Diagnostics of Anomaly Steam Turbine Behavior in Terms of Remote SHM and Cloud Computing

JINDRICH LISKA, JAN JAKL and VOJTECH VASICEK

ABSTRACT

Monitoring of structural health is the important task in terms of ensuring the reliability of the operated technology. It is important especially in case of the steam turbine operation where the unplanned outage is associated with the high financial losses.

The conventional approach for the evaluation of the normal turbine operation is based on precise specification of the trigger limits for each of the measured signals made by the technical expert. The abnormal operation is then determined when one of the signals is outside of the limits. However, it is a non-trivial task to specify trigger limits for all measured signals and sometimes it is even not practicable. The method described in this paper is based on the automatic detection of anomalies in the turbine behavior without the need to precisely specify the trigger limits manually.

The approach is based on two steps. The first is to find the behavior of the turbine that is related to the normal turbine operation. The signal trigger limits are evaluated automatically with probabilistic assessment. The second step is to investigate the actual operation state using the signal measurements. Then if the actual behavior of the turbine is out of the boundary of the normal turbine operation, the anomaly is detected.

The described method was validated using the measurement data acquired in operation of a steam turbine with a nominal power of hundreds MW. As an example of the method application, the paper shows the detection of an anomaly, which was subsequently identified as a contact between the stator and the rotor turbine part. This contact is potentially dangerous because it can change the structure of the machine.

The described method is being integrated into the remote monitoring system that is based on cloud computing and being developed by the authors of this paper. The remote sensing of the turbine operation is nowadays the key to reduce costs in terms of maintaining the installed system and frequent visits of technical personal support to collect the data. The architecture of the monitoring system itself is described in the paper. The system is important in terms of providing an early warning in case of an unexpected behavior of the turbine. This provides the maintainability and reliability of the operated technology. Nowadays more than 30 operated turbines are part of this monitoring system worldwide.

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INTRODUCTION

In the field of steam turbine operation diagnostics, which is dealt with in this paper, the use of machine learning methods can significantly help to improve orientation in the large amount of measured data and help with their interpretation. Anomaly detection is a typical task where the automatic processing of data and the determination of their normality can help to recognize a defect or an operational problem in the early stages of its development and thus prevent turbine structural failures and outages. There are several approaches of anomaly detection, including statistical methods, machine learning or deep learning. In [1], different clustering methods, such as K-means, Isolation Forest or Local Outlier Factor are used to separate anomalies from normal data. To increase the accuracy the use of clustering methods combined with classification algorithms such as K-nearest neighbor, support vector machine, decision tree, random forest and gradient boosting decision tree were used. In [2] uses the artificial neural network to detect novelties in vibration data from large steam turbine. Self-organization map is trained with the normal data obtained from a thermal power station and simulated with abnormal condition data from a test rig developed at a laboratory. [3] investigates the problem of gas turbine condition monitoring using Gaussian mixture and hidden Markov models. The use of Gaussian mixture models (GMM) is also the resulting approach used in this paper, which the authors decided to use based on the analysis of the methods mentioned in the previous text.

STEAM TURBINE BEHAVIOR MODEL BASED ON GMM

The data measured in the steam turbine and processed in this article are available from standard sensors measuring variables such as rotor vibrations, displacements, bearing temperatures, machine rotational speed and other parameters that are monitored for the purpose of control, regulation and protection of the turbine operation. For the purposes of creating a model of the standard turbine behavior, the signals are grouped according to the measured quantity or turbine component relation. Subsequently, the data are smoothed and standardized before creating the GM model, see Figure 1. This gives a multi-dimensional description of the turbine state at each sampled time. Subsequently, the goal is to create a model that will represent standard data in a multidimensional space and based on which it will be possible to detect anomalous or new data.

