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Application of artificial neural network in prediction of abrasion of rubber composites

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ABSTRACT

Abrasion of the rubber composite is related to its mechanical properties closely, and so establishing a model predicting the abrasion via mechanical properties is of interest. Based on twenty sets of sample data of abrasion and six mechanical properties (shore A hardness, stress at 100%, stress at 300%, tensile strength, elongation at break, tear strength) of styrene–butadiene (SBR) based rubber composites, an artificial neural network (ANN) model, which was composed of abrasion and these six mechanical properties of SBR-based rubber, was established by MATLAB7.0 software. According to the network training error, the number of hidden layer neurons, training functions, learning functions and performance functions were optimized. Compared the experimental value with predicted value, the accuracy of prediction for artificial neural network model was 96.0%. The target of predicted abrasion was achieved by ANN.

1. Introduction

Tire is a typical product of rubber composites. As one of its most important properties, abrasion has close relationship with the life of tire, so it is significant to research the abrasion of rubber composites. However, it is not easy to predict the abrasion mechanism of rubber, since it is complicated and affected by many factors [1,2]. Abrasion of rubber materials is related to mechanical properties closely which are simple to measure relatively [3]. So establishing a model predicting the abrasion via mechanical properties is of interest. During the past century, some statistical analysis attempts on abrasion mechanism were made by considering the relationships between abrasion and mechanical properties of the rubber. Schallamach A made great efforts in researching abrasion pattern and quantitative relationship between abrasion and mechanical properties [4,5]. Ratner SB found that abrasion on sharp tracks (silicon carbide paper) was closely related to tensile stress, tensile strain and energy density at break [6,7]. Manas D established a multiple linear regression model describing the relationship between mechanical properties (tensile strength, elongation, tear strength, Shore hardness, resilience, tensile modulus) and abrasion of NR/SBR/BR rubber. Linear correlation coefficient (R^2 = 0.85) is shown that there is a relationship between mechanical properties and abrasion of rubber but linear model fails to describe the relationship accurately enough [8].

ANN is biologically inspired computer program, which aims at simulating the way in which the human brain processes information [9,10]. It is featured by self-learning, self-adaptive, massive parallelism and highly non-linear description so that it can help us to find complex relationships among input variables and output ones [11–14]. ANN has been applied successfully to various fields, such as mathematics, engineering, medicine, economics, meteorology, psychology and neurology [15,16]. Therefore, ANN was used in this paper to predict the abrasion by utilizing mechanical properties which would promote the development of abrasion researches in rubber field.

The sample data in this paper are derived from abrasion and six mechanical properties (shore A hardness, stress at 100%, stress at 300%, tensile strength, elongation at break, tear strength) of twenty sets of SBR-based composites. A back-propagation ANN which consisted of abrasion and the six mechanical properties of SBR-based rubber was established by MATLAB 7.0 software. In addition, three sets of validation data were used to predict the abrasion of SBR-based rubber to verify the reliability of the back-propagation ANN.

2. Simulation

2.1. Artificial neural network (ANN)

ANN is consisting of a large number of neurons [17]. The basic artificial neuron which processes the input information into output information is shown in Fig. 1.$X_1, X_2, \ldots, X_n$ represents the input variables applied to the neuron; $W_{k1}, W_{k2}, \ldots, W_{kn}$ represents the

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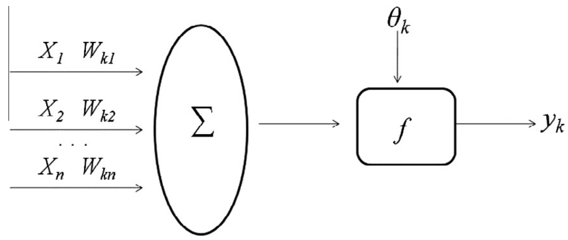

Fig. 1. The structure of basic neural neuron.

weight (probability of data transmission along a path) for input; θ_k represents threshold; f represents activation function; y_k represents the output variables of the neuron which is given by Eq. (1) [18–20].

$$y_k = f\left[\sum_{i=1}^{n}(W_{ki}X_i) - \theta_k\right] \tag{1}$$

Back-propagation ANN is a multilayered feed forward neural network with back propagation algorithm which is adopted in most situations among numerous artificial neural network models. It is trained and adjusted by reducing the error between the network output and the target [21]. Back-propagation ANN consists of three layers-input layer, hidden layer and output layer which are filled with different number of neurons [14,22]. There is no signal transmission process among neurons in the same layer due to they are not connected, while neurons in different layers achieve a full connection, which means each neuron in one layer is interconnected to each neuron in the next layer. Then the weights are adjusted to achieve the purpose of network training through self-learning under the threshold. The structure of back-propagation ANN is shown in Fig. 2 [23,24].

