EB2020-STP-015

Predicting Brake Pad Wear Using Machine Learning

Choudhuri, Kaushik[1]*, Shekhar, Dr. Amit[2]

[1]iGloble Software Solutions
Mansarovar Building, 401, 90 Nehru Place, New Delhi, India – 110019 (E-mail: kaushik@igloble.com)
[2]iGloble Software Solutions
Mansarovar Building, 401, 90 Nehru Place, New Delhi, India – 110019

https://doi.org/10.46720/EB2020-STP-015

ABSTRACT: For a brake system manufacturing company, finding the right combination of brake pad friction material and their percentage compositions for the brake pad has always been a challenge. The brake discs and the pads have to be designed so that the life of the brake pads are acceptable even under extreme driving conditions and have to be manufactured at the lowest possible cost. Companies spend a lot of time testing different combination of friction materials on dynamometers to arrive at the best possible combination.
This paper discusses a novel methodology for predicting the brake wear and disc wear using artificial neural network, thereby simulating the dynamometer-based testing. The neural network uses friction material compositions, initial speeds, final speeds, deceleration and disc sizes for predicting the brake pad and disc wear. The accuracy of the prediction from the neural network was found to be 85% when compared with the dynamometer-based wear measurement.

KEY WORDS: Brake Pad, Wear, Friction, Machine Learning, Neural Networks

1. Introduction

Wear of brake friction materials and coefficient of friction depends on many factors such as disc temperature, applied load, disc size, weight of the car, velocity, braking characteristics, ambient temperature, and proportion of friction materials. These factors and their effect on wear have been discussed by the author of reference (1). It has therefore been very difficult to predict the brake pad and disc wear with a certain degree of accuracy.

The artificial neural network application predicts the brake wear and disc wear virtually and dynamically. This is achieved without having to go through elaborate dynamometer tests and test track tests and without relying on any brake sensors resulting in shorter design to manufacturing cycle times.

A cloud based application using artificial neural network can predict brake pad and disc wear for any new design of a brake disc and pad on an existing car or a new car, for a particular kind of driving characteristics over a particular route to predict the wear. Currently, a new disc design is either tested on a dynamometer or on a test track driven for thousands of kilometres to determine the wear of the brake pads. The entire process of designing a new pad and disc might take as long as three to four months. The design time can be significantly shortened by using this application.

2. Data Collection for Training and Testing the Neural Network

In order to build an effective neural network, final brake temperature, disc wear and pad wear using different combinations of braking characteristics, disc sizes, vehicle inertia, rolling radius and brake pad compositions data is required. This required data was generated from actual tests on a dynamometer. Thirty different brake pads with different composition of the friction material were made. These are referred to as samples in the rest of the document. Each of these brake pads was tested for seven different braking regimes or Blocks. These braking regimes had a specific initial temperature, initial speed, a final speed and a deceleration value. These braking regimes are different for different OEMs, and are usually termed as Town Block, Country Block, Highway Block etc. For example, Town Block uses an initial speed of 40km/hr, final speed of 0km/hr, deceleration of 0.15g and initial temperature of 135^{o}C. As part of the setup, the application software in the dynamometer is set for these braking regimes. The dynamometer test is started and once the initial speed and temperature is obtained, brakes are applied to bring the speed to the required final speed. This forms one braking event. The wear due to this single braking event is however very small and cannot be measured. Therefore, the braking event is repeated 50 times and at the end of the test, the brake wear and the disc wear are measured. The pad and disc wear after each braking event is assumed to be an average of the total wear after 50 braking events. The wear values of last 20 braking events were used as data points.

Figure1 Brake Dynamometer

After all the braking regimes are repeated for all the thirty pads, 4200 data points (30x7x20) are obtained. These data points are used to build the neural network model. The input parameters and their ranges used for the dynamometer test are given in Table 1.

Table 1 Parameters used with their values and range

Parameters Used	***Range / Values***
Initial Temperature	20o C – 300o C
Final Temperature	130o C – 450o C
Initial Speed	30 km/hr – 150 km/hr
Final Speed	80 km/hr – 0 km/hr
Brake Disc Diameter	238 mm (constant)
Brake Pad Area	30 cm2(constant)
Required Inertia	76 kg-m2 (constant)
Number of different friction materials used for Pad. These are the different materials like Phenolic resin, Barites, Aluminum Oxide etc. which make up the brake pad	30
% of different friction materials that make up the brake pad (e.g. Phenolic resin, Barites, Aluminum Oxide etc.)	0-20%

3. The Neural Network Model – Data Pre-Processing

Data obtained from the dynamometer, was cleaned and standardized. Cleaning the data is required as all the ingredients of the friction material are not available in all the samples of the pad. For example, some samples of the pad might be missing brass chips and other pads might be missing copper powder. Small values of these ingredients are substituted in the respective data sets instead of zeros.