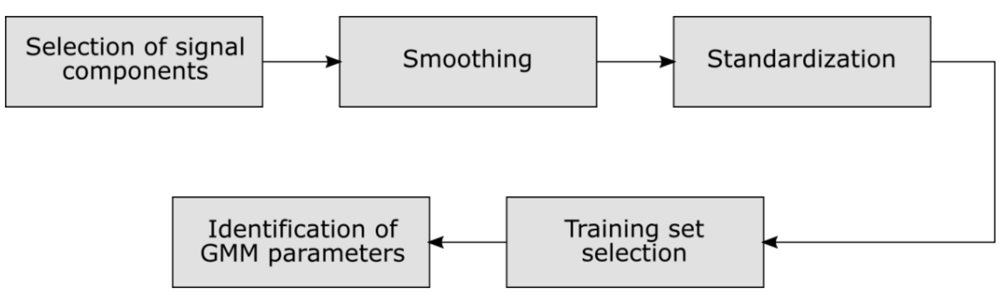

Figure 1. Data preparation scheme for GM modeling.

Gaussian Mixture Model (GMM) and Anomaly Detection

The overall probability distribution of the data is in GMM defined as a superposition of the component distributions. A wide range of different data distributions can be modelled with suitable mixture parameter settings [4]. Advantages of GMM include the ability to identify anomalies in many types of data structures, including multidimensional data, categorical data and skewed data distributions. GMMs also provide the ability to model complex data structures and reveal hidden relationships between data points and offers the possibility of relatively good interpretation in the form of individual model components visualization.

The task of choosing the number of components can be solved using the Bayesian Information Criterion (BIC) or heuristically [4]. In this paper we use a gradient of the BIC scores curve to determine the appropriate number of GMM components. The gradient shows how the BIC differs for a higher number of components compared to the previous lower number. If the gradient approaches zero, the GMM is fixed at the current number of components.

The task of anomaly detection using GMM determines how likely each data point is to come from each of particular distributions. However, the probability is related to the number of selected GMM components and the threshold for determining the anomaly is therefore variable. In this paper, we use the minimum of Mahalanobis distances of the current data point to all the GMM components. In multivariate space, Mahalanobis distance is the distance of each observation from the center of the data cloud, considering the shape (covariance) of the cloud. The minimum of distances therefore indicates the nearest component that is closest to the data point or directly contains it.

ANOMALY BEHAVIOR IDENTIFICATION – CASE STUDY

Method for anomaly detection, described in the previous section, was applied to vibration data collected during measurement of steam turbine rotor vibrations. The vibrations of high pressure (HP) and low pressure (LP) turbine rotor were measured by sensors in standard XY configuration at 4 bearing pedestals. Signal analysis was aimed mainly to diagnose rotor dynamic and so amplitudes and phases of 1X (spectral components related to the rotational frequency) were calculated. The vibrations of the turbine were measured for several days and during this measurement the behavior of the turbine was considered with no obvious deviations from normal.

To use all relevant information about rotor vibration behavior training data set for each time instant consists of a 16-dimensional vector consisting of amplitudes and phases of 1X in x a y direction from all 4 bearing pedestals, see equation (1). Vector set for each bearing pedestal follows the equation (2), where the case for bearing pedestal 1 is defined. Because the phase of 1X can jump between ± π in extreme values, sin(φ1X) is used instead.

$$x(k) = [x^{SV1}(k), x^{SV2}(k), x^{SV3}(k), x^{SV4}(k)]^T \tag{1}$$

$$x^{SV1}(k) = \left[A_{1X}^{SV1-x}(k), A_{1X}^{SV1-y}(k), \sin(\varphi_{1X}^{SV1-x}(k)), \sin(\varphi_{1X}^{SV1-y}(k))\right] \tag{2}$$

According to the scheme in the previous chapter the vibration characteristics were smoothed using Moving Average filter and standardized. Mean values and standard deviations used for standardization of the training data set were further used for standardization of evaluation data set.

Values of BIC and difference of BIC for different numbers of GMM components are in the following Figure 2. BIC has a descending trend and it can be seen that slope of descent is greater for lower numbers of GMM components. To avoid overfitting of GMM the optimal number of components was chosen based on differences of BIC values. Differences of BIC does not change too much for the number of components greater than 10. For a given number of GMM components the GMM model of the training data set was fitted.

