# Condition Monitoring of a Hydraulic Brake System Using Sequential Minimal Optimization (SMO) Algorithm

**Vishnu Mukundan, R. Jegadeeshwaran, V. Sugumaran**

***Abstract*— Brake systems are one of the most important systems in automobiles. Many accidents occur daily due to brake failure. Hence, brake system requires constant monitoring to ensure safety. It can be done using a machine learning approach. It is one of the condition monitoring techniques, which is used to predict the faults. In this study, the faults in hydraulic brakes are monitored through vibration signals. The vibration signals from the hydraulic brake arrangement are to be acquired using a piezoelectric type transducer and stored using a data acquisition system. From this vibration signals, the relevant statistical features were extracted. The extracted features were classified by using Sequential Minimal Optimization (SMO) algorithm. The classification accuracy and the performance level of the classifier was found.**

***Index Terms*—** Statistical features, Machine learning approach, Sequential Minimal Optimization, Vibration signals.

## INTRODUCTION

Brake system is the one of the most important component in an automobile. It guarantees control not only for the safety of the passenger, but also ensures the safety of the people outside the car, especially the pedestrians. The efficiency of the brake system depends on the ability to stop the vehicle at a safe distance from the obstacle. In addition to the main objective of stopping the vehicle at reasonable distance from the obstacle, the braking should be even and free from tremor. Also the rate of deceleration of the vehicle must be proportional to the pressure applied to the effort applied by the driver on the brake pedal of the vehicle. Any failure in the brake system indicates some substantial variation in its physical configuration. In order to ensure the proper functioning of the brake system, the state of the brake system must be observed constantly. Condition monitoring identifies the faults in the brake pads as well as the fault conditions that occur in the brake oil, wear of brake pad, insufficient brake oil and leakage in reservoir, etc.

Condition monitoring is a process of constant monitoring of the various parameters of a machine or mechanism to identify the problems that can occurs in its normal operation. Condition monitoring would rectify that problems and ensure its proper functioning. The monitoring process mainly involves the measurement of the vibration signals from the brake system during normal conditions and during the application of brakes under faulty conditions. These two signals are compared and the fault in the braking system is identified from the comparison data. The vibration signals from the brake assembly are captured using piezoelectric transducer and the analog signals from piezoelectric sensors are acquired and digitized using Data Acquisition (DAQ) system. The analysis of this data gives the fault in the brake system.

The process of fault diagnosis mainly consists of three stages namely, feature extraction, selection and classification. The feature extraction from the brake signals can be mainly done using two methods namely, histogram and statistical feature extraction. Statistical feature extraction includes the extraction of features using statistical calculation methods whereas the histogram extraction extracts the features from the readings by using histogram methods. In this study, the statistical features were used for feature extraction from the vibration signals that are obtained from the brake system after continuous levels of monitoring.

In feature selection process, various methods are used for the selection namely, principal component analysis (PCA), fuzzy and artificial neural network, genetic algorithm and decision tree. PCA is a variable reduction procedure which was used to determine which system is suitable for which criteria when a high dimensional input data is given to the system. This is also the case of neural networks and genetic algorithms. In this study, all the twelve features selected for classification.

**Manuscript received Aug 25, 2014**

**Vishnu Mukundan**, SMBS, VIT University, Chennai, Tamil Nadu, India
**R. Jegadheeswaran**, , SMBS, VIT University, Chennai, Tamil Nadu, India
**Dr. V. Sugumaran**, SMBS, VIT University, Chennai, Tamil Nadu, India

Fuzzy classifier and histogram feature were used for classification in bearing fault diagnosis [1]. Roller bearing fault diagnosis was done using SVM and PSVM as their classifier in another work [2]. According to Sugumaran *et al*[3], the feature selection process can be done using decision tree algorithm and PSVM was used to classify the selected features during the fault diagnosis of bearing. In another work, both histogram and statistical features were used to monitor the conditions of single point carbide tool and the classification was done using Baye's algorithm [4]. In an article, Kernel based Neighborhood and Multiclass SVM was applied for diagnosing faults in roller bearings. A paper was published by C.J. Li and J. Ma [10] the vibration signals were decomposed using wavelet decomposition for the recognition of contained defects on bearings. According to Xili Zhang *et al*[11], a SMO algorithm and fuzzy return can be developed for obtaining an optimized model for the portfolio adjusting problem analysis. There are more number of classifiers for fault diagnosis. There is no literature for fault diagnosis using SMO. Hence, an effort has been taken to study the brake related study using SMO techniques. Fig. 1 shows the flowchart of brake condition monitoring.

