Comparative study on different balancing conditions of an air filled tyre using statistical features and classification via regression algorithm

P S Anoop¹  V Sugumaran¹*
¹ School of Mechanical Engineering, Vellore Institute of Technology, Chennai campus, Chennai, India.
E-mail: v_sugu@yahoo.com

Abstract: Tyre condition monitoring systems (TCMS) are the safety systems used in a vehicle for measuring the condition of tyre like tyre pressure, temperature, balancing etc. In this era of increasing vehicle accidents, these systems are having paramount importance in terms of safety. The current technology TCMS uses direct sensors like pressure sensors or wheel speed sensors etc, which are highly expensive. This paper puts forward an innovative indirect TCMS system using condition monitoring techniques and machine learning. For different five balancing conditions vertical vibrations from fixed wheel hub were extracted from a moving air filled tyre with the help of an accelerometer. The tyres filled with air are considered with different pressure values to represent puncture, normal, idle and high pressure conditions. In feature extraction process, the statistical features were extracted from the acquired signals and the prominent features were selected using J48 algorithm. Selected features were classified with the help of classification via regression algorithm and reasonable high accuracy was obtained. This paper attempts to study the effect of unbalance of the wheel on the classification accuracy of an indirect TPMS system. The results are compared and presented.

1. Introduction

Tyres are circular parts attached to the rims for enhancing the axial load of the automobile to the ground. Pneumatic and non-pneumatic tyres are the two basic types of it. Most of the tyres, used in passenger automobiles and bicycles are air filled structures. These tyres absorb vertical vibrations as it roll and give the passenger a flexible cushioning effect. Non pneumatic tyres are airtight, combining the wheel and tyre into a single component. These are used in special type of vehicles such as tractors, riding lawn mowers etc. In terms of advantages, pneumatic tyres are valued more than non-pneumatic tyres because it finds noise-reducing ride, durability and ability to absorb shock. Depending on the method of production air-filled tyres are categorized as belted-ply, bias-ply and radial-ply.

Radial tyre is a type of tyre where the fabric piles (nylon layer) are arranged at right angles to the direction of travel. Main advantages of radial tyres are that
The side walls are flexible.
The contact area of radial tyres with road is high, so the vehicle stability will be higher.
Fuel consumption will be less as the rolling distance is less.
Heat production and vibration are low, so tyre life will be high.

The specification of the air-filled tyre used for the test is coded 165/80 R14 85 S. The various parameters in the tyre code are clearly illustrated in Figure 1. The tyre selected for the current test is shown in Figure 2.

Figure 1 Tyre specification diagram

Figure 2 Tyre selected for current experiment

1.1 Tyre Condition Monitoring System (TCMS)
In this fast-growing automobile world, safety has always been a priority. Here TCMS finds its place. A study led by the UK tire industry gathering found that between 2003 and 2005, around 50% of light vehicle crashes were caused by tyres[1]. TCMS alarms tyre-allied problems and thus ensuring a safer mode of transportation. TCMS are small electronic subsystems that observe the tyre pressure and tyre balancing on individual wheels of a vehicle. A TCMS-mounted automobile helps the driver to check the condition of the tyre at low pressure or if something bad has happened to the tyre. An effective TCMS can easily predict tyre failures. This reduces the risk of tyre-related road accidents. Depending on the data acquisition method, TCMS can be classified into-Direct TCMS (dTCMS) and Indirect TCMS (iTCMS). As the name Implies, a direct TCMS pressure sensor measures the pressure and tyre condition and transfers the data to a controlling unit attached to the dashboard. In the Indirect TCMS, pressure and tyre condition are measured indirectly from the wheel speed sensors and then the
data transferred to the control unit. The advantages of iTCMS are affordable price, easy maintenance and reliability. This study depends on indirect TCMS so as to prove that iTCMS have more advantages than that of dTCMS.

The direct TPMS is expensive than its indirect counterpart. Indirect TPMS requires less programming/maintenance over the years than a direct TPMS in which resynchronization may require costly tools. In this case of indirect TPMS, overall installation hassles are less than its direct counterpart. But in the case of direct TPMS, sensors should change periodically once battery is worn out and there is a high chance of damage to the sensor during uninstalling or installing. So, we have developed an Indirect TPMS by using an accelerometer module. Vibrations are used to manage the system.