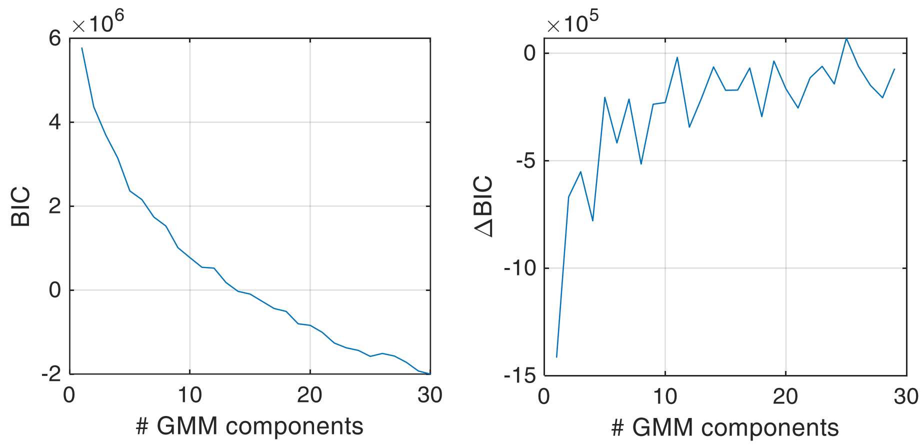

Figure 2. Values of BIC and ΔBIC for different number of GMM components.

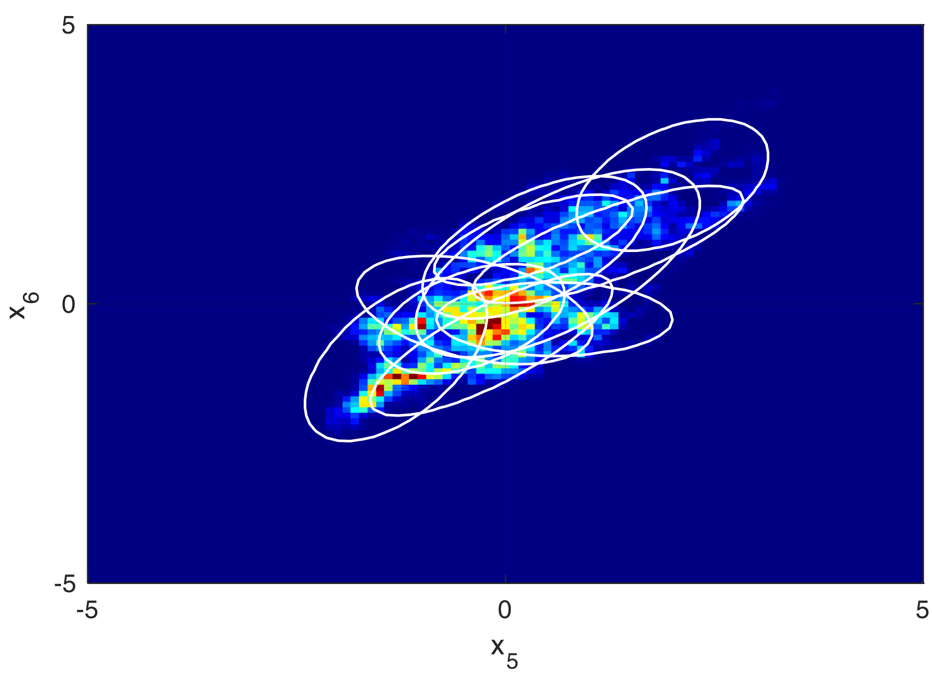

Figure 3. Histogram of components x5 and x6 with contours of identified Gaussian functions.

Mutual dependency of components x5 a x6 of training data set in form of histogram is in Figure 3. Contours of identified Gaussian Probability Density Functions for value 0.01 are depicted in white. It can be seen that contours surround test data very well.

During the next measurement campaign new data were collected and used as evaluation data set for anomaly detection. Time waveforms of amplitudes and phases of 1X for all measured signals are illustrated in Figure 4.

