Degradation detection for steam turbines

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Abstract. This work presents a novel method for regime estimation and degradation extrapolation for steam turbines. The proposed approach combines statistical techniques with machine learning algorithms to accurately predict the remaining useful life of the turbine components. The method was tested on experimental data from a steam turbine operating under varying regimes and showed promising results in terms of accuracy and efficiency. The findings of this study have implications for the maintenance and management of steam turbines, as it provides insights into predicting the lifetime of components, allowing for more effective maintenance practices and potentially extending the lifespan of the equipment.

Keywords. time series analysis, neural networks, predictive maintenance

1.1 Introduction

Steam turbines play a vital role in the global energy landscape, serving as the backbone of power generation plants worldwide. Ensuring the optimum performance and reliability of these turbines is essential to meet the ever-growing demand for energy and mitigate potential risks associated with equipment failure. To address these challenges, accurate assessment of steam turbine operating regimes and their degradation rates is necessary for effective maintenance and management practices.

Recent advancements in computational methods and data analytics have opened new possibilities to improve the state-of-the-art in steam turbine prognostics. Machine learning and statistical techniques provide promising tools for developing robust and efficient models capable of predicting component degradation under varying operating conditions. However, the complexity of steam turbines and the inherent variability in component wear present significant challenges that require tailored approaches to address effectively. The aim of this approach is to minimize maintenance costs and extend the turbine's availability by monitoring and health prognostics of a turbine. The health prognosis often include not only online anomaly detection but also remaining useful life (RUL) prediction.

In a past decade an area of machine and deep learning received a heavy boost which also effected an area of anomaly detection [1]. However relatively small research works appear in the area of steam turbines predictive maintenance and not succeeding in keeping up with modern capabilities. At 2010 Salahshoor et al. [2] used a support vector machine (SVM) classifier with an adaptive neuro-fuzzy inference system (ANFIS) to detect several steam turbine fault types, which included actuator fault, thermocouple sensor fault, fouling. For RUL prediction Khelif computed health indicators of the steam turbine time series via a linear regression with training on the 0 and 1 labels assigned correspondingly to normal and abnormal exploitation periods [3]. The authors use this model to transform historical data into a one-dimensional vector, divide it into windows and then apply the same transformation to the online data and calculate distances between online vector and historical vectors via dynamic time warping (DTW) technique to estimate RUL. In 2017 Khelif et al. [4] proposed to use Support vector regression to directly predict RUL from sensor time series data. Dhini et al. [5] utilized a fully connected neural network (FCNN) classifier basing on the features after principal component analysis (PCA) transformation. Authors also worked in a supervised learning paradigm aiming at prediction of 4 previously occurred (in historical data) fault types: misalignment, rotor browing, blade erosion and cracked case. The resent work was made by Que et al. [6]. The authors use a binary classifier based on Extreme gradient boosting (Xgboost) trained on the time series of the normal and fault work periods labeled as 0 and 1 correspondingly. For the RUL prediction authors used DTW similarly.

All the mentioned approaches require episodes of fault behavior in historical data. However various unsupervised techniques exist and might be used in fault detection of steam turbines while the data on usage of these techniques for steam turbines is lacking. Here we describe our framework for unsupervised anomaly detection for a steam turbine using recent approaches. We also propose a method of unsupervised RUL prediction for each sensor separately basing on their exploitation thresholds. This task could not be solved by classical methods like time series forecasting with SARIMA [7], Facebook Prophet [8] and similar algorithms. The cause is the transition of the overall system between steady states resulting from the change in system parameters made by operator of the turbine. For each of these states the time series of a particular sensor is fluctuating in a fixed range and the mentioned methods thus could not work even providing the information on the system parameters changes which also could be lacking.

2 Dataset description

The dataset comprised 180-200 time series, which represented various sensor signals such as pressure, temperature, and flow. These signals were measured in distinct steam turbine modules, including steam lines, high-pressure regeneration, low-pressure regeneration, condensation system, drainage system, oil supply, cooling, and seals. The sampling rate was set at 1 second, and the total data collection period spanned four months.

