# Neural Network Based Analysis of Thermal Properties Rubber Composite Material - Pneumatic Tire

P. Balaguru, N. Krishna Mohan and A. P. Sathiyagnanam, *Member, IAENG*

***Abstract* - The evolution of pneumatic tires has been alongside the evolution of the automobiles. The demand of the modern automotive industry has been driving the tire industry to come with high performance tire. The tire construction and geometry are very complex in nature especially tire design and stress analysis are very difficult. The study of tire performance and deformation are very challenging owing to the non-linearity associated with geometry as well as composition of material. The tire material is a cord-rubber composite, its properties anisotropic in nature. Failure analysis of cord-reinforced rubber composite tires may be useful to predict the lifetime of a tire. In this background, the present attempt is to analyze the tire using artificial neural network. The shear modulus and the temperature are measured against various frequencies. The above properties are analysed using artificial neural network. The study has been undertaken using MATLAB software. The results were compared with those of dynamic moduli master curves obtained through frequency–temperature reduction of data measured by a commercial dynamic mechanical thermal analyser (DMTA), by scanning temperature at various frequencies in the range 0.3–30 Hz. The results obtained by DMTA are trained in the Neural Network. Very good agreement of the data obtained by the two different approaches was found.**

**Keywords: Rubbers, Dynamic testing; Dynamic properties, Neural Network**

## I. INTRODUCTION

This work describes the research into thermal properties of tire as a non-homogeneous composite material [1]. The primary purpose of this work is to derive a neural network model for temperature and shear modulus at different frequencies. Dynamic properties of composite tires for different frequencies were obtained experimentally [2]. A Neural Network model has been developed for the experiment based dynamic properties. Furthermore, a computer implementation of this algorithm to interpret experimental result and neural network result has been generated.

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### *A. Thermal Conductivity and Heat Capacity*

The thermal conductivity is the property that describes the heat transfer capacity within the materials. In tests where tire are used the voids are also included in the heat transfer. The specific heat capacity is the amount of energy required to rise one degree Celsius. The thermal conductivity of glass belted tire was roughly 15% lower than the values for the steel belted tires at the same density.

The thermal property constants must be predicted for both modeling and computer implementation purposes, and are related by the following formula:

$$\alpha = \left( \frac{k}{\rho c} \right) \quad \rightarrow (1)$$

where $\alpha$ is thermal diffusivity, k is the thermal conductivity, $\rho$ is the material density, and c is specific heat. Density is found from the mass and volume of a given tire, whereas thermal conductivity and specific heat must be predicted.

### *B. Tire Composition*

Tire materials vary greatly between manufacturers. For proprietary reasons, most tire manufacturers are reluctant to publish information concerning the composition of the tires they produce. This composition includes the following elements: natural rubber (44.32%), butadiene compounds (15.24%), aromatic oils (1.85%), various carbon black substances (30.47%), stearic acid (1.07%), antioxidants (0.83%), and sulfur (1.42%) [3]. Those not listed are of negligible proportion.

### *C. Elastic Properties*

The elastic modulus is used as a measure of stiffness of a material, i.e., the elastic deformation under stress. In general the elastic modulus for tire material is not a constant but assumed constant in a specified stress interval. In general, the elastic modulus is defined as

$$E = \frac{\sigma}{\varepsilon} \quad \rightarrow (2)$$

Table 1 Material Properties

| Material | Thermal Conductivity W/m K | Specific Heat kJ/kg K |
|---|---|---|
| Natural Rubber | 0.055 | 0.001683 |
| Butadiene Compounds | 0.042 | 0.006518 |
| Aromatic Oils | 0.053 | 0.006304 |
| ISAF Black (1) | 0.124 | 0.002759 |
| GPF Black (2) | 0.126 | 0.00278 |
| FEF Black (3) | 0.126 | 0.002795 |
| Silica | 0.531 | 0.004835 |
| Stearic Acid | 0.056 | 0.008981 |
| Antioxidant (4) | 0.044 | 0.009027 |
| Sulfur | 0.047 | 0.00017 |

