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AN ANALYSIS OF AIR COMPRESSOR FAULT DIAGNOSIS USING MACHINE LEARNING TECHNIQUE

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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 fro mtheun healthy machines. Inordertodistinguishthestateofamachine,classificationalgorithmshas to beused.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 wave let packet transform. Thea ccuracy of the fit has been measured for all the five algorithms. Hyper-parametertuning has been done to make the fitbetter.

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

I. Introduction

Aircompressorisadeviceusedtoincreasethepressure 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 procedure. Fault diagnosis methods are explained in VIII. for vibration and non-vibrationparameters and methods used for valve fault diagnosis werealso compared. This paper presents the various methods for air compressor fault diagnosis. Different types of Air compressors Includes: Reciprocating compressors, Ionic liquid pistoncompressor,Rotaryscrewcompressors, Rotaryvanecompressors, 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 advancement to overcome the motor faults such as unbalance, rub/looseness,bearingfaults,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 thecompressor.

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 nois ecancellationmethodstodetectafault.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 energyentropy,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 faultdetection. Air compressor fault diagnosis in XXXVII compares time domain, frequency domain and time-frequency domain analysis forf eatureextraction. Non-stationary signals contain necessary information on machine fault diagnosis. XI, XVIII uses motor current sign at ureanalysis with FFT to monitor motor currentandforfaultdetection,tofindmotorfaultswithhighaccuracyMCSAandZSVCiseff ectivewhencomparedtoothersystems,forrectificationofsystems,theyarecombinedwith AI. XVIII uses FFT in electrical machinefaultdiagnosis.On the other side, VI FFT is not suitable forn on-stationary signals. XXII analyzednon-stationarysignalsusing STFT. XIII acousticemission (AE) characteristics obtained from STFT to comparedeeplearningmethods.Whenitcomestotime-frequency methodofsignalprocessing wavelet is preferred by most of the authors. XXXIII hasused two forms of wavelet entropy (WSFSE and WESE) and issuccessfulindiagnosing fault for a scroll compressor. XXIX hasproveddiscretewavelet transform is easier than continuous wavelet transformsandreducescomputational time X uses wavelet packet transformsbasedmultiscalenoisetuningstochasticresonanceinsteadoftraditionaldiscret ewavelet transform in MSTSR and showed better denoising effectandhighersignaltonoiseratioandIIalsoshowstheresultswithgreateraccuracy. XXIV applied wavelet transformsinaccumulatorpressuredropofanaircompressortomakepatternsintime-frequencydomain.AccordingtoXXV MorletwavelettransformsMWTanddiscrete wavelet transform shows poor frequency resolutionathigh-frequencyspectrumthanwaveletpackettransforms.Jayakumar2017presentedthatsignal decompositionbasedwavelettransformcouldgivebetteraccuracy.XII usesvibrationsignalsfromtheaircompressorandextractedstatisticalfeatures. XII presented the use of genetic algorithminvibrationdata.III hasmentionedtheSURFalgorithmtoextractfaultyfeaturesbyimageprocessingmethodsa ndachievedbetteraccuracy.Theamplitudeofthevibrationsignalgivestheseverityofthefau ltandfrequencyofthesignalgivesthesourceofthefault.XXV frequencydomainanalysis is sensitive to external noise. XXX uses choiwilliamdistributiontoindicateafaultinthefrequencydomain.XXXV usedtime-basedstatisticalfeaturesforgearfaultdiagnosisandhasachievedtheexpectedresults.Whereas inHassan2014Frequencyspectrummethodhigh-lightsthespectrumanalysistechniquetodetectthevibrationsignalsinthe machine.

Inordertoreducethedimensionalityofaproblem,dimensionalityreduction 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), NMIFS and mRMR and showed PCA is not reliable in all cases whereas mRMR and NMIFS 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 Bhattacharyyadistanceisslow.ExperimentalresultsofXshowedthat PCA can improve the accuracy of LVQ neural network in most cases. Ac- cording to the survey of many authors PCA is used widely for dimensionality reduction.Ontheotherhand,usedt-distributedStochasticNeighborEmbed-dingtoreducethedimensionality.Accordingtothesurveydone 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 artificialbeecolonyisgreaterthanthegeneticalgorithm.

