

Optimization of Brake Friction Materials Using Mathematical Methods and Testing

Amir Reza Daei, Nima Davoudzadeh, and Peter Filip
Southern Illinois University

ABSTRACT

Brake linings have complex microstructure and consist of different components. Fast growing automotive industry requires new brake lining materials to be developed at considerably shorter time periods. The purpose of this research was to generate the knowledge for optimizing of brake friction materials formula with mathematical methods which can result in minimizing the number of experiments/test, saving development time and costs with optimal friction performance of brakes. A combination of processing methods, raw materials and testing supported with the Artificial Neural Network (ANN) and Taguchi design of experiment (DOE) allowed achieving excellent results in a very short time period. Friction performance and wear data from a series of Friction Assessment and Screening Test (FAST) were used to train an artificial neural network, which was used to optimize the formulations. The averaged COF, COF variation and wear were used as the output parameters. Weight percentage of raw materials denoted as an input parameter and these data were used to train ANN. A two layer feedforward ANN with back propagation was used in this study. Back propagation learning algorithm can be divided into two phases: i) propagation and ii) weight update. The friction performance of the optimized friction materials was considerably better when compared to the baseline commercial brake lining materials. This method can be applied to development of any type of complex friction materials.

CITATION: Daei, A., Davoudzadeh, N., and Filip, P., "Optimization of Brake Friction Materials Using Mathematical Methods and Testing," *SAE Int. J. Mater. Manf.* 9(1):2016, doi:10.4271/2015-01-2661.

INTRODUCTION

Numerous raw materials were used in brake friction materials and the commercial brake pads mostly consist of various types of constituents. Typically more than ten different ingredients classified usually as binders, friction modifiers, fillers and reinforcing agents are used [1], [2]. Formulating a brake friction material is a complex task and it requires extensive testing at high costs and extended time to achieve an optimal performance. This paper surveys a mathematical approach using artificial neural network (ANN) combined with Taguchi design of experiment (DOE) to predict the efficient content of each constituent in an optimized brake friction material. Goal of formulation is optimizing to meet the required criteria such as low wear as well as a stable and desired friction level of different braking circumstances [3],[4].

EXPERIMENTAL

List of raw constituents is shown in [table \(1\)](#).

Table 1. List of raw materials need for sample preparation

Friction modifiers	Binder	Reinforcement	Fillers
Zirconium Silicate (ZrSiO ₄)	Phenolic Resin	Iron powder (Fe)	Calcium Carbonate (CaCO ₃)
Dolomite	Geopolymer	Steel fiber	Barium Sulfate
Clay minerals with nano-Titanium Dioxide (TiO ₂)	Nitrile Butadiene rubber (NBR)	Kevlar fiber	
Pyrite (FeS ₂)	Styrene Butadiene Rubber (SBR)	Hemp fiber	
Tin (Sn)			
Hexagonal Boron Nitride (h-BN)			
Silicon Oxide (SiO ₂)			
Magnesium Oxide (MgO)			
Graphite - Carbon (C)			
Potassium Titanate (K ₂ TiO ₃)			
Aluminum Oxide (Al ₂ O ₃)			
Coke (C)			

Resin was used as a binder in the baseline material. Due to binding capacity of the geopolymer matrix, it was replacing partially resin[5]. Furthermore, a geopolymer matrix is more temperature resistant than phenolic resin, geopolymers have combined properties of cements, ceramics and polymers due to their structure [6]. Eight samples were manufactured with different weight percentage of geopolymer as a replacement of resin. Due to some restrictions of using copper and hazardous materials which exhibit potential environmental impact in brake friction materials [7, 8, 9], hexagonal boron nitride, titanium dioxide and kaolinite were used in brake formulas and copper and antimony trisulfide, were eliminated. Formulation of baseline and seven other samples marked as A to G are shown in [Table 2](#).

