Predictive Maintenance of Gears In Gas Turbines Using SVM

Roshni Borse[1], Dr. Surendra Bhosale[2]
[1, 2] EED V.J.T.I, Mumbai, India

Abstract- *In order to occupy a competitive position in Gas Turbine industry the most important challenges, a fabrication plant has to face are the reduction of manufacturing costs and the increase of production yield. Predictive maintenance is one possible way to address these challenges. In this project I present an implementation of a universally applicable methodology based on the theory of classification of good and faulty data and Support Vector Machine (SVM) to predict tool maintenance operations. To fit the problem adequately and to allow a descriptive interpretation we introduce the remaining time until next maintenance as a response variable. By using Python and adequately analyzing data acquired SVM model is constructed. Later will show that under typical production conditions the model is able to predict a recurring maintenance operation sufficiently accurate. This project shows that better planning of maintenance operations allows for an increase in productivity and a reduction of downtime costs.*

Keywords- SVM, Gas Turbine, vibration analysis

I. INTRODUCTION

Predictive Maintenance aims at detecting faults to minimize production costs and optimize maintenance. Such process is often cumbersome since the detectability of faults depends on the geometry of the components under analysis, the type and severity of the fault, the speed regime, location of the sensors and signal processing applied. Gears are an important component of rotating machines, and often the faults in these components are the cause of catastrophic breakdown of industrial applications. For this reason, a great effort has been put into research of this subject. Every machine including rotating components has a specific sound and vibration signature related to its construction and structural health state. Thus, changes in the vibration signature can be used to detect incipient defects before they become critical. Accordingly, gearbox faults can be diagnosed through the changes that occur at particular frequencies. The time domain analysis consists of many descriptive statistics such as sample skewness, kurtosis and so on.

Feature extraction methods play an important role in machine condition monitoring and fault diagnosis, from which the diagnostic information can be obtained. Through gear vibration analysis, a lot of features are acquired, and the next step is optimization and classification. In the present work the authors present a review of a classification techniques for gearbox fault identification with particular regard to vibration analysis. Nowadays the demand for condition monitoring and vibration analysis is driven not only by the need to minimize the consequences of machine failure, but also to utilize the existing resources more effectively. A gas turbine is typically composed of the following key components: generator system, blades/pitch system, yaw system, convert system, gearbox system, and other systems. Generator faults account for the greatest down time among all faults. Develop fault prediction and diagnos is methods with good service accuracy and low deployment costs for turbine generators.

Section I represents the introduction and motivation behind this research. Section II gives general information about the dataset we have used for this project. Section III illustrates the entire methodology of the project that we had used. It gives the entire flow of the research work. The first part is focused on the baseline algorithm tuning of the classifier. The second part gives a brief introduction about cross validation technique. The next part is about SVM regression model. The next part depicts about algorithm tuning. Last part states the performance measure for result we have got. Section IV is the result part. Section V illustrates the conclusion and future scope of this research. Last part states all the references we have used.

II. DATASET

Radial vibration measurements taken on 3MW wind turbine pinion gear with nominal speed of 1800 rpm. For the fault case (case 1) initial vibration readings showed high vibration levels, the machine was stopped after one week and fault on pinion gear found as shown in image below. Two other vibration readings (case 2 and 3) are given from pinion gears of different wind turbines of the same model with no known faults. Measurements are made radially on gear shaft having sampling rate of 97656 Hz, recording length of 6 seconds with accelerometer.

III. METHODOLOGY

In this paper, we attempt three levels of classification: fault detection, fault diagnosis and fault prediction. The general methodology for all three types of classification is shown in Figure 1. As can be seen, there are four main steps following a general machine learning process, described in detail in this section.