## II. Dynamic Testing of Rubber Compounds

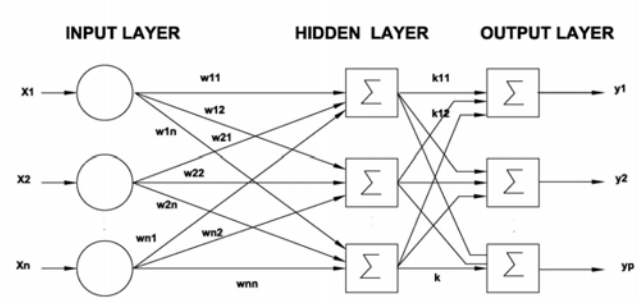
### A. *Dynamic Properties*

The overall performance of rubber components is governed by the dynamic behavior of the material, such as stiffness and damping. Due to the viscoelastic nature of rubber, their dynamic and thermal behavior is significantly dependent on frequency and temperature [1]. The material stiffness and hysteretic effects, associated with the energy dissipation and consequent heating within the material, are usually described in terms of the complex dynamic modulus E. The storage and loss components of the rubber composite respectively depend on temperature and frequency of the applied load [2]. The high content of carbon black is usually incorporated together with other additives within the compounds to optimize the mechanical performances of the rubber components [4]. Characterization of the dynamic moduli of elastomeric materials is usually performed using commercial Dynamic Mechanical Thermal Analyzers (DMTA) that enable testing by scanning temperature and frequency. These data were found consistent with the results of dynamic moduli master curves determined through frequency–temperature reduction of experimental data obtained by a DMTA apparatus, by scanning temperature at various frequencies in the range 0.3–30 Hz [1].

Dynamic tests were also carried out by a Dynamic Mechanical Thermal Analyser (DMTA) by Tire manufacture Laboratories that can perform dynamic testing by scanning temperature and frequency simultaneously [5]. Tests were performed at five different frequencies, 0.3, 1, 3, 10, 30 Hz and scanning temperature in the range from – 80 °C to +100 °C, at a heating rate of 0.4 °C/min.

## III. Neural Network Model

A neural network is a computational structure inspired by the study of biological neural processing. A layered feed-forward neural network has layers, or subgroups of processing elements. A layer of processing elements makes independent computations on data that it receives and passes the results to another layer. The next layer may in turn make its independent computations and pass on the results to yet another layer. Finally, a subgroup of one or more processing elements determines the output from the network. Each processing element makes its computation based upon a weighted sum of its inputs. The first layer is the input layer and the last the output layer. The layers that are placed between the first and the last layers are the hidden layers. The processing elements are seen as units that are similar to the neurons in a human brain, and hence, they are referred to as cells, neurons, or artificial neurons. A threshold function is sometimes used to qualify the output of a neuron in the output layer. Synapses between neurons are referred to as connections, which are represented by edges of a directed graph in which the nodes are the artificial neurons. Back-Propagation algorithm is employed in the present work.




x- input neuron w- weight for Input layer
y- output neuron k- weight for Output layer

Figure 1 Multilayer network

## IV. Result and Discussion

The results obtained from the DMTA test for various frequencies against the temperature are trained in the Neural Network. Based on the training, for every frequency a new set of Temperature and shear modulus were obtained and are tabulated in Table 2. These values are plotted against each frequency and are given in the Figure 2 -11. From the Figure 12 and Figure 13 it is evident the results generated by Neural Network and by the experimental DMTA coincide.

For any unknown value of the temperature, the corresponding shear modulus or vice versa can be obtained from this training model, even if the values are beyond the tested values. Here the test value of temperature varies from +5 to –80. Using the neural network model, shear modulus can be obtained even for the temperature higher or lower than +5 to –80.

