technique can be used to compute the persistence of samples over the threshold. The technique smooths the residual errors and maintains the data trend while accounting for data aging by assigning lower weights to older data. The EWMA value is computed by:

$$\hat{T}_{t+1} = \hat{T}_t + \lambda(T_t - \hat{T}_t) \tag{5}$$

where $\hat{T}_{t+1}$ represents the predicted value for time $t+1$, while $\hat{T}_t$ represents the predicted value for the instant of time t. T_t, on the other hand, represents the actual SCADA value measured at time t. (5) contains the parameter λ, which determines the memory depth of the EWMA computation. The value of λ is related to the parameter s, known as spans, which denotes the time interval over which the EWMA is computed. To determine the value of λ, we apply the following equation:

$$\lambda = \frac{2}{s+1} \tag{6}$$

where λ can take values between 0 and 1, and s must be greater than or equal to 1. It is important to obtain weekly residual errors even after the implementation of EWMA, particularly when using spans based on a weekly window, resulting in 7-day average residual errors. To determine if a residual error indicates a fault alarm or not, an additional step is necessary.

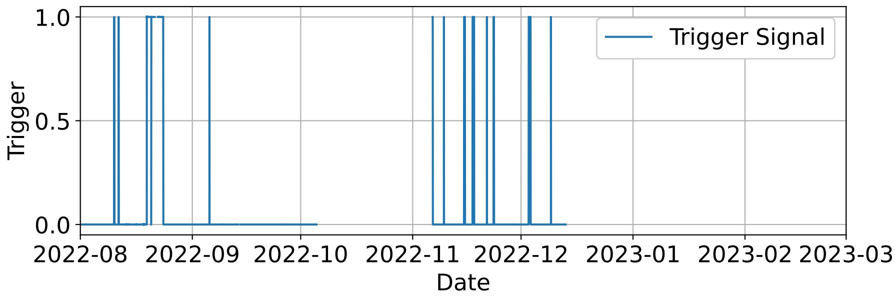

Figure 1: Signal Trigger with Missing Data.

Specifically, the mean (μ) and standard deviation (σ) of the averaged errors over the training dataset are calculated to establish a threshold. This threshold differentiates between normal and abnormal behavior in the system, and it is calculated by $th = \mu + \kappa\sigma$, being κ the spacing of σ to μ.

3 EXPERIMENTAL SET-UP

3.1 Data set description

The data utilized in this study was sourced from the generation unit of the Caldas Hydroelectric Power Plant (CHEC). We selected 87 signals associated with the generation system to predict potential system failures. These signals encompass parameters such as oil level, temperature, pressure, active power, reactive power, trip signals, among others. Data collection was between January 29th, 2022, and July 30th, 2023, spanning slightly over a year with a one-minute sampling frequency. Notably, within this timeframe, a generation unit failure was reported on March 28th, 2022. It is worth highlighting that the applied methodology relies on the normal operational behavior of the generation unit. Specifically, it was trained exclusively on healthy SCADA data to learn the typical behavior of the assets.

3.2 Data cleaning and imputation

Working with actual data can present several challenges, such as the presence of missing data and outliers. How these challenges are handled could significantly influence the data quality and, therefore, the predictive model's success. In this regard, it is mandatory to carry out a preprocessing stage of the SCADA data, which consists of a series of steps designed to treat and clean the data before using them in the predictive model. For handling potential missing data, a data imputation process was executed to address this issue. In this sense, the data includes a quality label that indicates whether the stored value accomplishes or not, therefore, data labeled that does not accomplish the quality criteria is removed from the time series to prevent errors in the model. Figures 1 and 2 display a selected trigger and temperature signals over a 7-month time interval, showing the necessity to perform missing data imputation. To cope with this, we use linear regression to preserve the signal's trend and ensure data completeness. Figures 3 and 4 show the signals with the imputed data generated by linear regression, demonstrating the coherence of the imputed data with the original signal.