3.1. Data Labelling: The processes for labelling the data for each classification level are given below.

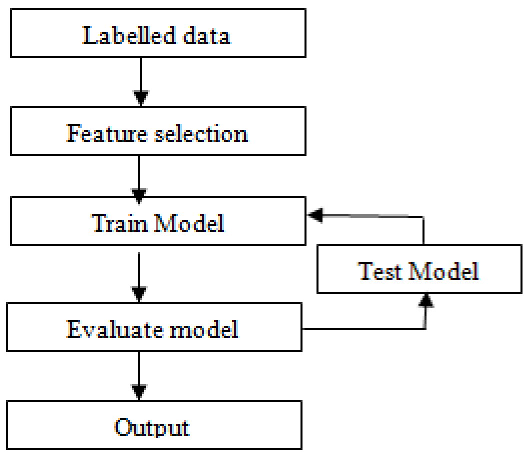

Fig 1: Methodology for a typical machine learning approach

3.1.1. Fault Detection

The first level of classification is distinguishing between two classes: “fault” and “healthy”. The fault data corresponds to times of operation under a set of specific faults in case 1 of dataset provided. For these faults, status messages with codes corresponding to the faults were selected. The healthy data corresponds to operations recorded in gas turbine case 2 and 3.

3.1.2. Fault Prediction

Fault prediction represents an advanced level of classification than fault diagnosis. The aim of this level of classification was to see if it was possible to identify that a specific fault was imminent from the full set of operational data. For fault prediction, the times during which the turbine was in faulty operation were not labelled as such. Instead, operational data points leading up to each fault were labelled as “pre-fault”, for each specific fault. When a specific fault started at time t, then all operational data points between time t−T and t−W were labelled as that fault’s “pre-fault” data. This means that by looking at a window of time between T and W before a fault occurs, useful warning could be given of an imminent fault at least W minutes/hours before it occurs. Once again, if different faults occurred concurrently, the data points were duplicated and given different labels.

3.2. Feature Selection

The FFT of the data from the channel 1 was further converted into time domain signal for further analysis. Time domain analysis consists of calculating various statistical values of the given signal such as the mean, root mean square (RMS), standard deviation, kurtosis and variance. A separate dataset of these values was created with corresponding healthy or faulty class data which were further analyzed using Python. This feature was further split into 75-25% for testing and training using train- test split library in Python.

3.3. Model Selection

Support Vector Machines are a widely used and successfulmachinelearningalgorithmforthetypeofclassification problem seen in this study, where the relationship between a high number of parameter scan be complex and nonlinear (Cortes &Vapnik, 1995; Boser, Guyon, &Vapnik, 1992). The basic premise behind the SVM is that a decision boundary is made between two opposing classes, based on labelled training data. A certain number of points are allowed to be misclassified to avoid the problem of overfitting. They have been used in other industries for condition monitoring and fault diagnosis with great success. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labelled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in other side. SVM constructs a hyperplane in multidimensional space to separate different classes. SVM generates optimal hyperplane in an iterative manner, which is used to minimize an error. The core idea of SVM is to find a maximum marginal hyperplane (MMH) that best divides dataset into two classes.

3.3.1. General Approaches Base Case(Base)

In the base case, i.e. “vanilla” SVM, a randomized grid search was performed over a number of hyper parameters to find the ones which yielded the best results on the full set of training data. These were then verified using 5-fold cross validation. The scoring metric used for cross validation was the accuracy score (see Eq. 4). The hyper parameters searched over were C, which controls the number of samples allowed to be misclassified, γ which defines how much influence an individual training sample has, and the kernel used. The three kernels which were tried were the simple linear kernel, the radial-basis (Gaussian) kernel and the polynomial kernel. The training data from all under sampling and oversampling methods were fed into an SVM following this approach. Additionally, the meta-learners using the ensemble methods also followed this approach.

3.4. Model Evaluation

A number of scoring metrics were used to evaluate final performance on the test sets for fault detection and fault diagnosis. A high number of false positives can lead to unnecessary checks or corrections carried out on the turbine and this was captured with the precision score(where a higher score represents a lower false positive rate). A high number of false negatives, on the other hand, can lead to failure of the component with no detection having taken place (Saxena et al., 2008). This is captured by the recall score, where a higher number indicates a low ratio of false negatives. The F1-Score was also used, which is the harmonic mean of precision and recall. Confusion matrices were used where appropriate to give a visual overview of performance and show absolute numbers. The formulae for calculating accuracy, precision, recall, the F1-score and specificity can be seen below:

$$\text{Accuracy} = (tn+tp)\ (tn+tp+fn+fp) \quad (1)$$

$$\text{Recall} = tp/(tp + fn)\ (2)$$

$$\text{Precision} = tp/(tp + fp)\ (3)$$

$$F1 = 2tp/(2tp + fp + fn)\ (4)$$

$$\text{Specificity} = tn/\ (fp + tn)(5)$$

where tp is the number of true positives, i.e., correctly predicted fault samples, fp is false positives, fn is false negatives, i.e., fault samples incorrectly labelled as no-fault, and tn is true negatives. The overall accuracy of the classifier on each test set was not used as a metric due to the massive imbalance seen in the data. For example, if 4990 samples were correctly labelled as fault-free, and the only 20 fault samples were also incorrectly labelled as such, the overall accuracy of the classifier would still stand at 99.6%. Specificity was not used as a metric for a similar reason, though was used in one specific case for benchmarking against specificity scores in a previous study

IV. RESULTS

4.1. Fault Detection

The results are obtained using confusion matrix in which 15 tn was obtained. There was 16 tp and 5 overall misclassifications in the matrix. Therefore, out of 36 test cases 31 are correctly classified using SVM. SVM on a scaled data and tuned parameters gives a cross-validation accuracy of 0.86 with tolerance of +/- 0.37%A precision score of 0.89 was overall obtained with the help of above equation (1) and confusion matrix. The true positive rate or Recall was 0.86. The F1 score was at 0.86 and a support of 36 was obtained

4.2. Fault Prediction

For the regression model, a mean square error of 0.13 was obtained, which can be further minimised using tuning. R2 score was low at 0.49 which

V. CONCLUSION AND FUTURE SCOPE

Various classification techniques based on the use of SVMs to classify and predict faults in gas turbines based on data were investigated. Two levels of fault classification were looked at: fault detection, i.e. distinguishing between faulty and healthy operation and, fault prediction, where a specific fault was identified as being likely to occur in advance of the fault using probability theory.

The classification techniques employed involved various different ways of training SVMs, including hyper parameter tuning. The results were very promising and show that distinguishing between fault and healthy operation is possible with very good precision and recall and F1 score. In general, this was also the case for classifying afault. More importantly, predicting certain types of faults for a 6 second data was quite difficult by observing the low R2 score. Improving the R2 scores would represent a very important step forward in being able to rely on data for accurate fault prediction. This represents a limitation in what can be achieved; with additional data, i.e., from moreturbinesoveralongerperiod,betterfaultpredictionwillbepossible due to more positive examples being available for training. As well as this, advanced feature extraction and selection would enable even higher scores.

VI. ACKNOWLEDGMENT

The results and knowledge included herein have been obtained owing to support from Dr. Surendra Bhosale, Associate professor at VeermataJijabai Technological Institute, Matunga, Mumbai – 400019. Acknowledgement is made for the measurements used in this work provided through data-acoustics.com Database.

REFERENCES

[1] Edward J. Diehl and J. Tang, Predictive Modeling of a Two-Stage Gearbox towardsFault Detection, Shock andVibration, 2016

[2] A.Mauricio, C.Freitas, J.Cuenca, B.Cornelis, K.Janssens, Condition Monitoring of gears under medium rotational speed, International Congress on Sound and Vibration, 2017

[3] GDiwakar, Dr.M.R.S.Satyanarayana, P.Ravi Kumar, Detection of Gear fault using vibration analysis, International Journal of Emerging Technology and Advanced Engineering ,2012

[4] Yingying Zhao, Dongsheng Li, AoDong, Dahai Kang, Qin Lv and Li Shang, Fault Prediction and Diagnosis of Wind Turbine Generators Using SCADA Data, 2017

[5] H Shah and H Hirani, Online condition monitoring of spurgears,2014

[6] Boser, B. E., Guyon, I. M., &Vapnik, V. N. (1992). A Training Algorithm for Optimal Margin Classifiers. Proceedings of the Fifth Annual ACM Workshop on Computational Learning Theory, 144–152. doi: 10.1.1.21.3818

[7] Breiman, L. (1996). Bagging Predictors. Machine Learning, 24(421), 123–140. doi: 10.1007/BF00058655

[8] Chang, C.-c., & Lin, C.-j. (2011). LIBSVM : A Library for Support Vector Machines. ACM Transactions on Intelligent Systems and Technology (TIST), 2, 1–39. doi: 10.1145/1961189.1961199