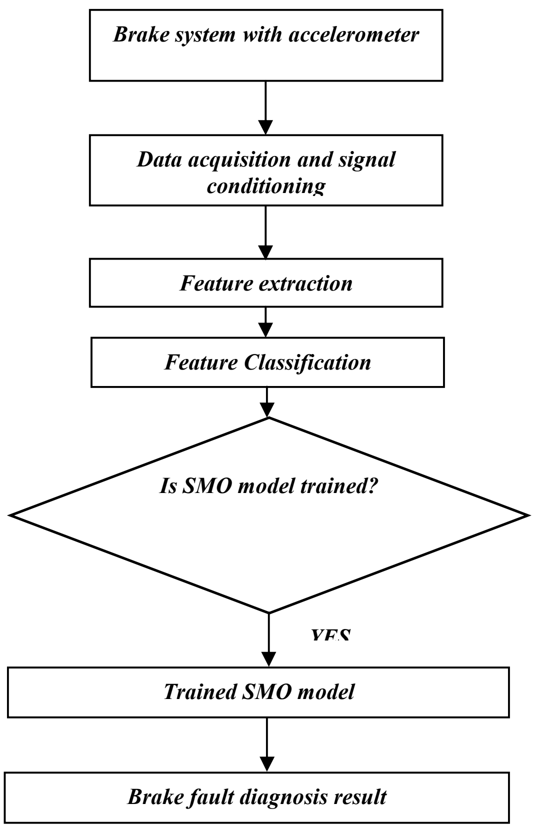


Fig. 1. Flow chart of Brake Condition monitoring

## II. EXPERIMENTAL WORK

Experimental setup and the procedure used for this work were described in detail below.

### *A. Experimental Setup*

The test used for the work was a hydraulic braking system of a commercial passenger's car in which a shaft is used to couple together the disc and the rear drum brake. This shaft was operated by a DC motor using a belt drive system. The power of the motor used was 1HP. A piezoelectric uniaxial of range 50g and sensitivity of 100mV/g was mounted on the drum brake using a suitable adhesive to monitor the vibration signals from the brake. The accelerometer was tuned to a resonant frequency of 40Hz. The vibration signals from the brake system were acquired by using a DAQ system NI USB4432 model. The readings were stored in computer and used in the further stages. Fig. 2 shows the experimental setup.

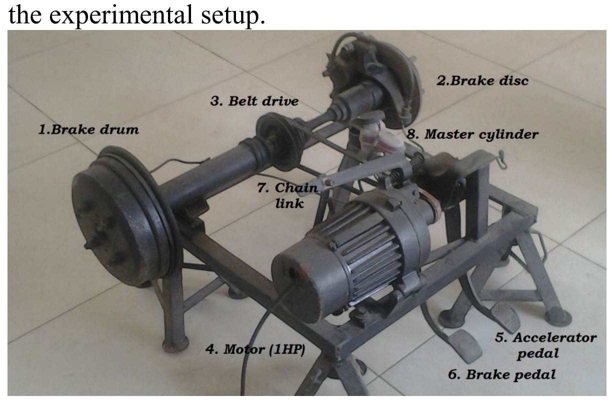


Fig. 2. Experimental setup

### *B. Experimental Procedure*

At the starting, an assumption that the brake system of the test rig is to be in good condition. The vibration signals from the brake set up were measured under constant brake conditions. For the experiment, the sampling length of the vibration signal was taken as 1024 samples. Also, using the Nyquist theorem, the sampling frequency was taken as 24kHz and a total of 55 samples were considered. These signals were monitored using DAQ system and the readings were viewed in NI LabVIEW. The fault conditions were simulated individually while all other components remain in good condition and the resultant vibration signals were captured. The vibration signals under different fault conditions were acquired. The variation of the readings in each of these conditions indicates the faulty operation of the brake system [12].