Next, we applied a mean filter to each continuous signal to achieve signal smoothing and minimize abrupt changes while preserving the underlying trend. In fig. 5, we provide a compar-

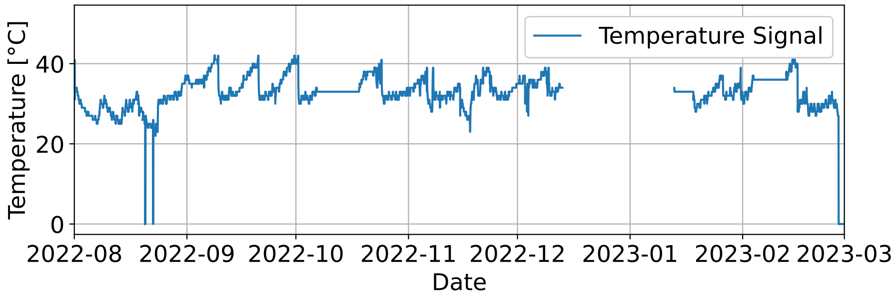

Figure 2: Temperature Signal with Missing Data.

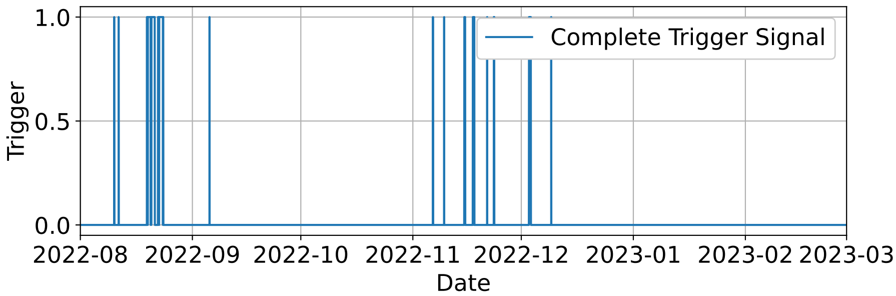

Figure 3: Complete data-trigger signal using linear regression.

ative analysis of the temperature signal. It is possible to see that before filtering (solid line), the signal exhibits specific peaks that disrupt its trend. After applying the mean filter (dashed line), these peaks conform to the expected behavior of the signals. However, it is worth noting that the signal still contains peaks that may be regarded as outliers.

As mentioned, the data should represent the machine under normal operating conditions. Therefore, we removed the records corresponding to the reported failure dates and performed data imputation. In this study, we separate the continuous signals from the trigger signals (binaries), so for the continuous signals, we use a technique known as piece-wise cubic Hermite interpolation polynomial [14], and for the binary signals, we take the last measured value and use it to complete the data. These techniques are used to preserve the data monotonicity, ensuring that the data values follow a coherent sequence. Additionally, this technique guarantees the continuity of the first derivative, meaning that changes in the data values will be smooth and gradual rather than abrupt. For detecting outlier data points in continuous signals, we calculated the mean and standard deviation for each of the signals to determine the detection threshold. The upper and lower thresholds are fixed as the mean plus/minus three times the standard deviation. In fig. 6, the temperature signal with outliers is depicted (solid line), as well as the same signal after removing the anomalous data points, highlighting the suppression of signal spikes.

3.3 Data split

In this study, actual SCADA data was used, which was divided into three sets: training, validation, and testing. The main objective was to develop a fault prediction method not influenced by operational or environmental variables. To achieve this, data from all working

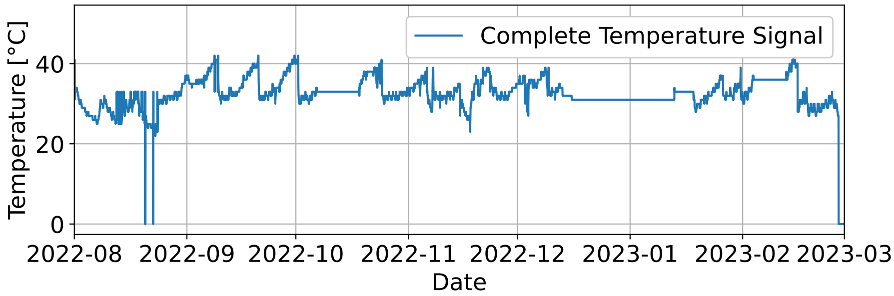

Figure 4: Temperature signal with complete data employing linear regression.