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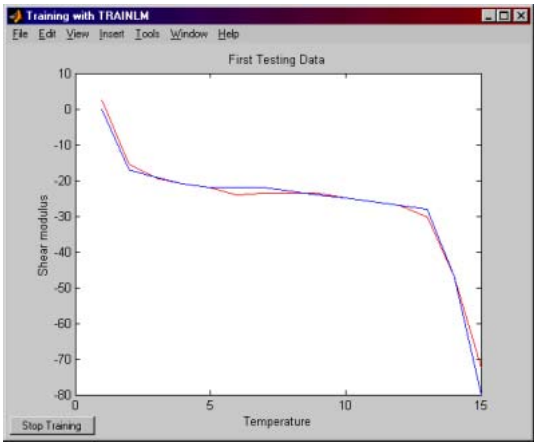


Figure 2 Neural Network Trained Values -DMTA analysis for frequency 0.3 Hz

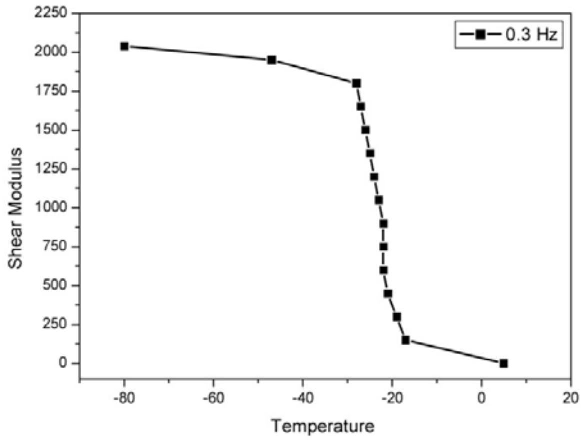


Figure 3 Neural Network result for Frequency 0.3 Hz Temperature Vs Shear modulus

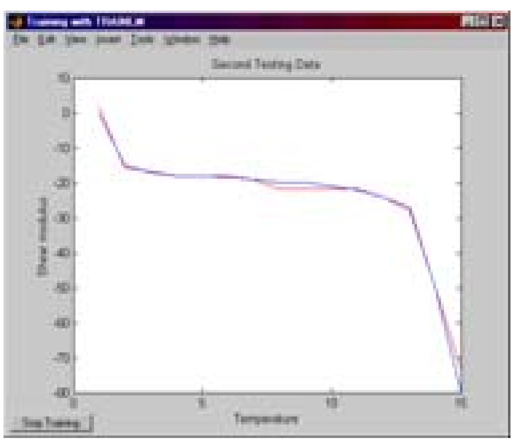


Figure 4 Neural Network Trained Values -DMTA analysis for frequency 1.0 Hz

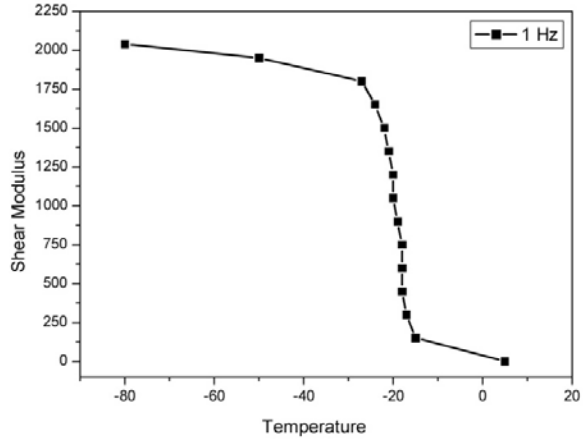


Figure 5 Neural Network result for Frequency 1.0 Hz Temperature Vs Shear modulus

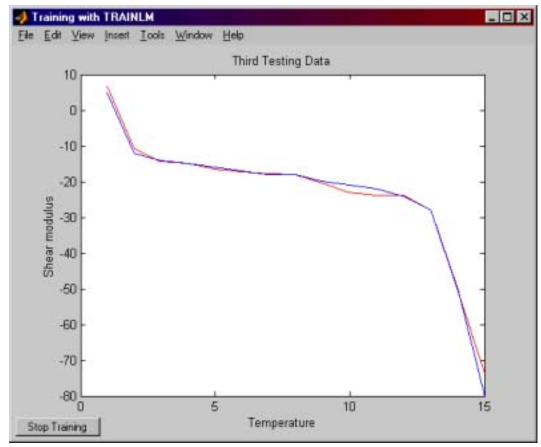


Figure 6 Neural Network Trained Values -DMTA analysis for frequency 3.0 Hz

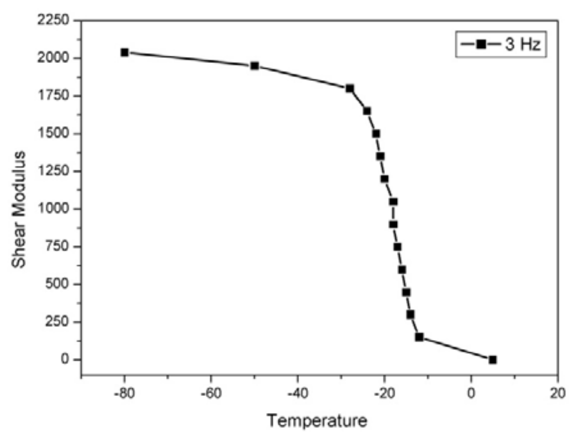


Figure 7 Neural Network result for Frequency 3.0 Hz Temperature Vs Shear modulus

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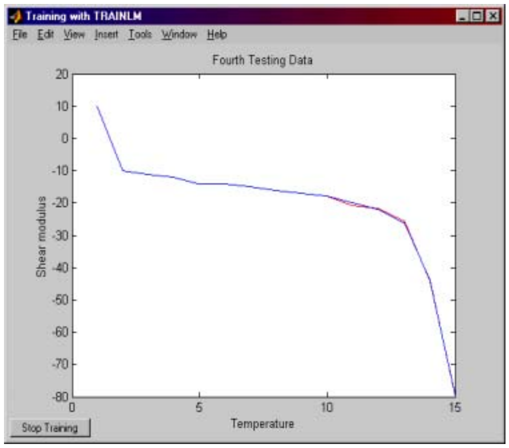