Identified GMM was further used for calculation of Mahalanobis distance of evaluation data, see Figure 5. Threshold for anomaly detection is shown by a red dashed line and it was set 21.3 as twice of maximal Mahalanobis distance for training data. Mahalanobis distance crossed the anomaly threshold several times indicating presence of anomaly states, i.e. states that were not included in the training phase and may indicate turbine behavior different from normal state. And indeed, anomaly detection algorithm detects anomaly states in such cases where synchronous rotor/stator rub occurred. Rotor stator rub is turbine malfunction resulting from low clearances and high rotor vibrations.

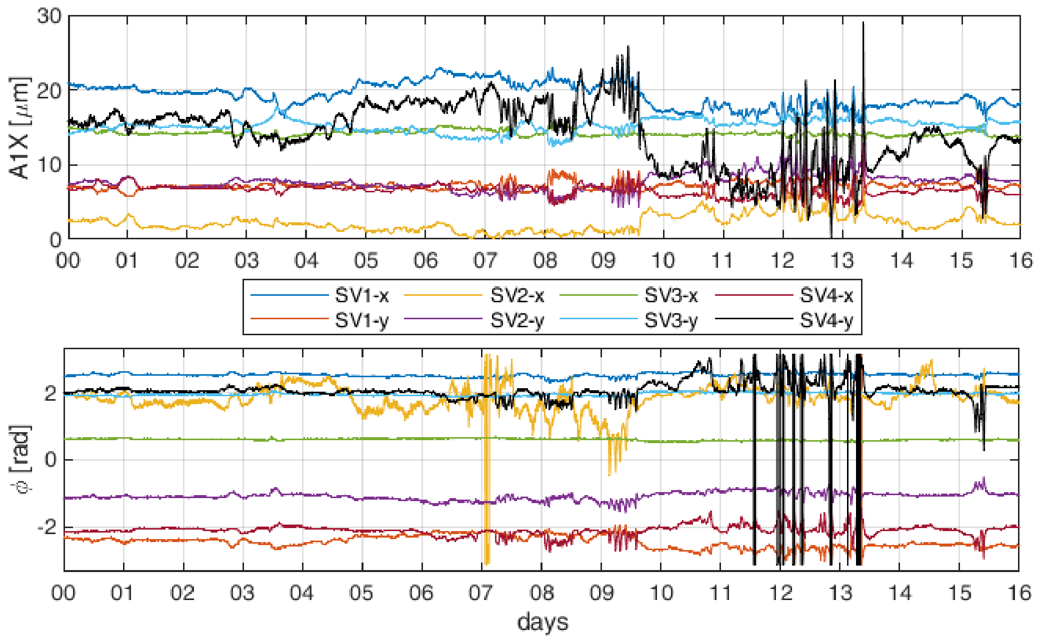

Figure 4. Time waveforms of 1X amplitudes and phases – evaluation data.

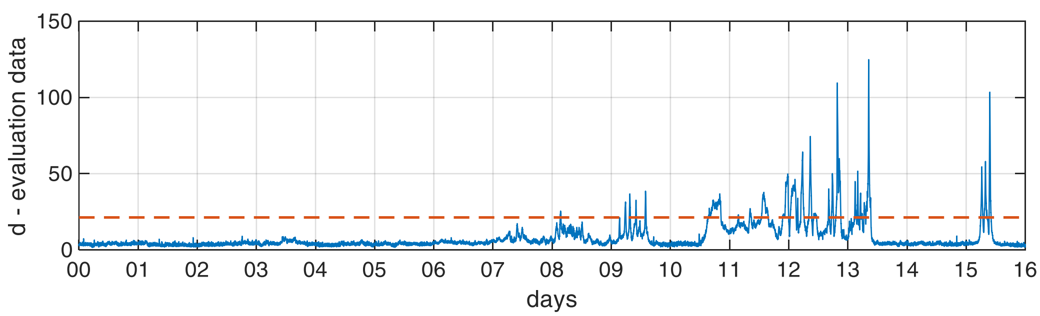

Figure 5. Mahalanobis distance of evaluation data.

