AN ANALYSIS OF AIR COMPRESSOR FAULT DIAGNOSIS USING MACHINE LEARNING TECHNIQUE

Prakash Mohan¹, Manikandan Sundaram²

¹Professor, Data Science and Analytis Center, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India.
²Head, Data Science and Analytics Center, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India.

Email: salemprakash@gmail.com

Corresponding Author: Prakash Mohan

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Abstract

Machine Fault Diagnosis is an important domain in Mechanical Engineering which concerns about finding fault in the machine parts. Among many techniques to identify and classify the faults, this paper concerns about using machine learning algorithms to distinguish healthy machines from unhealthy machines. In order to distinguish the state of a machine, classification algorithms have to be used. The accuracy of an algorithm depends upon the pattern, that the data set follows. The suitability of the five most commonly used classification algorithm has been discussed. Various transforms can be applied to such sensor data. Here various algorithms have been tested for wavelet packet transform. The accuracy of the fit has been measured for all the five algorithms. Hyper-parameter tuning has been done to make the fit better.

Keywords: Principal Component Analysis, Support Vector Machine, Fault Prognosis, Air Compressor

I. Introduction

Air compressor is a device used to increase the pressure of atmospheric air. It has many applications in various fields. Among various types of air compressors, fault diagnosis in positive displacement type has been worked by many authors. As mentioned in XXI fault diagnosis is important as it is sensitive and requires monitoring performance of the machine for better yield and safety of the employees. XXIV worked with 7 common air compressor faults. General procedure for fault diagnosis was proposed in some journals as fault feature extraction, fault feature selection, fault classification, etc. Preprocessing the collected signals like sampling, modulation has also been proposed by some journals for better accuracy. Different
journals propose different methods that are used for the different procedures. Fault diagnosis methods are explained in VIII. for vibration and non-vibration parameters and methods used for valve fault diagnosis were also compared. This paper presents the various methods for air compressor fault diagnosis. Different types of Air compressors include: Reciprocating compressors, Ionic liquid piston compressors, Rotary screw compressors, Rotary vane compressors, rolling piston, Scroll compressors, Diaphragm compressors, Air bubble compressor. The reciprocating air compressor has been used in this paper.

Diagnosis and prognosis are important for ensuring the healthy condition of machines XXVI presents about the various advancements to overcome the motor faults such as unbalance, rub/looseness, bearing faults, etc. VIII also explained that fault diagnosis is done with the help of Finite Element methods. XXXIV describes the fault recognition method which is based on MDTW where DDTW is easy to process because it is the only method where classifiers are not needed and DTW is an effective way to shorten the length of time series. Where in industrial fan the spectrum analysis technique is highlighted to detect the vibration signals and the FFT filtering method is also been highlighted. In RBF Neural Network is used to train sample data based on which overall sound signals that are achieved through condition monitoring and are processed in order to detect faults in the compressor.

Fault features can be extracted from vibration signals, image processing techniques, etc. V used the internet of things for fault detection. Most authors have used vibration signals for extracting features. VII also used noise cancellation methods to detect faults. XXXVII have collected data using sensors by doing sensitive position analysis (SPA). In order to make the SPA more effective EMD is been used by IV classification is done through EMD based energy entropy, artificial neural network. Also, XVI research shows that the ensemble empirical mode decomposition (EEMD) algorithm is suitable for analyzing non-stationary and non-linear signals. XVI shows that accuracy is more in EEMD with DBN. XIV presented that EEMD gives a better result for fault detection. Air compressor fault diagnosis in XXXVII compares time domain, frequency domain and time-frequency domain analysis for feature extraction. Non-stationary signals contain necessary information on machine fault diagnosis. XI, XVIII uses motor current signature analysis with FFT to monitor motor current and for fault detection, to find motor faults with high accuracy MCSA and ZSV Ciseff ective when compared to others systems, for rectification of systems, they are combined with AI. XVIII uses FFT in electrical machine fault diagnosis. On the other side, VI FFT is not suitable for non-stationary signals. XXII analyzed non-stationary signals using STFT. XIII acoustic emission (AE) characteristics obtained from STFT to compare deep learning methods. When it comes to time-frequency method of signal processing wavelet is preferred by most of the authors. XXXIII
has used two forms of wavelet entropy (WSFSE and WESE) and is successful in diagnosing fault for a scroll compressor. XXIX has proved discrete wavelet transform is easier than continuous wavelet transforms and reduces computational time. X uses wavelet packet transforms based on multiscalenoise tuning stochastic resonance instead of traditional discrete wavelet transform in MSTSR and showed better denoising effect and higher signal to noise ratio and has shown the results with greater accuracy. XXIV applied wavelet transforms in an accumulator pressure drop of an air compressor to make patterns in time-frequency domain. According to XXV Morlet wavelet transforms (MWT) and discrete wavelet transform shows poor frequency resolution in high-frequency spectrum than wavelet packet transforms. Jayakumar 2017 presented that signal decomposition based wavelet transform could give better accuracy. XII used vibrations signals from the air compressor and extracted statistical features. XII presented the use of genetic algorithm in vibration data. III has mentioned the SURF algorithm to extract faulty features by image processing methods and achieved better accuracy. The amplitude of the vibration signal gives the severity of the fault and frequency of the signal gives the source of the fault. XXV frequency domain analysis is sensitive to external noise. XXX uses Choi William distribution to indicate a fault in the frequency domain. XXXV uses time-based statistical features for gear fault diagnosis and has achieved the expected results. Wherein Hassan 2014 frequency spectrum method highlights the spectrum analysis technique to detect the vibration signals in the machine.