During the first month, several instances of system reboot were observed, wherein the rotor rotation speed decreased from 3000 rpm to significantly lower values or even reached zero. These occurrences indicated the process of system adjustment. Since these periods might not represent typical operational trends, the decision was made to exclude the first month of data from the analysis.

Additionally, certain sensors were found to exhibit inaccurate physical measurements, such as negative steam temperature. Some vibration sensors were identified as defective, primarily displaying values near zero. Both categories of sensors were subsequently omitted from further analysis.

2.1 Regime extraction

A steam turbine is a complex system that can be configured in various ways to maintain specific power levels and direct a portion of the steam to other sources for industrial and/or heating purposes. The system comprises several modules, which aim to enhance its efficiency and are automatically adjusted to accommodate external factors such as temperature. These adjustments and external conditions significantly impact the absolute and relative values displayed by the sensors, as well as the correlations between them, resulting in the occurrence of multiple steady states. To accurately detect anomalies, it is essential to analyze the data within these steady states or their groups, as the parameter distributions within them exhibit some degree of order. However, no logs of system setting changes were provided, which necessitated the development of an automatic regime extraction method based on sensor data.

Various approaches to address this issue were explored, and experts in the field evaluated the results. Additionally, the following constraints were considered:

1) The duration of a steady state must not be less than 20 minutes.

2) The steam turbine must operate in a steady state for more than 60% of the total time. The remaining time is attributed to the transitions between steady states.

Experts identified 9 sensors that respond first to changes in settings and provided threshold values for the variance of these sensors that could be observed in steady-state conditions. We conducted a comparative analysis of the chosen sensor time series at various time scales, ranging from 30 minutes to 1 week, for each sensor independently. This comparison resulted in specific time scales for each sensor, which were selected for further analysis and included 24.0, 18.0, 8.0, 2.0, 1.0, and 0.5 hours.

The overall procedure for the proposed regime extraction is outlined as follows:

1) Select the largest time period from the set (initially, 24 hours).

2) Apply a rolling window analysis to the time series for the chosen nine sensors, using a window size corresponding to the period in step 1 and a step size of 20 minutes.

3) For each window, verify whether all time series parameters are below the threshold and save the window if the condition is satisfied.

4) For each saved window, apply the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [9] test to check the stationarity of each sensor time series and compute the product of the results.

5) Sort the windows in ascending order based on the multiplied KPSS values and iteratively add each window to a final set:

a. If a new window does not overlap with any of the previous ones, assign it a new steady-state label.

b. If a new window overlaps with any of the previous ones, check if the parameters are below the threshold, as in step 3:

i. If all checks pass, combine the windows.

ii. If not, assign the union of the two windows to the one with the highest KPSS value, and label the remaining part of the overlapping new window separately.

6) Repeat steps 1-5 for smaller scales.

However, upon examining the results of the proposed approach, experts noted some steady states that fell within the given thresholds but contained two or three smaller states internally, which they visually identified by analyzing the active power time series. Reducing the threshold could further segregate these states but would also result in a decrease in the overall percentage of steady states relative to transition states, which is undesirable. Consequently, we decided to perform post-processing using Bayesian Gaussian Mixture [10] on the active power time series and pressure measurements in the key regulation leads of the system.

1) For each previously extracted steady state, we attempted to apply the Bayesian Gaussian Mixture with a convergence threshold of 1e-4 and a number of components equal to 2.

2) If the algorithm converged, we calculated the overall duration of each component during the steady state, and only retained those with durations exceeding 1 hour (based on the assumption that a component might appear multiple times during a steady state, with each part lasting at least 20 minutes).

3) We compared the difference between the mean values of the components to the mean of the components; only those steady states with a ratio not less than 2.5% were further divided into components. The value of this threshold was visually adjusted through the analysis of various steady state examples containing two components.

4) For the selected steady states, the segregation into components, represented as a sequence of 0 and 1 (numeric representation of the two components), was filtered using a moving average with a window size of 20 minutes and rounded to remain binary.

5) For each of the resulting components, if it comprised less than 20 minutes, we assigned a transition period label to it; otherwise, we assigned a new steady state label.