Table 2. Baseline and sample (A to G) formulations

Raw materials	Weight Percentage(%) of samples							
	Baseline	A	B	C	D	E	F	G
Phenolic Resin	9.5	9.5	7.6	6.7	5.7	4.8	3.8	2.9
Geopolymer	0	0	1.9	2.9	3.8	4.8	5.7	6.7
Kevlar	3.4	0	0	0	0	0	0	0
Hemp	0	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Copper	8	0	0	0	0	0	0	0
Hexagonal Boron Nitride	0	8	8	8	8	8	8	8
Antimony Trisulfide	3.6	0	0	0	0	0	0	0
60% TiO ₂ + 40% Kaolinite	0	3.6	3.6	3.6	3.6	3.6	3.6	3.6
Other constituents	75.5	75.5	75.5	75.5	75.5	75.5	75.5	75.5

Design of Experiment (DOE)

By using Taguchi DOE method [10] an orthogonal array was created to reduce the number of experiments. Artificial neural network was used in this survey to optimize formulation of brake friction materials [11]. Orthogonal array was generated by using six parameters (X1 to X6) and two levels (low and high). Experiments with low and high level are listed in Table 3.

Table 3. List of experiments designed by using Taguchi DOE method

Parameters	X1	X2	X3	X4	X5	X6
1	LOW	LOW	LOW	LOW	LOW	LOW
2	LOW	LOW	LOW	HIGH	HIGH	HIGH
3	LOW	HIGH	HIGH	LOW	LOW	HIGH
4	LOW	HIGH	HIGH	HIGH	HIGH	LOW
5	HIGH	LOW	HIGH	LOW	HIGH	LOW
6	HIGH	LOW	HIGH	HIGH	LOW	HIGH
7	HIGH	HIGH	LOW	LOW	HIGH	HIGH

Artificial Neural Network (ANN)

A neural network with back propagation supervised learning was implemented in order to model the DOE for Brake friction material process.

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1. Propagation, Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Back propagation of the propagation's output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

Phase 2. Weight update, for each weight-synapse:

1. Output delta and input activation are multiplied to get the gradient of the weight.
2. The weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.

This ratio influences the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight indicates where the error is increasing, this is why the weight must be updated in the opposite direction [12].

The phase 1 and 2 repeated until the performance of the network is acceptable.

The Experiment

Using the feed forward back propagation network with, average COF, COF variation and thickness loss as an input and composite materials weight percentage as the output, the network was designed in three layers. The schematic of the implemented ANN is depicted In Fig (1).

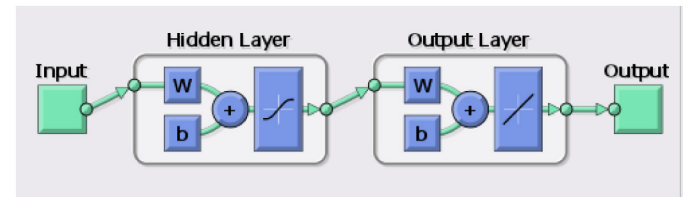


Figure 1. Schematic of implemented ANN

The input layer consists of 2 neurons and the output layer consists of 8 neurons and the hidden layer was chosen to have 20 neurons, with Tran sigmoid firing function [13]. The hidden layer fed the output layer with linear transfer function.

The training phase started by feeding the network with 6 set of samples. After this phase two more samples were used for validation and regression calculations. Finally one sample was used for simulating the ANN.

Sample Preparation

Aforementioned materials were weighted precisely in OHAUS Explorer Pro analytical balance with accuracy ± 0.001 gr. Weighted constituents were mixed using 2786 Stephen Machinery mixer. Mixed materials were loaded in a cylindrical mold with diameter of 50 mm and subjected to hot pressing at 175°C for 20 min. Cylindrical samples were post-cured in Fisher Scientific Isotemp furnace for four hours at 180°C friction samples with dimensions 15*15*5 mm³ were cut of cured cylinders to be tested in FAST machine.

Friction Test

Testing the coefficient of friction of samples to investigate their friction performance was done using Friction Assessment Screening Test (FAST) machine, which was developed by Ford Motor Company [14]. Schematic picture of this machine is shown in Fig (2).

FAST ran on constant speed and pressure for 90 minutes and the coefficient of friction is measured for every five seconds. Pressure on loaded arm and the tangential arm (connected to valve spool) were set on 8 and 80 psi respectively, and the rpm of the motor driven friction disk was set on 875. Data from FAST were used to train the artificial neural network for optimizing brake friction materials formulation. Three phases of FAST were performed:

1. Phase One - generate data (friction and wear) to train the ANN
2. Phase Two - generate additional data (friction and wear) to re-train ANN

3. Phase Three - optimize formulations