In order to reduce the dimensionality of a problem, dimensionality reduction techniques are used in many papers. XVII has used PCA with a rotation forest algorithm for fault diagnosis. XXV has compared PCA, MIFS, Bhattacharyya distance (BD), NMIIFS and mRMR and showed PCA is not reliable in all cases whereas mRMR and NMIIFS are better with less number of features. XXV showed if a number of features are high then the performance of MIFS is also high whereas Bhattacharyya distance is slow. Experimental results of XX showed that PCA can improve the accuracy of LVQ neural network in most cases. According to the survey of many authors PCA is used widely for dimensionality reduction. On the other hand, used t-distributed Stochastic Neighbor Embedding to reduce the dimensionality. According to the survey done by XXV t-SNE could avoid information loss. According to I feature selection is done by an algorithm called XXI. Presented the application of thermography in fault diagnosis where the genetic algorithm was used for feature selection. But genetic algorithm demands a classifier as presented by XXI survey has compared the artificial bee colony algorithm with a genetic algorithm and found that the accuracy of an artificial bee colony is greater than the genetic algorithm.
XXXX has used SVM in extracting vibration signals and showed better accuracy. IX shows that fault feature extracted from the P-V diagram of an air compressor is given as input to SVM for fault classification. Also, XXV SVM showed better classification performance with DNN than RF classification. XVII. SVM and ANN are slow and sometimes give inaccurate results whereas random forest is efficient in fault classification. Trained ANN by using multiplier feed forward backpropagation Mar Quadratic algorithm. XXVII has proposed a particle swarm optimization algorithm and back propagation neural network to obtain better accuracy. I showed a better classification rate by applying the back-propagation algorithm with trained ANN. XXV stated for non-separable problem SVM cannot give effective results, so C-SVM with multiclass decomposition technique is used. XIV has used OAA-MCSVM for fault classification. But XXV has discussed that feature selection graph did not change much when multiclass methods are changed. X. et al. (2017) used the C4.5 decision algorithm for classification. XII could classify at high accuracy using the C4.5 decision algorithm. XXIV C4.5 algorithm was compared with SVM and Nu-SVM and found that SVM was better than C4.5. XXIV showed that when a number of features are more, Nu-SVM shows better classification but when less C-SVM is better. Review of VI shows that artificial neural network and fuzzy clustering is widely used for classification. XXVIII also speaks about NN, fuzzy and AI for fault extraction. XIII compared LAMSTAR neural network with CNN and showed LAMSTAR has better performance than CNN. XXII proposed a multi-channel convolution neural network with a stack of denoising auto encoders for extracting features of vibration signals. XXVIII, XVI, XXXIX has used ENN for fault classification after extracting features using wavelet packet decomposition. According to XXX deep learning could increase computational power and is best suited for large scale data. According to XXXI fuzzy logic could overcome the drawback of ANN. XIX uses fuzzy logic for fault detection and diagnosis for rotor fault. XXIII used neural networks and fuzzy logic to process IAS signals from dieseling in for the purpose of CM. Many authors proposed a motor current signature analysis for detecting rotor faults. XXIII proposed an egative selection algorithm that was accepted by industries to remove faults. XXXVI has compared a hybrid deep belief network with original deep belief network and showed that the performance of hybrid deep belief network is better in diagnostic accuracy.