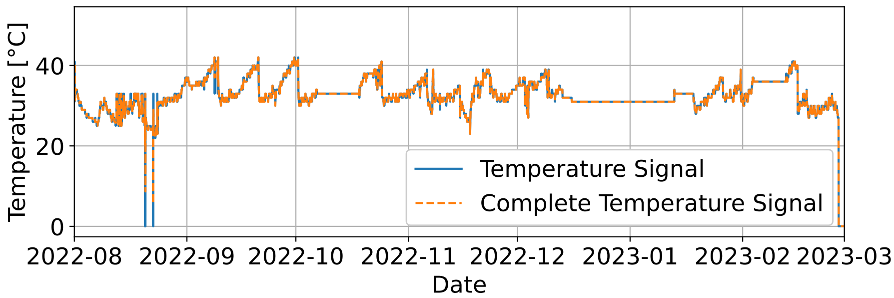

Figure 5: Comparison of the temperature signal before and after mean filtering.

situations was included in the training and testing sets. Additionally, each data set was divided into segments of one year to avoid any anomalies detected due to seasonality. Specifically, the training and validation sets covered the period from January 2022 to January 2023, which amounts to 525,600 samples. Approximately 70% of the data (360,000 samples) was allocated to the training set, while the remaining 30% (165,600 samples) was reserved for validation. For this analysis, we will perform outlier removal only on the training and validation sets. This choice stems from our intention to glean insights into the healthy operational patterns of the plant. On the other hand, the testing set corresponded to a period from January 2023 to July 2023, with a total of 214,560 samples. As for the test set, we refrain from removing outliers, as doing so may result in the loss of valuable information crucial for damage detection [15].

3.4 Data normalization

In a dataset, variables may come from various sources and therefore have different magnitudes. If this situation is not properly addressed, variables with larger scales may have a disproportionate influence on the model output. Therefore, a fundamental task in data preprocessing is normalization. In this study, the Min-Max normalization strategy was used. It is important to note that this normalization was applied initially to the training dataset. Then, using the maximum and minimum values obtained from that dataset, the validation and test datasets were normalized. This was done to avoid information leakage between datasets and to avoid adding biases to the model. In summary, data normalization should be applied after the division of datasets to avoid problems.

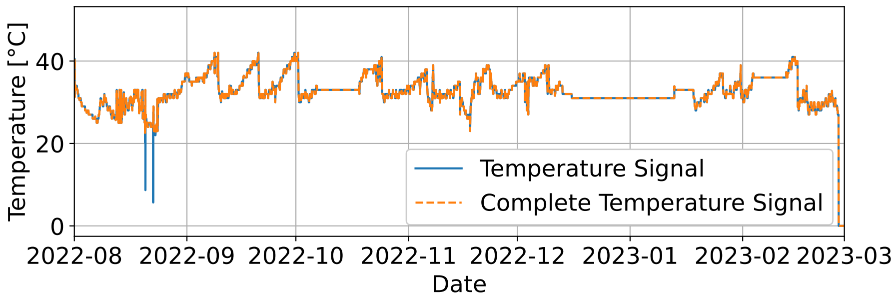

Figure 6: Temperature signal with outliers (solid line) and after removal of anomalous data points (dashed line) demonstrating the suppression of signal spikes.

3.5 Feature selection

We computed key statistical measures for each variable, including the mean, minimum, maximum, and standard deviation, within 10-minute time segments (equivalent to 10 samples per segment). In this approach, variables exhibiting greater variance are considered to convey more significant information. It is important to notice that our analysis focuses on individual variables. Consequently, we calculated the variance for each statistical measure and identified those variables displaying the highest variance. Subsequently, we organized this data into a matrix where the rows represent the number of samples in each dataset (training, validation, or test), whereas the columns correspond to the selected variables.

3.6 Data reshaping

In this work, we aim to convert time series data into image information, which requires defining the temporal length of each series (in our case, one day) to create a 2D image dimension. Then, a CAE designed to capture the temporal features of the image and reconstruct the input is used. As there are 87 inputs and each day contains 144 samples (with a sampling frequency of 10 minutes), the constructed image is of size 12x12x1, equivalent to an image of size 12x12 with one channel. In total, we obtained 250 training matrices, 115 validation matrices, and 183 test matrices after data reshaping.