MATLAB 7.0 software was used to establish back-propagation ANN in this paper. It specializes in numerical calculation which can handle a large number of data with relatively high efficiency.

2.2. Sample data and validation data

Six mechanical properties (shore A hardness, stress at 100%, stress at 300%, tensile strength, elongation at break, tear strength) and abrasion of twenty-three sets of SBR-based composites are shown in Table 1. The data in Table 1 arranged orderly according to Akron abrasion. Three sets of data (Samples 2, 13 and 22) were chosen randomly as validation data. The other twenty sets of data were used as sample data to train the BP-ANN.

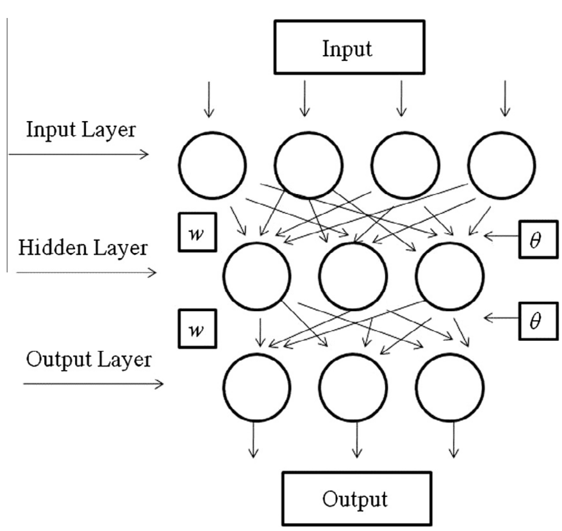

Fig. 2. The structure of back-propagation ANN.

All the data were obtained from experimental database of Key Laboratory of Beijing City on Preparation and Processing of Novel Polymer Materials, Beijing University of Chemical Technology. The recipes are shown in Table 2.

3. Test of abrasion performance

The abrasion performance of the composites were measured by an Akron abrasion tester (Jiangsu Mingzhu Science and Technology Development Co. Ltd., China), and the abrasion tested in accordance with GB/T1689-1998 [25].

3.1. Test of Shore A hardness

The tests for Shore A hardness were carried on XY-1 rubber Shore A hardness tester (Shanghai Chemical Machinery Fourth Factory, China) according to GB/T 531.1-2008 [26].

3.2. Test of tensile and tear performance

The tests for tensile and tear strengths were carried on SANS tensile tester (MTS Systems Co. Ltd., China) according to GB/T 528-2009 [27]. The test speed of tensile and tear is 500 mm/min.

3.3. Selection of back-propagation ANN parameters

To design a back-propagation ANN model, the number of hidden layer neurons and some functions are needed to be determined according to network training error.

3.3.1. Number of hidden layer neurons

“Trial and error” method is used to determine number of hidden layer neurons generally because there are no rules a priori to determine it [28]. A smaller number of neurons (4–6 units) in the hidden layer are given to form a smaller structure of back-propagation ANN for training, and then a model is formed until the network training error reaches minimum value through increasing the number of hidden units gradually [29]. In this paper, number of hidden layer neurons (5, 10, 15, 20) was used respectively.

3.3.2. Performance functions

Two performance functions were used in the process to train the back-propagation ANN. The functions and their introductions are shown in Table 3.

3.3.3. Learning functions

Two learning functions were used to train the back-propagation ANN. Both of them and algorithms are shown in Table 4.

3.3.4. Training functions

Four training functions were chosen in this process. They are suitable for training back-propagation ANN because they all follow the standard of gradient descent. All the functions and different algorithms are shown in Table 5.

In this paper, epoch number and error goal were selected as 1000 and 0.001, respectively.

4. Results and discussion

4.1. Number of hidden layer neurons

It is universally acknowledged that increasing the number of hidden layer neurons can reduce back-propagation ANN training error and improve its accuracy, but also make it more complicated, thus increase the training time. Four different back-propagation