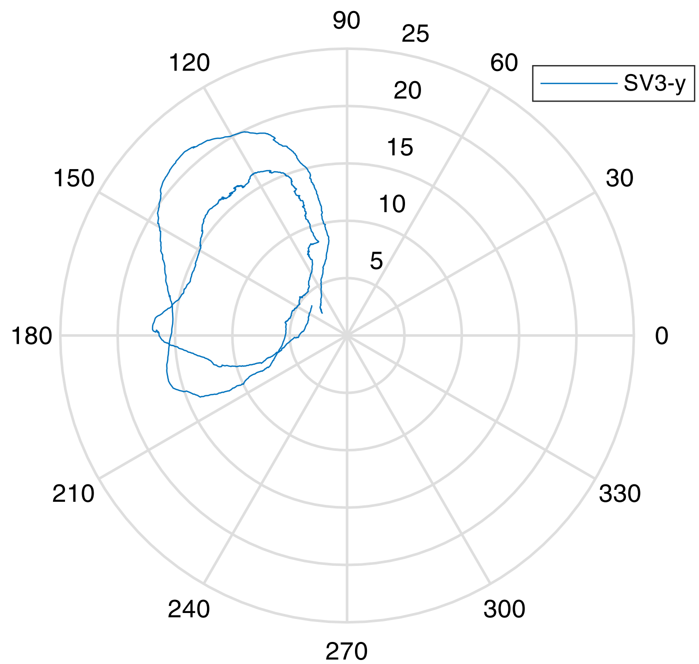

Figure 6. Vibration polar plot with typical symptom of synchronous rub.

Phenomena connected with rub occurrence is temporal rotor bow, which can be diagnoses by moving of 1X phasor illustrated in polar plot in Figure 6.

REMOTE SHM AND CLOUD COMPUTING

Anomaly detection module that was introduced in previous part of this paper is being integrated into the remote monitoring system of the steam turbines that was also developed by the authors of this paper [5]. The remote sensing of the turbine operation is the key to reduce costs in terms of maintaining the installed system and frequent visits of technical personal support to collect the data. The measurement data collection and its storage on the turbine site is made using the industrial PC (IPC) that runs the open-source database server. The data from the turbine control system and other installed systems for monitoring and diagnostics are connected to the IPC using the standard protocols that are supported like Modbus, OPC UA, OPC DA, etc. The integration of the anomaly detection system described in previous part of the paper is illustrated in green at the bottom part of Figure 7. The measurement data are stored in database that is used as a data backup for the case the connections to the RMS Web Server is temporary unavailable.

RMS Web Server is remote server where the data are stored in relational database permanently. The Web Server is a cloud high-performance machine that is dedicated to run the cloud computations to serve the requests from the users of the remote monitoring system and to run the database server that store the data from all monitored turbine units. The interaction between the users and stored data is secured by the Web Service that provides the communication between devices over the internet.