3.7 Setup of the CAE model

The model utilized in this study consists of two 2D convolutional layers and two 2D transpose-convolutional layers. All hidden layers employ the ReLu function, while the output layer uses the Sigmoid function to scale the data within the range of [0, 1]. The Adamax optimization technique was implemented to fine-tune the model parameters, with some of its hyperparameters previously established. The training model sets an initial learning rate of $\alpha = 0.1$, which is a commonly used value. Additionally, we set the parameter $\rho = 0.95$ to control the accumulation rate of the second-order moments. and a value of $\epsilon = 1e^5$. The number of epochs is a crucial hyperparameter that determines the number of times the model undergoes training. If the model undergoes training with a small number of epochs, it may not achieve the best performance. Conversely, if it is trained with a large number of epochs, both the computational cost and training time may increase, and the model may even suffer from overfitting. Therefore, to balance these factors, 2500 epochs were selected. Finally, we train a CAE model for each of

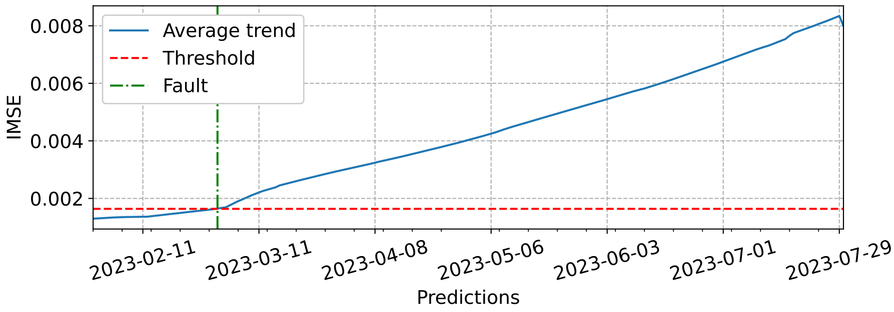

Figure 7: Average trend of the test data set for the hydroelectric power plant generation unit.

the signals.

4 RESULTS AND DISCUSSION

Once the CAE models were fine-tuned, we proceeded with the evaluation using the test dataset. Given that we have an error associated with each of the signals, we calculated the average IMSE to establish the fault trend. The trend of the average fault is illustrated in fig. 7. Furthermore, The fault threshold, denoted by the red dashed line, was determined as explained in section 2.2. It was computed by averaging the errors from both the training and validation datasets and then adding 3 standard deviations ($\kappa = 3$). This behavior aligns with expectations, as failures were reported after March 4th, and the trend exceeded the failure threshold on March 1st, thereby achieving early anticipation of the potential fault.

To determine the signals that caused the overall trend to exceed the threshold, we calculated the average error for each of the models and selected the top 5 signals with the highest error. In fig. 8, it can be observed that 4 out of the 5 signals exhibit a similar trend to the overall pattern, with a growing behavior over time. Furthermore, the remaining signal (dashed red line with a star) shows a distinct trend, where the error initially increases but later stabilizes at a specific value, resulting in a deceleration in its growth.

We calculated the percentage of change for the previously selected 5 signals to identify which one deviates the most from the normal machine operation. As illustrated in fig. 9, the signal with the most significant change is *ESPLG1CU15MBRE_PRERCGILSE*, followed closely by *ESPLG1CU15MBRE_PRERCGDLSE* and *ESPLG1CU15MBRE_PREACGILSE*. This analysis is crucial to understanding the deviations that might indicate potential issues in the system.

We have successfully identified that the five aforementioned signals are associated with the same asset, which is classified as a highly critical component within the power generation unit. Failure of this asset has the potential to result in unexpected downtime. This information holds significant value for the maintenance team, as it allows them to pinpoint the asset with a potential issue and prioritize its inspection based on its level of criticality.