2.2 Variational Autoencoder

The application of autoencoders and variational autoencoders is widely used for anomaly detection [11 - 15]. In order to obtain information about the state of the turbine according to the readings of its sensors, the procedure of training the variational autoencoder was carried out [16].

The input layer was configured to process a tensor that represents parameter evolution during a single time frame, with a duration of 180 seconds. The encoder consisted of four 2D convolution layers, with 32 filters in the first layer and 64 filters in the subsequent three layers. The kernel size was set to 3, and the activation function employed was the rectified linear unit (ReLU) function. After the convolution layers, a fully connected layer with 32 neurons and a ReLU activation function was implemented. The latent dimension layer had a size of 2, enabling the visualization of the results.

The decoder was designed with an input layer consisting of 2 neurons, followed by a fully connected layer with a ReLU activation function. The subsequent decoder layer was a fully connected layer with a size equal to M * N/2, where M and N represent the input tensor's shape. The next decoder layer was a transposed convolution layer (also known as deconvolution) with 16 filters and a kernel size of 3. Transposed convolutions were employed to implement a transformation in the reverse direction of a conventional convolution. Finally, the decoder contained a convolution layer to obtain a tensor size equivalent to the input tensor size.

The loss function was computed using a reconstruction term and a regularization term in the form of Kullback-Leibler divergence. The reconstruction term of the loss function was based on the binary cross-entropy loss:

$$H_1 = -1/\ N\ \Sigma\ y_i \log(p(y_i)) + (1 - y_i) \log(1 - p(y_i))$$

The regularization term in form of Kullback-Leibler divergence was rewritten in the following form [17]:

$$H_2 = -\ ½\ \Sigma(1 + \sigma + \mu^2 - e^{\sigma})$$

Where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the individual means and standard deviations.

The total loss function was a mean of H_1 and H_2 loss:

$$H_{total} = (H_1 + H_2) / 2$$

Additionally, the reparameterization trick [18] was utilized to enable backpropagation through the network.

The neural networks were trained for three epochs, during which the loss decayed on the validation dataset. During the model training process, a mean squared error (MSE) of 0.012 was achieved. After model training, the encoder was used to transform the multidimensional time series into a 2-dimensional latent space.

Subsequently, each identified steady state was transformed into a point cloud in the latent space. Within each steady state, the time series was divided into 180-second frames. The variational autoencoder's encoder was applied to each frame, resulting in two coordinates in the latent space for each frame. The collection of points in the latent space was condensed into a single central point by calculating the average value for each point cloud coordinate.

2.3 Degradation detection

A prediction model for the turbine sensor readings can be constructed within the context of a single steady state, which lasts for a duration of several hours. The transition between steady states is controlled by operators and cannot be accurately predicted. Parameter degradation is expected over time scales exceeding 14 days, which is considerably longer than the time scale of each regime.

Considering the data characteristics described above, the following assumptions were made:

- Steady states with similar parameter distributions occur over an extended time scale of more than 14 days.
- Long-term parameter degradation can be observed within the context of steady states that exhibit closely related parameter distributions.
- A regression model can be developed to predict the sensor readings over an extensive time scale.
- A distinct upward/downward trend in the extrapolation of the regression model for the turbine parameter within the framework of steady states can help identify a degrading parameter among other parameters.

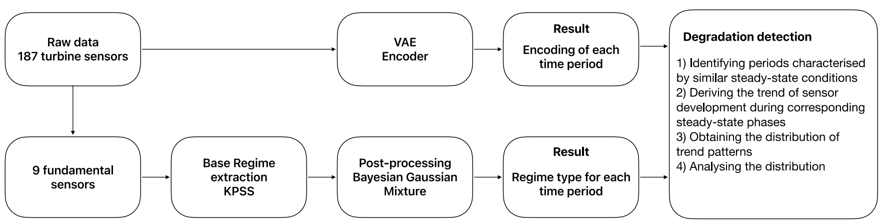

Figure 1: the schema of degradation detection workflow

The implementation of the degrading parameter search, based on the above assumptions, was conducted as follows (fig. 1):

1) All selected steady states were transformed into the variational autoencoder's latent space and characterized by a single set of latent space coordinates.