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 andANNareslowandsometimesgiveinaccurateresultswhereasrandomforest 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 SVMcannotgiveeffectiveresults,soC-SVMwithamulticlassdecomposition 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) usedtheC4.5decisionalgorithmforclassification.XII couldclassify 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 lessC-SVMisbetter.Reviewof VI showsthatartificialneural networkandfuzzyclusteringiswidelyusedforclassification.XXVIII alsospeaksaboutNN,fuzzyandAIforfaultextraction.XIII compared LAMSTAR neural network with CNN and showed LAMSTAR has betterperformancethanCNN.XXXII proposedamulti-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 XXXX deep learningcouldincreasecomputationalpowerandisbestsuitedforlargescale data. According to XXXI fuzzy logic could overcome the drawback of ANN. XIX (uses fuzzy logic for fault detection and diagnosisforrotorfault. XXusesneuralnetworksandfuzzylogic to process IAS signals from dieseling in es for the purpose of CM. Manyauthors proposed a motor current signature an alysis for detect in grotor faults. XXIII proposed an egativeselectionalgorithmthatwasacceptedbyindustries to remove faults. XXXVI has compared a hybrid deep belief network withoriginaldeepbeliefnetworkandshowedthattheperformanceofhybrid deepbeliefnetworkisbetterindiagnosticaccuracy

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 has been discussed.

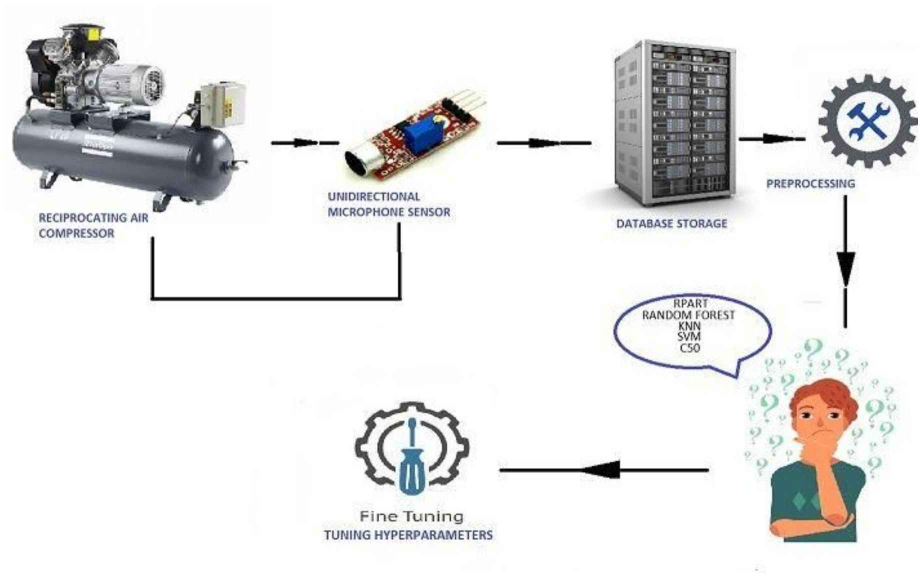

Fig-1. Frame Work on Air Compressor and Fault Diagnosis

Data Collection AndPreprocessing

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, 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 fortesting.

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.

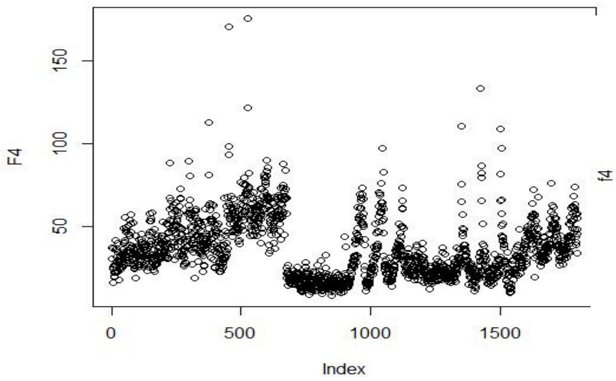

Fig 2. plotbefore preprocessing

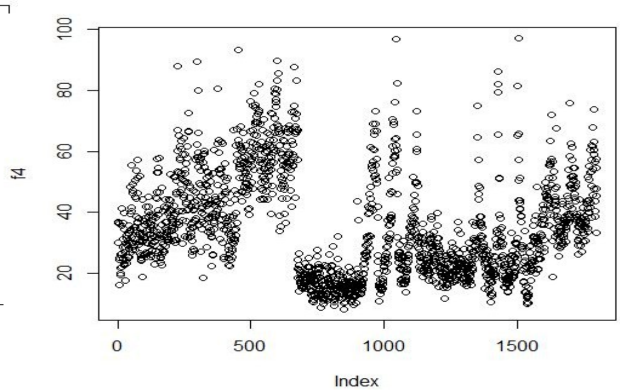

Fig 3. plot afterpreprocessing

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 ParametricTurning

Inordertooptimallysolveaproblemhyper parametertuningisdone.Itisdonetocontrolthelearning 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 touse.