In standardization, all the values used in neural network are transformed such that the mean of the values is 0 and the standard deviation is 1. This is done to prevent the model from assigning bigger weights for larger numbers. The data pre-processing was done in Python.

The data is also segregated into the training and validation data. 70% of the data was used for training the model and the trained model was then validated on the remaining 30% of the data to determine the efficiency of the neural network model. The inputs and the output parameters of the model are as follows:

Neural Network Model – Inputs

a. Car Inertia
b. Rolling Radius
c. Disc Parameters
d. Initial Brake Temperature
e. Initial Speed
f. Final Speed
g. Deceleration
h. Number of braking instances
i. Pad Composition (friction materials and their percentages)

The parameter “number of braking instances” has been suggested by author of reference (1) to increase the number of data points in the input data set.

Neural Network Model – Outputs

a. Disc Wear
b. Pad Wear
c. Co-efficient of Friction

4. The Neural Network Model – Data Analysis

All the analysis in this project was done using the Deep Learning Toolbox in MATLAB. As part of finding the right neural network model, different activation functions like Levenberg-Marquardt, Scaled Conjugate Gradient, Bayesian regularization backpropagation and Gradient descentwith momentum backpropagation were attempted.

The Gradient descent with momentum backpropagation was found to give the best results. The model reads the input and predicts the output. The error is then determined by the model and used to update the weight and biases while moving in reverse to the original values. The final step was to set the number of iterations so that the model did not over-fit.

Error of prediction is calculated using the Mean Squared Error metric given as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2 \qquad (1)$$

Where N is the number of data points

f_i is the value returned by the model and

y_i is the actual value for data point i

The accuracy generally came to be around 60%. It was seen that the error for the prediction of wear for the speed of 80, 120 km/hr and

150 km/hr was higher than the lower speed. Similar observations are reported by authors of reference (2) and (3). Obviously, suggesting that at higher speeds the error of prediction for the final temperature was more when compared to the prediction of final temperature for lower speeds. Since there is a high correlation between the wear and the final temperature, the errors in the final temperature predictions would lead to error in the wear predictions as well. Results of multiple trials were analysed to validate this theory. Plotting the wear values for different speeds indicate different wear dynamics for lower and higher speeds. This is shown in Figure 2 below.

The y axis is a unit less quantity, where the wear of the brake pad in mm has been normalized between 0 and 180.

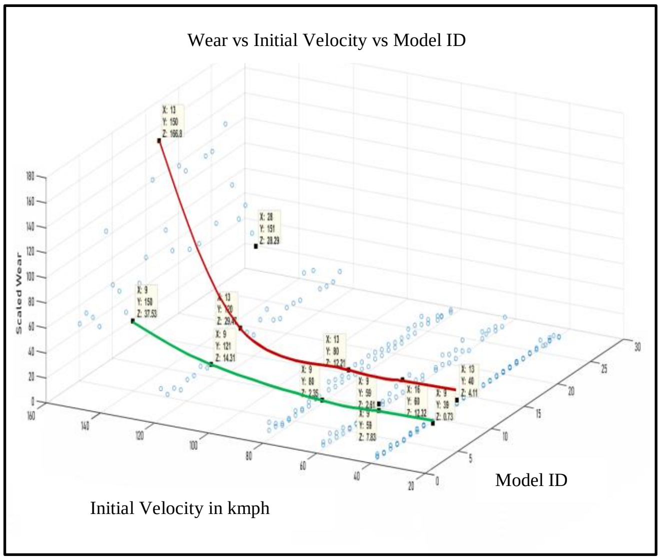

Figure 2 Changes of wear at higher speeds for 2 different samples (labelled as Model ID)

The green line is the plot of scaled wear versus initial velocity for sample 10 and the red line is the plot of scaled wear versus initial velocity for sample 15. It is very clear from the graphs that the wear increases rapidly beyond a velocity of 100 km/h and hence we need two different neural networks, one to predict the wear for low speeds and another to predict the wear for higher speeds.