1) Brake Oil Spill on disc brake (BO)
2) Drum Brake Pad Wear (DRPW)
3) Disc Brake Pad Wear (Even) – Inner (DWI)
4) Disc Brake Pad Wear (Even) – Inner and Outer (DWIO)
5) Disc Brake Pad Wear (Uneven) (UDWI) - Inner
6) Disc Brake Pad Wear (Uneven) – Inner and Outer (UDWIO)
7) Reservoir Leak (RL)
8) Drum brake Mechanical Fade (DRMF)

## III. FEATURE EXTRACTION

The first step in feature extraction of the obtained signals was the extraction of different statistical features. The process of computing some measures which will represent the signal is called feature extraction. A fairly wide set of statistical parameters were selected as the basis of the study. They are mean, standard error, sample variance, kurtosis, skewness, minimum, maximum, standard deviation, count, and mode and median. These features were extracted from vibration signals. The definition and process of extracting statistical features are described in [12].

## IV. FEATURE CLASSIFICATION

The classification process was done using various classifiers namely, Baye's algorithm, fuzzy classifier, decision tree algorithm etc. In this study, Sequential Minimal Optimization technique has been used for the classification of the selected features from the decision tree.

The sequential minimal optimization (SMO) algorithm was introduced for finding solution for the support vector machine (SVM) quadratic programming problem. The SMO algorithm provides a good solution in a very effective manner for possibilistic selection problems. Unlike SVM learning algorithms in which the inner loop was an arithmetical quadratic programming (QP), analytic QP step is used in the SMO. The smallest possible optimization problem is chosen by SMO at every step. The smallest possible optimization problem for the standard SVM quadratic programming problem involves two Lagrange multipliers. It is so because a linear equality constraint is followed by the Lagrange multipliers. The two Lagrange multipliers are chosen and jointly optimized by SMO at every single step to find optimal values and these optimal values are used to update the SVM.

The main advantage of SMO is that the two Lagrange multipliers can be solved analytically, thereby avoiding the numerical quadratic programming optimization. A small amount of C code is used to express the inner loop of the algorithm instead of raising an entire quadratic programming library routine. The overall quadratic programming problem is solved quickly as each sub-problem is very much fast even though there are more sub-problems to be solved in the course of the algorithm. Also the need for extra matrix storage is nil for SMO. Due to this, very large SVM training programs can be stored in ordinary personal computer or workstation memory. SMO is very much less vulnerable to numerical accuracy problems as no matrix algorithms are used. The SMO algorithm carries out joint optimization of two chosen parameters in each of its iteration steps. Each of these two parameters is usually selected either heuristically or randomly and the optimizations of the parameters are done dynamically. The optimization of the two parameters provides an analytical solution that eliminates the use of an iterative program optimizer in the algorithm, which is the key feature of SMO algorithm. This makes the algorithm to be implemented more easily, which in turn increases the speed of operation.

## V. RESULTS AND DISCUSSIONS

The extracted features were classified using Sequential Minimal Optimization algorithm. The following parameters were selected for classification.

- The complexity parameter C: 30
- Kernal: The Pearson VII function-based universal kernel
- Randomseed: 1
- Tolerence parameter: 0.001
- Epsilon: 1.0E-12
- Number of support vectors: 18

The input to the algorithm is set of statistical features. The output of the algorithm is a confusion matrix. The confusion matrix obtained after the implementation of SMO algorithm is shown in Table I. The accuracy obtained is 94.36 %. Incorrectly classified instances obtained during the classification using decision tree algorithm as 5.64 %.

| | | |
|---|---|---|
| Correctly Classified Instances | 519 | 94.36 % |
| Incorrectly Classified Instances | 31 | 6.64 % |
| Total Number of Instances | 550 | |

The accuracy levels obtained using SMO techniques, it was found that the misclassified instances for SMO technique was considerably less. Hence the sequential minimal optimization algorithm can be suggested for predicting the brake faults.