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 andtest.
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 AndDiscussion

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.

pred	Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
Bearing	69	1	0	0	2	0	0	0
Flywheel	0	67	0	0	0	0	0	0
Healthy	0	0	68	0	2	1	0	1
LIV	0	0	0	68	18	0	0	0
LOV	0	0	0	0	46	0	0	0
NRV	0	0	0	0	0	67	0	0
Piston	0	0	0	0	0	0	68	0
Riderbelt	0	0	0	0	0	0	0	67

Fig 4. SVMconfusionmatrix

preds	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

Fig 5. Fine Turned SVM confusionmatrix

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 deferreduntil classification...This is a method used to classify a given observation using the highest estimatedprobability.

$$Pr(Y = j|X = x0) = 1/ K \sum I(yi = j)$$

K is a positive integer and x0 is the test observation. The classifier first identifies k points that are close to the test observation x0. It then estimates the conditional probability of the testobservation.

It is observed that the value of k has a drastic effect on the model's accuracy of classification. It is iterated and testedbybuildingaconfusionmatrixforeachiteration.Thekvaluewithmaximumaccuracyisfinalized.

pred	Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
Bearing	56	0	0	0	2	0	1	0
Flywheel	13	68	0	0	0	1	4	0
Healthy	0	0	68	0	0	0	0	0
LIV	0	0	0	64	8	0	0	0
LOV	0	0	0	1	52	0	0	0
NRV	0	0	0	3	4	67	0	0
Piston	0	0	0	0	2	0	63	3
Riderbelt	0	0	0	0	0	0	0	65

Fig 6. KNNconfusionmatrix

pred	Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
Bearing	53	0	0	0	2	0	0	0
Flywheel	15	68	0	0	0	1	6	0
Healthy	0	0	68	0	0	0	0	0
LIV	0	0	0	63	9	0	0	0
LOV	0	0	0	1	51	0	0	0
NRV	0	0	0	4	4	66	0	0
Piston	1	0	0	0	2	0	62	5
Riderbelt	0	0	0	0	0	1	0	63

Fig 7. Fine Tuned KNN confusion matrix

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 thealgorithm

predictions	Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
Bearing	67	9	0	0	3	0	6	2
Flywheel	2	52	0	0	0	0	1	0
Healthy	0	0	68	0	2	0	0	0
LIV	0	1	0	68	10	0	11	0
LOV	0	0	0	0	49	0	1	7
NRV	0	0	0	0	0	68	1	0
Piston	0	6	0	0	0	0	48	0
Riderbelt	0	0	0	0	4	0	0	59

Fig 8. RPART confusion matrix

Like the other model this model also couldn't predict LOV correctly. As mentioned in figure 8 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 a_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 capturenoise.

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

Fig 9. Random forestconfusionmatrix

Predicted State	0	1	2	3	4	5	6	7
Actual State								
Bearing	69	0	0	0	0	0	0	0
Flywheel	3	65	0	0	0	0	0	0
Healthy	0	0	68	0	0	0	0	0
LIV	0	0	0	68	0	0	0	0
LOV	1	0	0	11	55	0	1	0
NRV	0	0	0	0	0	68	0	0
Piston	0	0	0	0	0	1	67	0
Riderbelt	0	0	0	0	0	0	0	68

Fig 10. Fine Tuned 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

predictions	Bearing	Flywheel	Healthy	LIV	LOV	NRV	Piston	Riderbelt
Bearing	69	3	0	0	1	0	0	0
Flywheel	0	65	0	0	0	0	0	0
Healthy	0	0	68	0	0	0	0	2
LIV	0	0	0	68	10	0	0	0
LOV	0	0	0	0	47	0	1	2
NRV	0	0	0	0	1	68	0	0
Piston	0	0	0	0	4	0	67	0
Riderbelt	0	0	0	0	5	0	0	64

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

AccuracyTable

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.

Table 1 : Accuracy of Algorithms

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

KNN	90.64
RPART	87.88

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. Onimplementing5algorithmsitisfoundthattheRandomforestshowsbetteraccuracy, butonfine-tuning, it is found that the accuracy of SVM is better than other algorithms. Fine Tuned random forest did not give appreciablechange.
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 batchanalytics.

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