2) The following sequence was executed iteratively:

a. One steady state was randomly selected.

b. A set of steady states with close coordinates in the latent space was identified.

c. The chosen set of steady states defined the time frame on which the regression model was subsequently trained.

d. The extrapolation trend of the trained regression model was recorded for further analysis.

3) As a result, the trend distribution was obtained for each parameter.

4) If the parameter trend distribution was normal, symmetric, and the mean value was close to 0, the degradation hypothesis for the parameter was rejected.

5) If the parameter trend distribution was asymmetric and the mean value was shifted relative to 0, the degradation hypothesis for the parameter was confirmed.

To detect degradation in its early stages, the algorithm used a constraint when initially selecting a random steady state (2.a): only states observed during the last two months were employed. Simultaneously, the sample of the stable state family also included similar regimes with more distant historical distributions.

3 Expert Validation and Analysis

To further validate the proposed approach for regime estimation and degradation extrapolation in steam turbines, an expert test was conducted involving industry professionals with extensive experience and knowledge in the field. The objective of this test was to assess the reliability and practicality of the suggested methodology in predicting degradation parameters that could lead to turbine failure.

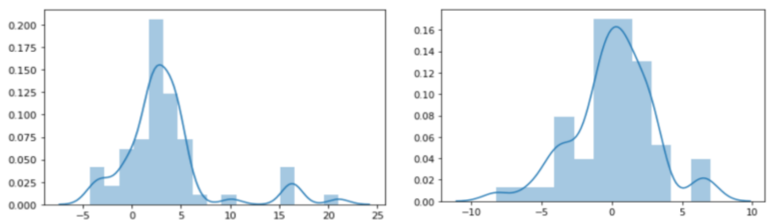

Figure 2: Comparison of normalized distribution densities for long-period trends. The X-axis represents the trend of randomly subsampled time series exhibiting the same steady-state conditions, while the Y-axis denotes the normalized distribution density. The left one corresponding to a steam turbine sensor exhibiting degradation and the right one representing a sensor without degradation

3.1 Expert Test Setup

A panel of experts, consisting of engineers and technicians specializing in steam turbine maintenance and operation, participated in this test. These experts were provided with the predicted degradation parameters obtained from the proposed model, along with pertinent contextual information about the steam turbine's operating conditions. The participants were asked to evaluate the degradation parameters and determine their potential impact on turbine performance and longevity.

3.2 Degradation Parameters

Two primary degradation parameters were identified by the proposed approach: Degradation Parameter 1 (DP1) and Degradation Parameter 2 (DP2). DP1 and DP2 were associated with vibration sensors. The analysis indicated that DP1 tends to reduce vibrations and has a minor effect on turbine performance, while DP2 tends to increase vibration and can lead to critical failures if not addressed in a timely manner.

3.3 Expert Evaluation Results

The majority of the experts agreed on the relevance and significance of the identified degradation parameters. Furthermore, they agreed that DP2 could potentially lead to turbine failure within a timeframe of 7 to 10 years if left unaddressed.

In conclusion, the expert validation and analysis demonstrated the effectiveness of the regime estimation and degradation extrapolation method in predicting degradation parameters that can lead to steam turbine failure. The results of the expert test provide strong support for the proposed approach, highlighting its potential application in practice for enhanced steam turbine maintenance and management.

4 Conclusion

In conclusion, this scientific paper has presented an innovative approach to regime estimation and degradation extrapolation for steam turbines by integrating statistical methods with machine learning algorithms. The proposed technique has demonstrated promising results in predicting the remaining useful life of turbine components, paving the way for improved maintenance and management practices.

While the current study has shown significant advancements in steam turbine prognostics, future research could explore the extension of this methodology to other power generation equipment and the incorporation of additional sensor data for more accurate predictions. Additionally, advances in machine learning algorithms could further enhance the performance of the proposed technique in terms of speed and accuracy, elevating its utility across the energy sector.

Overall, this research serves as a stepping stone in addressing the challenges of maintenance and management in the steam turbine domain, ultimately contributing to a more sustainable and efficient global energy landscape.

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