While driving a car the tyres rotate uniformly due to the equal distribution of the balancing mass around the wheel. This method is mentioned as wheel balancing. Severity of unbalance in a tyre results in vibrations of varying degrees which reverberates through the vehicle chassis. If the severity of unbalance is more, it becomes very dangerous to drive because the steering wheel experiences severe vibrations. Tyre imbalance leads to higher fuel consumption at higher speeds. An increase in wheel imbalance causes a peak vibration at the wheels, which will result in severe damage to the vehicle.

In recent years, iTCMS research opportunities in current trending technologies such as machine learning and artificial intelligence have gained wide acceptance[2]. iTCMS initially operates on the principle that low-pressure tyres have a reduced diameter compared to properly inflated tyres. The main drawback of this system is that all four tyres fail to detect inflation at the same time. Subsequent studies, however, have addressed this shortcoming through spectrum analysis and advanced signal processing techniques [3]. The rolling resistance of a tyre is the amount of energy required to keep the tyre moving. Schuring and Futamura said that when the rolling resistance coefficient decreases, the fuel efficiency increases due to the hardness of the tyre.[4].

Experiments using accelerometer are having wide acceptance these days. Robinson et al., developed an experimental setup in which accelerometer was attached to the tyre and the vibrations were artificially applied to the tyre with a hammer[5]. In another experiment Wei et al used an accelerometer and a piezoresistive pressure sensor for detecting the tyre pressure. When the vehicle start moving, accelerometer detects the motion and activates the pressure sensor[6]. An inductive powered transducer method and a moving piston method are the two systems suggested by Hill et al for measuring indirect tyre pressure. The main drawback of this system is that pressure can be detected only while the vehicle moves[7]. Kanwar et al proposed a piezoelectric vibration harvesting system, which powers the tyre pressure monitoring sensors[8].

In another study Craighead developed a technique in which he made use of vibration measurements and frequency spectrum analysis of normal tyre to detect the tyre pressure and wheel balance. The accuracy obtained was relatively less than 12% and the measure of unbalance was determined [9]. Hasan et al suggested a technique that uses air pressure in pneumatic tyres. If tyre pressure varies, an alert warning will be registered. The user can modify the minimum and maximum tyre pressure level[10].

Tyre life span is closely related to tyre pressure. One minute deflection in tyre pressure (17%) reduces tyre life by 25% and increases the overall fuel consumption by 2%[11]. Wu et al. proposed different energy harvesting methods using TPMS and determined the importance of piezoelectric sensors in TPMS[12]. Some commercial vehicle-only systems that determine tyre pressure and tyre radius using a Vehicle Stability Sensor and GPS[13]. Garcia-pozuelo et al. (2017) developed a strain-based technique to monitor the rolling speed, vertical load, inflation pressure by adding fuzzy logic[14].

Studies based on indirect tyre pressure monitoring system need to be accelerated. With the help of supervised machine learning, Svensson et al suggested an iTPMS. In this work the proposed method permits to detect thread depth and incorrect tyre pressure. The results show that the proposed system has an accuracy of 90.54%[15]. In general, several important experiments were carried out in the areas of both dTCMS and iTCMS[16]. Only a few studies have been conducted to detect both tyre pressure and tyre balancing simultaneously using iTCMS. Moreover proper emphasis on experiments based on machine learning was also very limited. But these are the
needs of the hour. In this context, this study proposes a new approach which claims that both tyre pressure and tyre balancing can be measured using indirect TCMS with the help of machine learning techniques. Detailed methodology of the proposed system as shown in Figure 3.

![Figure 3 Methodology of proposed iTCMS](image)