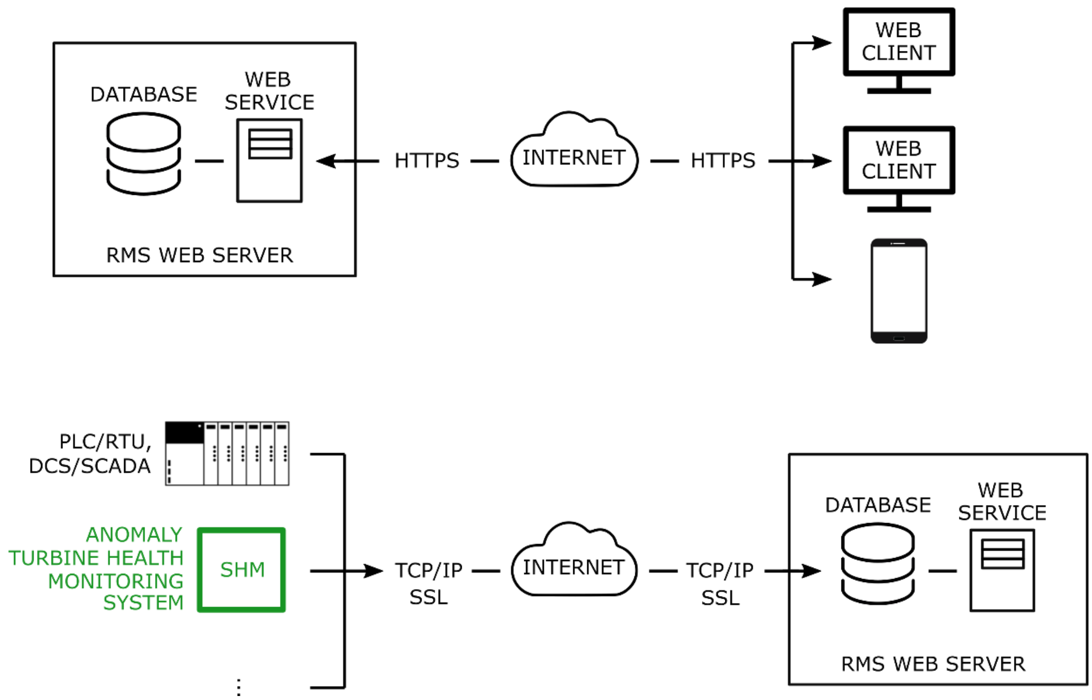

Figure 7. Architecture illustration of the structure health remote monitoring system.

To provide convenience for entering commands by the users of the system and see the results, the Web Client was developed and its architecture is illustrated at the top of Figure 7. The Web Client is a graphical user interface environment, where the user can monitor the actual state of the remote turbine in a real time. Along the Web Client, the application for the Android and iOS was developed as well. The user has several modules available to be able to investigate and analyze the turbine behavior that is needed. In addition to basic time series monitoring module, advanced analysis modules and time-frequency analysis, etc. are also available.

Anomaly detection method takes part here as an independent module. The measured live data is being processed on the cloud Web Server using the steam turbine behavior model that is based on GMM. Anomaly detection runs automatically and the identified events can be accessible using the Web Client along with the early warning to the users that are responsible for turbine proper operation by the email notification.

Because of the turbine operation measurement data is confidential and its value is high as well as the user trust against data leakage, the cybersecurity is a crucial part of such remote monitoring system. For this reason, the data is transferred only in encrypted form. The developed system uses TCP/IP with SSL protocol – Secure Sockets Layer for data transfer from the power plant to the cloud server and HTTPS protocol for secure data transfer from the cloud to the Web Client. In addition, the connection to the database can be done only locally through Web Service making the remote monitoring system protected from internet side.

CONCLUSIONS

Monitoring of structural health is the important task in terms of ensuring the reliability of the operated technology. It is important especially in case of the steam turbine operation where the unplanned breakdown results in high financial losses. It is therefore crucial to monitor the actual state of the operated technology especially the structural health of the turbine and provide the early warning in case the turbine behavior is non-standard. This request resulted in development of the structure health monitoring system that is based on anomaly detection in turbine operation using Gaussian mixture model – GMM.

The relative vibration signals that were measured on 4 bearing pedestals were used as a reference data to fit GMM in the case study described in this paper. The period of 20 days where any non-standard behavior of turbine was not observed was used. According to the fitted GMM the Mahalanobis distance was evaluated and was used to detect anomaly turbine behavior.

The detection of anomalies was made then on the evaluation data and several non-standard states were detected. Detailed analysis of the signals later showed that these states are connected to synchronous rub – the contact between rotor and stator that is possibly dangerous in term of structure health of the rotor. Corresponding figure is given in the paper that validates the results of anomaly detection approach.

The presented approach is being integrated into the remote monitoring system that was developed by the authors of this paper. The architecture of the system is described in the presenting paper together with the challenges including cybersecurity, etc. The users of the system can monitor and evaluate the actual state of the turbine in a real time from any location just using the internet connection This together with the cloud computing, that uses the computing capacity of the cloud server, are the main advantages of such system applicable as a strong tool in terms of turbine investigation and diagnostics. Nowadays, this system is used for monitoring of tens of the turbines worldwide.

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