Figure 8 Neural Network Trained Values -DMTA analysis for frequency 10 Hz

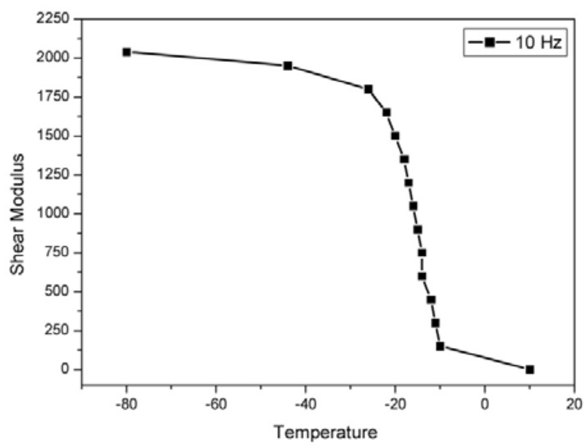


Figure 9 Neural Network result for Frequency 10 Hz Temperature Vs Shear modulus

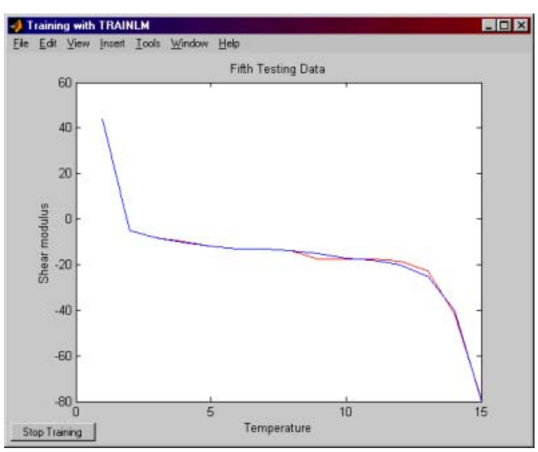


Fig 10 Neural Network Trained Values -DMTA analysis for frequency 30 Hz

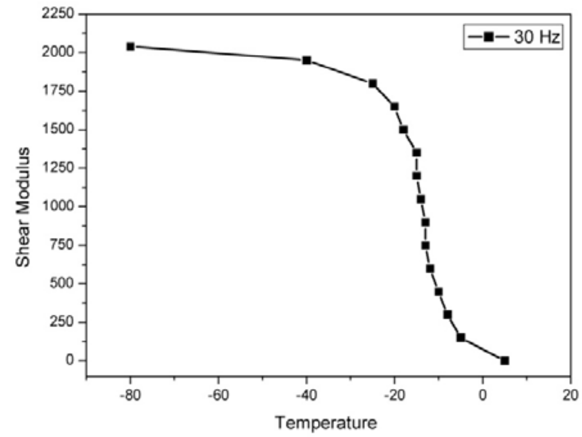


Figure 11 Neural Network result for Frequency 30 Hz Temperature Vs Shear modulus

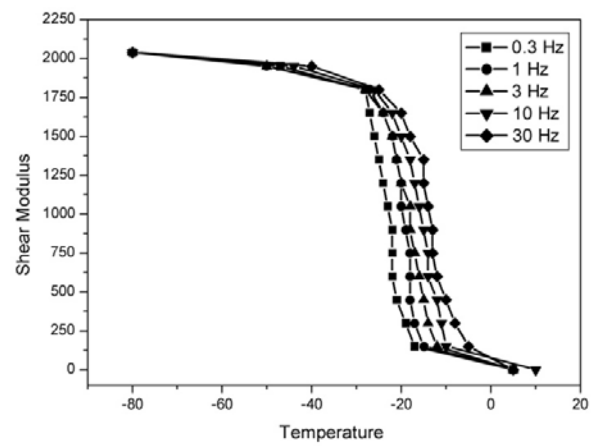


Figure 12 Neural Network Trained Result of Temp Vs Shear Modulus for Various Frequencies

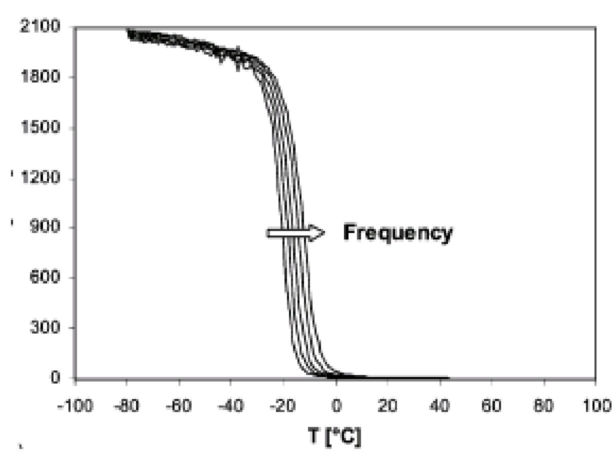


Figure 13 DMTA Test Result of Temperature Vs Shear Modulus for Various Frequencies

Table 2 Temperature against shear modulus

| Shear Modulus | Frequency 0.3 Hz | Frequency 1 Hz | Frequency 3 Hz | Frequency 10 Hz | Frequency 30 Hz |
|---|---|---|---|---|---|
| 0 | 5 | 5 | 5 | 10 | 5 |
| 150 | -17 | -15 | -12 | -10 | -5 |
| 300 | -19 | -17 | -14 | -11 | -8 |
| 450 | -21 | -18 | -15 | -12 | -10 |
| 600 | -22 | -18 | -16 | -14 | -12 |
| 750 | -22 | -18 | -17 | -14 | -13 |
| 900 | -22 | -19 | -18 | -15 | -13 |
| 1050 | -23 | -20 | -18 | -16 | -14 |
| 1200 | -24 | -20 | -20 | -17 | -15 |
| 1350 | -25 | -21 | -21 | -18 | -15 |
| 1500 | -26 | -22 | -22 | -20 | -18 |
| 1650 | -27 | -24 | -24 | -22 | -20 |
| 1800 | -28 | -27 | -28 | -26 | -25 |
| 1950 | -47 | -50 | -50 | -44 | -40 |
| 2040 | -80 | -80 | -80 | -80 | -80 |

## V. CONCLUSION

This work mainly deals with thermal properties of cord rubber composite extended to tire. The thermal properties are analysed using neural network. Here, the thermal properties like temperature are measured against shear modulus. The test results of temperature and shear modulus are trained in the neural network, and the results are obtained. For any unknown value of the temperature, the corresponding shear modulus or vice versa can be obtained from this training model, even if the values are beyond the tested values. Here the test value of temperature varies from $+5^{o}$C to $-80^{o}$C. Using the neural network model, shear modulus can be obtained even for the temperature higher or lower than $+5^{o}$C to $-80^{o}$C.

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