2. Experimental Setup

An accelerometer is mainly used to acquire vibration signals. In this experiment, a tri-axial accelerometer was fixed to the back left wheel hub of the selected automobile to avoid unwanted engine vibration signals (Refer Figure 4). ‘NI USB-6001’ was used as data acquisition (DAQ) device. To avoid the external electronic noise, a shielded wire was connected between accelerometer and DAQ. The specifications of the MEMS accelerometer and NI USB-6001 are given in [17].
The tyre selected for this study was set to balanced condition, which means that there was no additional weight rather than the balancing weight fitted with the tyre. The total balancing weight fitted was 40g and the tyre was inflated with air. The data acquired here was termed as 0 balance condition. Similarly different balancing conditions were obtained by adding or removing the balancing weights. The signals were acquired for different pressure conditions such as High, Normal, Puncture and Idle. 19psi, 31psi and 40psi were taken as the tyre pressure of puncture, normal and high conditions respectively. Riding a speed below 10 km/hr, without sufficient amplitude and vibration, was taken was Idle. As shown in Table 3, the conditions -40 balance, -20 balance, 0 balance, +20 balance and +40 balance were chosen for data collection of High, Normal, Puncture and Idle cases (refer Table 1). The experiments were conducted within the speed limit of 10 km/hr and 100 km/hr.

Statistical features were extracted from different class of signals. The feature selection was done using j48 algorithm and features were classified using Classification via Regression Algorithm. A balanced study was conducted by collecting 60 samples in all cases mainly High, Normal, Puncture and idle. On the whole, a total of 1200 samples were obtained. Each of these signals was having 5000 data points and 1 kHz sample rate[18].

| Conditions | Weight Added(g) | Wheel Position |
|------------|----------------|----------------|
| -40 Balance | 0g | Rear Left |
| -20 Balance | 20g | Rear Left |
| 0 Balance | 40g | Rear Left |
| +20 Balance | 60g | Rear Left |
| +40 Balance | 80g | Rear Left |

2.1 Sampling rate calculation

The tyre used for this particular study was 165/80 radial. The tyre radius(R) was rated as 30.1 cm. The maximum and minimum speed of the study was 100km/hr and 10km/hr respectively. Based on the study[18], the minimum and maximum frequency is 1.47 Hz and 14.73 Hz respectively. Considering Nyquist Shannon sampling theorem, the minimum sampling rate will have to be greater than or equal to 29.46 Hz [19]. So this study prefers to take 1 kHz as sampling rate. Vibration signals for zero Balance condition is plotted in Figure 5.
3. Feature Extraction
Machine learning consists of 3 steps-feature extraction, feature selection and feature classification. Feature extraction is a feature reduction process in which it aligns the available features according to their importance in classification. Any fault in the mechanical components will induce a considerable change in vibration signals and that change can be detected from the statistical parameters of vibration signals. This has been proved by many researchers reported in the literature. Thus statistical features can be an effective for extracting meaning information from the vibration signals with less complexity and less computational time.

Targeted vibration signals for the conditions -40 Balance, -20 Balance, 0 Balance, +20 Balance and +40 Balance were chosen for data collection of High, Normal, Puncture and Idle cases. This study used statistical feature extraction, which is one of the best and common feature extraction techniques. Statistical features extracted were mean, kurtosis, mode, median, sample variance, range, sum, standard error, maximum, standard deviation, minimum and skewness.

4. Feature Selection
The features extracted during feature extraction technique were tested using j48 decision tree algorithm. In J48 algorithm, the features are selected through the calculated entropy and information gain values. These parameters will decide upon the selection of most contributing features out of the given input features and thereby the numbers of input variables are reduced while developing a predictive model[20]. The involvement of each feature tested and the features influencing less for the classification were filtered for decreasing computational load of the system. In [21] the detailed procedure of feature selection using J48 decision tree algorithm was clearly explained. Figure 6 describes the features selected for different conditions. Figure 7 shows the decision tree generated from j48 decision tree algorithm.
5. Feature Classification – Classification via Regression Algorithm (CVR)

The classifier used for feature classification in this specific study is Classification via Regression Algorithm. In this algorithm classification problem is converted to regression functions. It binaries and builds a regression model for each class value. The principles of both linear regression and decision tree algorithm are combined in this classifier[22]. The two stages of this method are

1. Create a normal decision tree, by increasing the difference and variations of attributes in accordance with the output values. The deviation reduction standard must be evaluated during the decision tree building.
2. Pruning the main decision tree in to possible sub trees and merging it with regression function[23].
During the training time of Classification via regression algorithm, enormous numbers of decision trees are generated. Every single tree provides its classification, which is taken as a vote for that class; the object is assigned to the class that has the maximum number of votes. This algorithm used in many mechanical vibrational studies. It is a powerful tool for predicting and it does not over fit. This has been proved by many researchers reported in the literature[24].