II. Material and Methods

The dataset obtained has been processed through many stages in a sequential manner to get the desired output. The various stages involved in predicting the machine faults have been discussed.
Data Collection And Preprocessing

Data has been taken from its dataset repository which was obtained by using a unidirectional microphone. The dataset contains 254 parameters for each recording. There are 7 states of the machine fault namely LIV, LOV, Bearing fault, flywheel fault, Rider Belt fault, piston fault, NRV fault, and one healthy state. The preprocessing part includes normalizing the data, removal of null values and encoding class variables. Normalization technique used is maxed min normalization which is given by, \( \frac{X - \min(x)}{\max(x) - \min(x)} \). The dataset is split into training and testing in such a way that 70 percent of each state is for training and the remaining 30 percentage of each state is for testing.

Null values in the dataset are not tolerable so the data is checked for null values and outliers.

On plotting the data existence of outliers has been found and it is shown in figure 2. These outliers are removed by replacing it with the average value. Then the data is plotted again and it is observed that outliers have been replaced which is shown in figure 3.
Algorithm

From the dataset it is observed that the problem of interest is classification problem. Various vibration features contribute to any one of the 8 states of machine faults. Among various machine learning algorithms SVM, Random Forest, Rpart, C50 and KNN has been tested for classification. As different machine learning algorithm is applied for dataset of different patterns it is hard to decide which algorithm suits a dataset.

Hyper Parametric Tuning

In order to optimally solve a problem hyperparameter tuning is done. It is done to control the learning method. In the KNN algorithm, K value is iterated to make a better prediction of the class variable. The k value chooses k training data points that are close to the new testing data point. In the case of the SVM algorithm kernel, gamma and cost values are adjusted to improve the accuracy. Gamma is the kernel coefficient. If gamma value is increased the model will try to fit the training dataset. This may sometime result in overfitting which leads to inaccurate predictions. Among many kernels available ‘poly’ is chosen. In the case of random forest n_jobs, random_state and estimators are adjusted. N_estimators is the number of trees before taking the votes for prediction. If the number of trees included is high the computational time will also increase. N_jobs tells a number of processors to use.
Algorithm

The workflow of this paper is done sequentially as mentioned below. The process includes starting from reading the CSV file to concluding the most suitable algorithm for the dataset.

Step-1: read.csv()
Step-2: na.omit()
        max-min normalization
Step-3: Split dataset to train and test.
Step-4: knn()
        svm()
        randomForest()
        c50()
        rpart()
Step-5: Apply model for test dataset
Step-6: table(predicted,testing)
Step-7: Find max(accuracy(algorithms))
Step-8: Hyperparameter tuning.

III. Results And Discussion

SVM

In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Vora, Gaikwad, & Kulkarni, 2015 et al [43] SVM with wavelet is reliable for fault classification and WSVM is used for greater accuracy. In addition to performing linear classification, SVMs can also efficiently perform a non-linear classification. Here the gamma values and kernel is adjusted to improve the accuracy of the model. It is found that kernel being poly gives better results than RBF, sigmoid and linear.

![Fig 4. SVM confusion matrix](image-url)
It is observed in figure 4 that the accuracy of the entire model is affected by LOV. It is observed that out of 545 observations only 520 has been predicted correctly. On comparing SVM with fine turned SVM, it is observed from figure 5 that fine turned has better efficiency.

**KNN**

KNN is a type of instance-based learning where the function is local and all the computation is deferred until classification. This is a method used to classify a given observation using the highest estimated probability.

$$Pr(Y = j|X = x_0) = \frac{1}{K} \sum I(y_i = j)$$

K is a positive integer and $x_0$ is the test observation. The classifier first identifies $k$ points that are close to the test observation $x_0$. It then estimates the conditional probability of the test observation. It is observed that the value of $k$ has a drastic effect on the model's accuracy of classification. It is iterated and tested by building a confusion matrix for each iteration. The $k$ value with maximum accuracy is finalized.

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**Fig 5. Fine Turned SVM confusion matrix**

|     | Bearing | Flywheel | Healthy | LIV | LOV | NRV | Piston | Riderbelt |
|-----|---------|----------|---------|-----|-----|-----|--------|-----------|
| Bearing | 69      | 0        | 0       | 0   | 1   | 0   | 0      | 0         |
| Flywheel | 0       | 68       | 0       | 0   | 0   | 0   | 0      | 0         |
| Healthy  | 0       | 0        | 67      | 0   | 0   | 0   | 0      | 0         |
| LIV     | 0       | 0        | 0       | 68  | 9   | 0   | 0      | 0         |
| LOV     | 0       | 0        | 0       | 0   | 55  | 1   | 0      | 0         |
| NRV     | 0       | 0        | 0       | 0   | 0   | 67  | 0      | 0         |
| Piston  | 0       | 0        | 1       | 0   | 3   | 0   | 68     | 0         |
| Riderbelt | 0      | 0        | 0       | 0   | 0   | 0   | 0      | 68        |
In this model accuracy is greatly affected as the model couldn't predict LOV fault correctly. It is observed in figure 6 that out of 545 observations only 494 has been predicted correctly. The K parameter of the known model is adjusted in order to improve the accuracy of the model. This model also shows maximum error in predicting LOV than any other faults. From figure 6 it is observed that there is change in accuracy of knn model after tuning.