TABLE I. CONFUSION MATRIX FOR SMO
(C-PARAMETER = 30)

| CATEGORY | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| AE | 55 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 0 |
| BO | 0 | 52 | 1 | 0 | 2 | 0 | 0 | 0 | 0 | 0 |
| DPWI | 0 | 0 | 53 | 0 | 2 | 0 | 0 | 0 | 0 | 0 |
| DPWIO | 0 | 0 | 0 | 55 | 0 | 0 | 0 | 0 | 0 | 0 |
| UDPWI | 0 | 0 | 1 | 0 | 54 | 0 | 0 | 0 | 0 | 0 |
| UDPWIO | 0 | 3 | 2 | 0 | 6 | 44 | 0 | 0 | 0 | 0 |
| DRMF | 0 | 0 | 2 | 0 | 0 | 1 | 51 | 0 | 0 | 1 |
| DRPW | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 53 | 0 | 1 |
| GOOD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 | 0 |
| RL | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 47 |

TABLE II shows the detailed accuracy by class by using which the classification accuracy can be effectively studied.

TABLE II. DETAILED ACCURACY BY CLASS

| *TP Rate* | *FP Rate* | *Precision* | *Recall* | *F-Measure* | *ROC Area* | *Class* |
|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 1 | 1 | AE |
| 0.945 | 0.006 | 0.945 | 0.945 | 0.945 | 0.999 | BO |
| 0.964 | 0.012 | 0.898 | 0.964 | 0.93 | 0.991 | DPWI |
| 1 | 0.002 | 0.982 | 1 | 0.991 | 0.999 | DPWIO |
| 0.982 | 0.02 | 0.844 | 0.982 | 0.908 | 0.988 | UDPWI |
| 0.8 | 0.002 | 0.978 | 0.8 | 0.88 | 0.979 | UDPWIO |

| | | | | | | |
|---|---|---|---|---|---|---|
| 0.927 | 0.016 | 0.864 | 0.927 | 0.895 | 0.967 | DRMF |
| 0.964 | 0 | 1 | 0.964 | 0.981 | 0.983 | DRPW |
| 1 | 0 | 1 | 1 | 1 | 1 | GOOD |
| 0.855 | 0.004 | 0.959 | 0.855 | 0.904 | 0.992 | RL |
| 0.96 | 0.004 | 0.961 | 0.96 | 0.96 | 0.978 | Wt.Avg |

Table II shows the detailed accuracy by class for SMO. For an Ideal classifier, the true positive rate (TP rate) must be 1, whereas the false positive rate (FP rate) should be 0. TP (True positive) rate is the proportion of the conditional class that was correctly identified as belonging to that particular conditional class. FP (false positive) is the proportion of the misclassified cases that were incorrectly classified as positive.

Referring, Table 4, the weighted verge of the TP rate is close to one (0.96) and the FP rate is very close to 0 (0004). The small deviation is due to some misclassification among the different fault conditions. Hence the overall classification accuracy was calculated as 94.36 % which is equivalent to the TP rate. Similarly, the precision, recall and F-measure value is also close to 1, which is an expected value of an ideal classifier. An F-measure is the harmonic mean of precision and recall, and a larger F-Measure value indicates a higher classification quality. F-measure depends on precision and recall. Hence for all the three cases, the average value is close to 1 (0.96). The above encouraging results have been obtained through the 10-fold cross validation. The overall classification accuracy of the SMO algorithm was found to be 94.36 %.

## CONCLUSION

From the studies done above, the condition monitoring of the brake system test rig was carried out using Decision Tree and SMO algorithms. The variations in the vibration signals were monitored using DAQ system and the features obtained were selected. The accuracy levels of each sample values were calculated using SMO algorithm. The SMO algorithm was used to classify the extracted features and the classification accuracy was obtained. The accuracy level obtained using SMO having good candidates for fault prediction. Thus it can be concluded that the fault diagnosis of brake system can be effectively determined using SMO algorithm when compared to SMO algorithm.

## Acknowledgment

I thank VIT for giving me such a great opportunity to do research on this topic also for providing all the necessary facilities.

## REFERENCES

[1] V. Sugumaran, K.I. Ramachandran, Roller bearing fault diagnosis using histogram features and fuzzy classifier, Expert System with is Application vol.38, 2011, pp. 4901-4907.

[2] V. Sugumaran, K.I. Ramachandran, Roller bearing classification using SVM and PVSM, Expert systems and with applications, 2011, pp. 4088-4096.