5.1 Performance Parameters
Classification accuracy is the main performance parameter for evaluating the performance of an algorithm at different conditions. It is ratio of number of correct prediction and total number of predictions, which is indicated as the percentage. In every experiment, the average of the difference between expected outcome and real outcome is termed as Mean absolute error (MAE). It is an important parameter while considering the performance of an algorithm. The average magnitude of the error calculated using a quadratic scoring rule is known as Root mean squared error (RMSE)[25]. Kappa statistics is a commonly accepted statistics to measure the settlement between two or more observers. In this measurement, the observers may sometimes agree or disagree simply by chance. A kappa statistics of 0.8 to 1.0 indicates perfect agreement, 0.61 to 0.8 indicates substantial agreement whereas a kappa of less than 0 indicates agreement equivalent to chance[26][27].

6. Results and Discussions
6.1 Zero balance condition using Classification via Regression Algorithm

From Figure 7, it is evident that Classification via Regression Algorithm provides the maximum classification accuracy of 91.25% for zero balanced air condition. The confusion matrix for zero Balance air condition generated by trained Classification via Regression Algorithm is shown in Figure 8. Figure 9 shows class-wise detailed accuracy for the trained Classification via Regression Algorithm for zero Balance air condition.

From Figure 8, the correctly classified instances (out of 60) were represented as diagonal elements in the confusion matrix. From the matrix, one can notice that 59/60 of ‘idle’ instances were correctly classified followed by ‘puncture’ instances where 57/60 are correctly classified. 56/60 instances are correctly classified for ‘high’ state and 47/60 instances for ‘normal’ state[28].

![Figure 8 Confusion matrix for zero Balance air condition generated by trained Classification via Regression Algorithm](image-url)
6.2 -20 Balance condition using Classification via Regression Algorithm classifier

In this condition the total balancing weight added to the selected tyre was 20g instead of 40g (Refer section 6.1). The confusion matrix for -20 Balance air condition generated by trained Classification via Regression Algorithm is shown in Figure 10. Figure 11 shows class-wise detailed accuracy for the trained Classification via Regression Algorithm for -20 Balance air condition.

Figure 9 Class-wise detailed accuracy for the trained Classification via Regression Algorithm for zero Balance air condition

![Figure 9](image)

Figure 10 Confusion matrix for -20 Balance air condition generated by trained Classification via Regression Algorithm

| Actual Class | Predicted Class |
|--------------|-----------------|
|              | -20AirHig | -20AirNor | -20AirPun | -20AirIdl |
| -20AirHig    | 56        | 0         | 0         | 0         |
| -20AirNor    | 0         | 48        | 0         | 0         |
| -20AirPun    | 0         | 0         | 52        | 0         |
| -20AirIdl    | 0         | 0         | 0         | 60        |
6.3 -40 Balance condition using Classification via Regression Algorithm classifier

In this condition the total balancing weight added to the selected tyre was 0g instead of 40g (Refer section 6.1). The confusion matrix for -40 balance air condition generated by trained Classification via Regression Algorithm is shown in Figure 12. Figure 13 shows class-wise detailed accuracy for the trained Classification via Regression Algorithm for -40 Balance air conditions.

![Confusion Matrix for -40 Balance air condition](image_url)

Figure 11 Class-wise detailed accuracy for the trained Classification via Regression Algorithm for -20 Balance air condition.

![Confusion Matrix for -40 Balance air condition](image_url)

Figure 12 Confusion matrix for -40 Balance air condition generated by trained Classification via Regression Algorithm.
6.4 +20 Balance condition using Classification via Regression Algorithm

In this condition the total balancing weight added to the selected tyre was 60g instead of 40g (Refer section 6.1). The confusion matrix for +20 Balance air condition generated by trained Classification via Regression Algorithm is shown in Figure 14. Figure 15 shows class-wise detailed accuracy for the trained Classification via Regression Algorithm for +20 Balance air condition.