On comparing KNN with fine turned KNN, it is observed from figure 7 that fine turned has better efficiency.

**RPART**

RPART is also a classification algorithm based on a decision tree. A single variable that makes the best split of data is identified. The data is separated and the process is applied to each group for maximum improvement. The R package found in R has been used for executing the algorithm.

Like the other model this model also couldn't predict LOV correctly. As mentioned in
Out of 545 observations, only 479 observations have been predicted correctly. In the above confusion matrix, we use bearing, flywheel, healthy, LIV, LOV, NRV, piston, rider belt as columns and rows.

**RandomForest**

Random forest is a black box that takes input and gives output. It takes a subset of variables and observations and builds a decision tree and uses them to make their predictions. A class is predicted based on the maximum voting concept. Though there is very less calculations involved it is possible to tune some parameters which may have a severe impact on the prediction. It is possible to increase the `max_features` which improves the performance of the model but there is a chance for decreasing the speed of the model. The model's performance can also be increased by increasing the number of estimators. Multiple leaf size is tried to find an optimal solution. If the leaf size is smaller then the model is prone to capture noise.

| Predicted State | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|-----------------|---|---|---|---|---|---|---|---|
| Actual State    | Bearing | 69 | 0 | 0 | 0 | 0 | 0 | 0 |
|                 | Flywheel | 4 | 63 | 0 | 0 | 0 | 0 | 1 |
|                 | Healthy | 0 | 0 | 66 | 0 | 2 | 0 | 0 |
|                 | LIV | 0 | 0 | 0 | 68 | 0 | 0 | 0 |
|                 | LOV | 3 | 0 | 0 | 8 | 55 | 0 | 1 |
|                 | NRV | 0 | 0 | 0 | 0 | 0 | 68 | 0 |
|                 | Piston | 2 | 0 | 0 | 1 | 0 | 1 | 64 |
|                 | Riderbelt | 0 | 0 | 0 | 0 | 2 | 0 | 0 |

**Fig 9. Random forest confusion matrix**

The model shown in figure 9 gives better results on comparing with the previous model. This model could predict 519 observations correctly. On comparing random forest with fine tuned random forest, it is observed from figure that that the fine tuned random forest showed better result.
On comparing Random forest with fine turned Random forest, it is observed from figure 10 that fine turned has better efficiency

**C50**

C50 is also a widely used decision tree algorithm used for classification. In R, the C50 package has been used for classification of faults. This model is based on entropy and information gain. It splits the sample based on the parameters that provide information gain.

Fig 11. C50 confusion Matrix

The model shown in figure 11 couldn’t predict the LOV fault accurately. Out of 545 observations, only 516 is predicted correctly

**Accuracy Table**

The accuracy of different algorithms is calculated and it is mentioned in the table 1. From the table it is clear that Fine turned SVM algorithm has more accuracy.

| ALGORITHM                  | ACCURACY |
|----------------------------|----------|
| FINE-TUNED SVM             | 97.25    |
| FINE-TUNED RANDOM FOREST   | 96.88    |
| FINE-TUNED KNN             | 92.29    |
| RANDOM FOREST              | 95.23    |
| SVM                        | 95.41    |
| C50                        | 94.67    |
V. Conclusion

1. The data was taken from Air compressor using unidirectional microphone by placing it in different positions. The vibrations produced by the air compressor is collected as data and if there is any fault in the air compressor, it causes different noise and the data is loaded to 5 algorithms.

2. On implementing 5 algorithms it is found that the Random forest shows better accuracy, but on fine-tuning, it is found that the accuracy of SVM is better than other algorithms. Fine Tuned random forest did not give appreciable change.

3. So far the algorithm has been tested for static dataset. This may not be appreciated well in industries. So it has to be tested dynamically while the machine is running. Also in future the algorithms shall be designed in such a way that it could predict the fault before the fault even occurred. This may help in estimating Remaining Useful Life of a machine. In the future, the finely tuned SVM algorithm shall be applied for the dynamic data set as it showed better accuracy for batch analytics.

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