We have therefore created two neural networks, one for prediction of wear for lower speed (40 and 60 km/hr) and one for higher speed (80, 120 and 150 km/hr). Block Numbers 3, 4, 5 and 6 given in the results graph were for higher speeds and Block numbers 7, 8 and 9 were for lower speeds. This improved the wear prediction accuracy to about 85% for both the lower and higher speeds. Block numbers 1 and 2 are not considered as these blocks are used to smoothen out any surface irregularities of the brake pad surface.

Subsequent to characterizing them as two distinct classes, various models were tried for prediction of wear. A proportion of 70:30 of the data was kept for training and validation. To validate the models k-fold cross validation was utilized. In k-fold cross validation entire data is separated in samples and each sample is taken as the validation sample. This methodology eliminates the bias of sampling, and allows the model to include each sample as a training data.

5. Results

In order to determine whether the neural network model is able to predict the relationship between the input and the output parameters, a term R2 is calculated. R2is called the Goodness of Fit. Higher values of R2, indicate an accurate model. R2 for Pad Wear given in Figure 3 has a value of 0.98873.

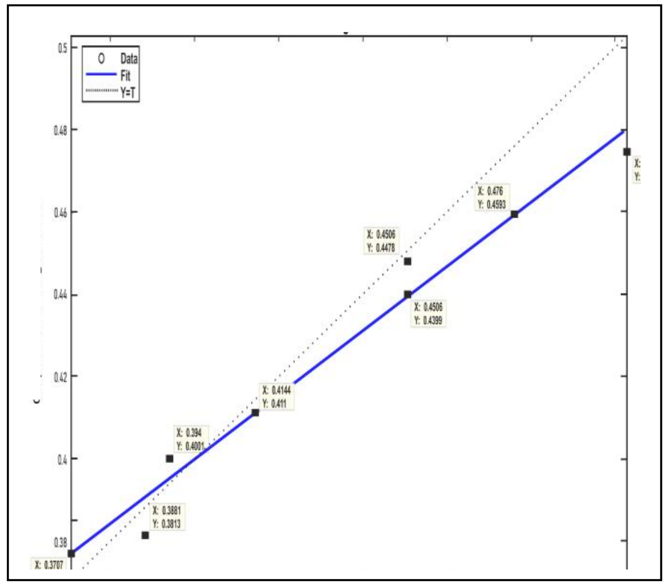

Figure 3 R2 for Pad Wear

The values of disc and pad wear (as measured on the dynamometer test and as predicted by our model) are shown in Figure 4 to Figure 6. The samples mentioned below as Sample A, Sample B and Sample C are each made of different composition of the friction material and are a part of the 30% data set aside for validation. Here block number signifies the various braking regimes. Block numbers 7, 8 and 9 are for lower speeds such as 40km/h to 60km/hr. Block numbers 3, 4, 5 and 6 are for speeds of 80, 120 km/hr and 150 km/hr. Two different neural networks are used, one for the lower speeds and another for the higher speeds. For brevity the comparison for only 2 samples for pad wear and 1 sample for disc wear are shown. The wear values are given in mm. The comparisons show that the Neural Network model is able to predict the pad wear and the disc wear quite well. The error of prediction is between 10% - 15%. The same trend is seen for other samples as well.

The following figures (4-6) are discussed above. In the figures the predicted values of wear are compared to the actual values of wear obtained from testing. The pad wear is shown for two samples (each sample has different percentages of friction materials). The pad wear is shown for higher speed blocks and lower speed blocks. Each block may have different wear values for the samples, as wear is measured for different numbers of braking instances.