In further discussing the results, this methodology has proven effective in early fault detection by focusing on the deviations of individual signals from normal machine operation. The ability to identify and prioritize assets with potential issues, especially those of high criticality, enhances maintenance strategies by enabling proactive intervention before catastrophic failures occur. This approach contributes to reducing operational disruptions and maintenance costs, thereby optimizing the reliability and performance of the system. Furthermore, the method's

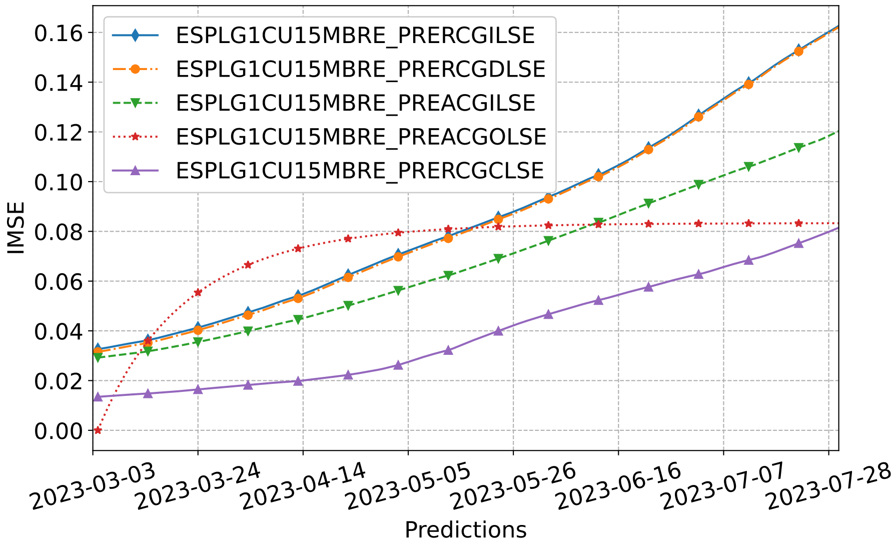

Figure 8: Trend of the 5 signals with the highest image mean square error (IMSE) after exceeding the mean fault threshold.

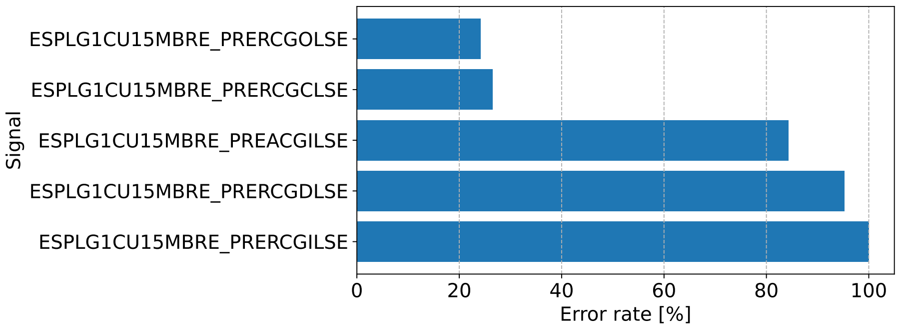

Figure 9: Top 5 signals with the highest errors when exceeding the failure threshold.

adaptability and effectiveness in real-world operational conditions are evident, offering a promising tool for predictive maintenance in industrial settings. However, it's essential to acknowledge the importance of continuous data monitoring and periodic model retraining to maintain its accuracy and reliability as machine conditions evolve over time

5 CONCLUSIONS

This paper presented a novel fault early detection strategy for a hydroelectric power plant generation unit based on a convolutional autoencoder (CAE) model. The proposed methodology aims to provide operators with early fault alarms, allowing them to plan maintenance operations and reduce downtime. The CAE model was trained and validated using only healthy SCADA data. In contrast, a test dataset containing both healthy and faulty data was used to evaluate the methodology's ability to detect abnormal behavior properly. This ensures that the model is robust to operational conditions. The results demonstrate that the detection system generates minimal false alarms, as the residues in some sensors exceed the threshold but show a decreasing trend. However, applying predictive maintenance to complex systems, such as hydroelectric power plants, remains an open challenge. The proposed methodology can contribute to developing more efficient and reliable fault detection systems for complex systems, ultimately reducing maintenance costs and improving system performance.

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