[3] V. Sugumaran, V.Muralidharan, K.I. Ramachandran Selection using decision tree and classified using PSVM for bearing fault diagnosis, Mechanical system and processing of signals, vol.21, pp. 930- 942.

[4] V. Sugumaran, M. Elangovan, K.I. Ramachandran, Monitoring of single point carbide tool using histogram and statistical features and classified used on Baye's Algorithms, Expert System with the Application, vol.37, 2010, pp. 2059-2065.

[5] V. Sugumaran, G.R. Sabareesh, K.I. Ramachandran, Roller bearing fault diagnosis by Kernel based Neighborhood and Multiclass SVM, Expert System with its Applications vol.34, 2008, pp. 3090-3098.

[6] M. Amarnath, Hemantha Kumar and V. Sugumaran, Variation of sound signals fault diagnosis using decision tree classifier, vol.46, pp.1250-1256.

[7] C.J.C. Burgess, Research based on SVM for pattern recognition. Mining of Data and Knowledge discovery 2, pp. 955-974.

[8] V. Sugumaran, K.I. Ramachandran, Roller bearing fault diagnosis using decision tree and fuzzy classifier, Mechanical based System and Signal Processing, vol.21, 2007, pp. 2237-2247.

[9] V. Sugumaran, K.I. Ramachandran, N.R. Sakthivel, M. Saimurugan, Rotational mechanical system by multi component fault diagnosis using decision tree and with SVM, Expert System with its Applications, vol. 38, 2011, pp. 3819-3826.

[10] C.J. Li, J. Ma, Wavelet decomposition of vibrations for detection of bearing localized defects, NDT & E International vol. 30, No.3, 1997, pp. 143– 149.

[11] Xili Zhang, Wei-Guo Zhang , Wei-Jun Xu, An optimization model of the portfolio adjusting problem with fuzzy return and SMO algorithm, Expert Systems with Applications, vol.38, 2011, pp. 3069–3074.

[12] Jegadeeshwaran. R, Sugumaran. V, Comparative study of decision tree classifier and best first tree classifier for fault diagnosis of automobile hydraulic brake system using statistical features, Measurement, vol.46, 2013, pp. 3247–3260.

**Vishnu Mukundan,** was born in Malappuram district, Kerala, in 1991. He completed his B. Tech. in Electronics and Communication Engineering at LBS College of Engineering, Kasaragod, Kerala, India, in the year 2013. At present he is pursuing his Masters degree in Mechatronics at VIT University, Chennai, Tamil Nadu, India he is pursuing his research in the field of fault diagnosis in brakes.

**R. Jegadeeshwaran,** was born in Erode district, Tamil Nadu, in 1981. The author completed his Under Graduate course in Mechanical Engineering at Institute of Road and Technology, Erode, Tamil Nadu, India, in the year 2002. He pursued his Masters degree in Mechatronics Engineering at Kongu Engineering College, Perundurai, Tamil Nadu, India, in 2009. At present he is pursuing his doctoral degree in VIT University, Chennai, Tamil Nadu.

He worked as an Assistant professor, at Kongu Engineering College, Perundurai for a period of two years. At present he is working as an assistant professor at VIT University, Chennai, Tamil Nadu, India. He has six international / National conference publications. He has published five papers in peer reviewed international Journals. He is doing research in the field of fault diagnosis.

**Dr. V. Sugumaran** received the B.E. degree in Mechanical Engineering from the Amrita Institute of Technology & Science, 1998 and the M.Tech in Production Engineering, from The National Institute of Engineering, 2003. Ph.D. degree in Fault Diagnosis, from Amrita School of Engineering, Amrita University, Coimbatore, Tamil Nadu, India, in 2008.

From 2000 to 2009, he was an Associate Professor, with the Amrita School of Engineering, Coimbatore, Tamil Nadu. From 2009 t0 2011, he was working with SRM University, Chennai, Tamil Nadu. Since 2011, he has been an Associate Professor with the School of Mechanical and Building Sciences, VIT University, Chennai, Tamil Nadu, India. He is the author of two books, more than 87 international journal publications. He has also filed three patents. His research interests include Condition Monitoring & Fault Diagnosis, Machine learning / Data mining in manufacturing and Mechanical Engineering. He presented papers in 43 International / National Conferences. He is also acting as a Reviewer for many international journals and editor for four international journals.