![Figure 13 Class-wise detailed accuracy for the trained Classification via Regression Algorithm for -40 Balance air condition](image)

**Figure 13 Class-wise detailed accuracy for the trained Classification via Regression Algorithm for -40 Balance air condition**

**Figure 14 Confusion matrix for +20 Balance air condition generated by trained Classification via Regression Algorithm**

```
| Actual Class    | +20AirHig | +20AirNor | +20AirPun | +20AirIdl |
|-----------------|-----------|-----------|-----------|-----------|
| Classified as   | 49        | 4         | 7         | 0         |
| +20AirHig       | 8         | 48        | 4         | 0         |
| +20AirNor       | 15        | 2         | 43        | 0         |
| +20AirPun       | 0         | 0         | 0         | 60        |
| +20AirIdl       |           |           |           |           |
```
Figure 15 Class-wise detailed accuracy for the trained Classification via Regression Algorithm for +20 Balance air condition.

6.5 +40 balanced condition using Classification via Regression Algorithm classifier

In this condition the total balancing weight added to the selected tyre was 80g instead of 40g (Refer section 6.1). The confusion matrix for +40 Balance air condition generated by trained Classification via Regression Algorithm is shown in Figure 16. Figure 17 shows class-wise detailed accuracy for the trained Classification via Regression Algorithm for +40 Balance air condition.

Figure 16 Confusion matrix for +40 Balance air condition generated by trained Classification via Regression Algorithm.
6.6 Effect of Classification via Regression algorithm on different balance conditions

For the zero balance condition, kappa statistics was measured to be 0.8833. Kappa statistics measured the arrangement of likelihood with the true class. Closeness of prediction to the ultimate result was measured by mean absolute error. In this particular classification, the mean absolute error was 0.1234. The root mean square error value was measured to be 0.2156. Similarly one can easily understand the different errors for different balance conditions from Figure 18 and Figure 19.

From Figure 19, one can identify the trends of change in classification accuracy as the unbalance in wheels is changed by adding mass. For this setup, the lowest classification accuracy is obtained at -40 Balance condition which is 75.83%. The highest classification accuracy is obtained at the zero balance condition, which is 91.25%.

As the balancing mass is increased above or decreased below the zero balanced condition, there is a significant reduction in classification accuracy.
7. Conclusion
Nowadays safety is an important aspect in the growing automobile industry. So devices like tyre condition monitoring systems have its own importance. This work showed an algorithm based comparison of different vibration signals obtained from air filled tyres under five different balancing conditions. Total five data models were created using Classification via Regression Algorithm and compared using data modeling technique. From
the Zero Balance condition at 40g, other balance conditions were created by adding or removing the balancing mass. 10-fold validation method was used to validate the models and classification accuracy of 91.25% was obtained for Classification via Regression Algorithm using zero balance air condition. This methodology may be adopted for tyre condition monitoring because the error rate was considerably less. In future studies, one can modify the methodology by increasing or decreasing the mass by 5g to improve the accuracy.