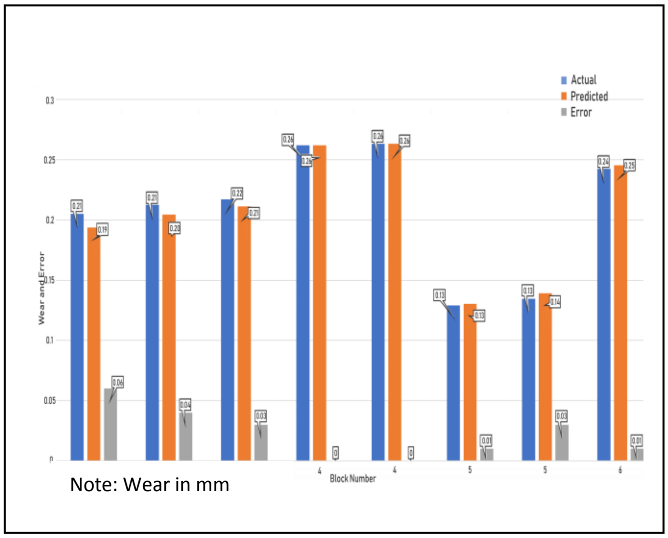

Figure 4 Actual and Predicted Pad Wear for Sample A

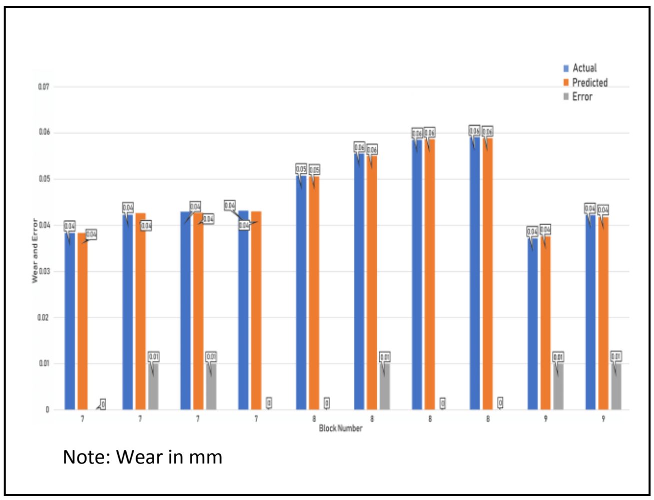

Figure 5 Actual and Predicted Pad Wear for Sample B

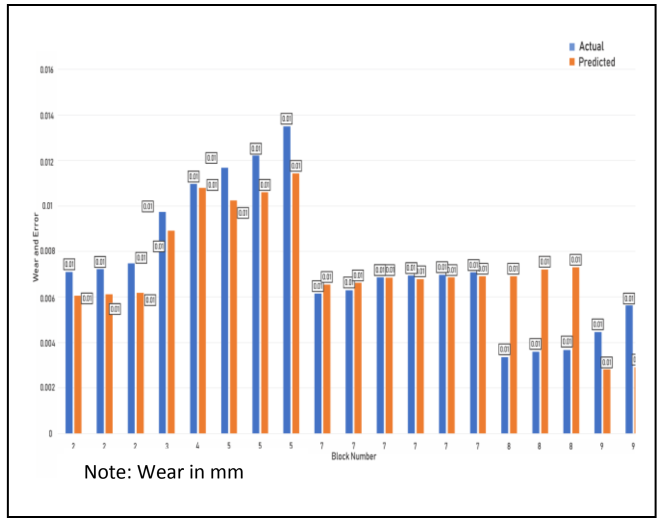

Figure 6 Actual and Predicted Disc Wear for Sample C

6. Conclusions

A friction material's performance and wear characteristic depending on the ingredients is very difficult to predict. The presence of as many as 30 different friction materials in the brake pads makes the predictions of its performance all the more difficult. An approach using Neural Networks is suggested using different parameters like braking characteristics and brake pad friction materials. The neural network model was able to predict the disc and pad wear for different braking characteristics and different composition of brake pad friction materials at an accuracy of 85% compared to the wear measured using the dynamometer. Since the lower speeds (40 and 60 km/hr) and the higher speeds (80, 120 and 150 km/hr) have different wear dynamics, two separate neural networks models were designed. These novel algorithms can be an alternative methodology to dynamometer-based wear testing, resulting in identifying the correct brake pad and disc in a shorter time. Furthermore, the accuracy of the neural network model can be improved by including different manufacturing parameters and by reducing the ranges of the input parameters.

References

[1] Dragan Aleksendri, "Neural network prediction of brake friction materials wear" Elsevier, Wear 268 (2010) 117–125

[2] B. Surya Rajan,*, M. A. Sai Balaji, C. Velmurugan, "Correlation of field and experimental test data of wear in heavy commercial vehicle brake liners", Friction 5(1): 56–65 (2017) ISSN 2223-7690, DOI 10.1007/s40544-017-0138-x

[3] Adriaan Neys, "In-Vehicle Brake System Temperature Model", Master Thesis in the Master's programme in Automotive Engineering, Department of Applied Mechanics ChalmersUniversity University Of Technology, Göteborg, Sweden, 2012 Report No. 2012:38