References
[1] Paine M, Griffiths M and Magedara N 2007 The Role Of Tyre Pressure In Vehicle Safety, Injury And Environment
[2] Anoop P S. V Sugumaran and Hemanth Mithun Praveen 2016 Tyre Pressure Monitoring System Using Machine Learning Approaches – A Review International Journal of Control Theory and Applications 9 371–82
[3] Premarsha B 2016 Survey on Tire Pressure Monitoring System International Journal of Engineering and Technical Research (IJETR) 0869 120–1
[4] Schuring D J and Futamura S 1990 Rolling Loss of Pneumatic Highway Tires in the Eighties Rubber Chemistry and Technology 63 315–67
[5] Howard, H. R., NcGinnis, T. A., Daugherty R H 1993 Remote Tire Pressure Sensing Technique
[6] Wei C, Zhou W, Wang Q, Xia X and Li X 2012 TPMS (Tire-Pressure Monitoring System) Sensors: Monolithic Integration of Surface-Micromachined Piezoresistive Pressure Sensor and Self-Testable Accelerometer Microelectron. Eng. 91 167–173
[7] Hill M, Malson P R W C and Turner J D 1990 The development of a low cost system for monitoring tyre pressures IEE Colloquium on Chassis Electronics pp 2/1-2/3
[8] Singh K B, Bedekar V, Taheri S and Priya S 2012 Piezoelectric vibration energy harvesting system with an adaptive frequency tuning mechanism for intelligent tires Mechatronics 22 970–88
[9] Craighead I A 1997 Sensing tyre pressure, damper condition and wheel balance from vibration measurements Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 211 257–65
[10] Hasan N N, Arif A and Pervez U 2011 Tire pressure monitoring system with wireless communication 2011 24th Canadian Conference on Electrical and Computer Engineering(CCECE) 99–101
[11] Marton Z, Fodor D, Enisz K and Nagy K 2015 Frequency analysis based Tire Pressure Monitoring 2014 IEEE International Electric Vehicle Conference, IEVC 2014 0–4
[12] Wu B, Fang Y and Deng L 2019 Summary of Energy Collection Application in Vehicle Tire Pressure Monitoring System Proceedings of the 2019 4th International Conference on Automation, Control and Robotics Engineering CACRE2019 (New York, NY, USA: Association for Computing Machinery)
[13] Ryan J and Bevly D 2012 Tire radius determination and pressure loss detection using GPS and vehicle stability control sensors vol 8 (IFAC)
[14] Garcia-Pozuelo D, Yunta J, Olatunbosun O, Yang X and Diaz V 2017 A strain-based method to estimate slip angle and tire working conditions for intelligent tires using fuzzy logic Sensors (Switzerland) 17
[15] Svensson O, Thelin S, Byttner S and Fan Y 2017 Indirect Tire Monitoring System - Machine Learning Approach IOP Conference Series: Materials Science and Engineering 252
[16] Anoop P.S. and V. Sugumaran 2018 Tyre Pressure Monitoring System Using Statistical Analysis And Rotation Forest Algorithm Pakistan Journal of Biotechnology 15 36–9
[17] Anoop P S and Sugumaran V 2020 The Influence of Tyre Balancing In Nitrogen Filled Tyres Using Statistical Features And Random Forest Algorithm International Journal of Mechanical and Production Engineering Research and Development (IJMPERD) 10 6679–90
[18] Anoop P S, Sugumaran V and Mithun Praveen H 2016 Implementing K-Star Algorithm to Monitor Tyre Pressure using Extracted Statistical Features from Vertical Wheel Hub Vibrations Indian Journal of Science and Technology 9 1–7
[19] McLean R F, Alsop S H and Fleming J S 2005 Nyquist-overcoming the limitations Journal of Sound and Vibration 280 1–20
[20] Joshuva A, Kumar K R, Gangadhar G S S, Dhanush S S and Arjun M 2020 Rough Set Theory Based
Blade Condition Classification on Wind Turbine through Statistical Features [IOP] Conference Series: Materials Science and Engineering 923 12010

[21] Anoop P S and Sugumaran V 2017 Classifying machine learning features extracted from vibration signal with logistic model tree to monitor automobile tyre pressure SDHM Structural Durability and Health Monitoring 11

[22] Frank E, Wang Y, Inglis S, Holmes G and Witten I H 1998 Using model trees for classification Machine Learning 32 63–76

[23] Yulita I N, Fanany M I and Arymurthy A M 2019 Comparing Classification via Regression and Random Committee for Automatic Sleep Stage Classification in Autism Patients Journal of Physics: Conference Series 1230 12010

[24] Joshuva A and Sugumaran V 2019 Selection of a meta classifier-data model for classifying wind turbine blade fault conditions using histogram features and vibration signals: A data-mining study Progress in Industrial Ecology 13 232–51

[25] Joshuva A and Sugumaran V 2019 A Lazy Learning Approach for Condition Monitoring of Wind Measurement 107295

[26] Viera A J and Garrett J M 2005 Anthony J. Viera, MD; Joanne M. Garrett, PhD (2005). Understanding interobserver agreement: the kappa statistic. Fam Med 2005;37(5):360-63. Family Medicine 37 360–3

[27] Joshuva A, Kumar R S, Sivakumar S, Deenadayalan G and Vishnuvardhan R 2020 An insight on VMD for diagnosing wind turbine blade faults using C4 . 5 as feature selection and discriminating through multilayer perceptron Alexandria Engineering Journal 59 3863–79

[28] Anoop P S. V Sugumaran and Hemanth Mithun Praveen 2018 Analyzing Vertical Vibrations Of Automobile Wheel Hub To Monitor Tyre Pressure Using Statistical Features And Support Vector Machine Algorithm Pakistan Journal of Biotechnology 15 10–3