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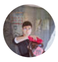
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Tribological behavior prediction of friction materials for ultrasonic motors using Monte Carlo-based artificial neural network

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ABSTRACT: In this article, the relationship of complexity, diversity, and uncertainty between components and tribological properties of friction materials based on a Monte Carlo-based artificial neural network (MC-ANN) model was predicted precisely. Meanwhile, the grey relational analysis was applied to figure out weight of factors, optimize formulation design, and calculate nonlinear dependency of ingredients. The accuracy of model was studied by comparing experimental and simulated values on the basis of statistical methods (root-mean-squared error). It was found that the model exhibited an excellent performance in predicting and fitting effect. Moreover, comprehensive analysis of weight indicated that nano-SiO_2 and mica exerted a significant role in improving the friction stability and wear resistance. According to different contents of each ingredient, the corresponding friction coefficient and specific wear rate could be obtained by virtue of a well-trained MC-ANN model without experiments, which saved a lot of time and money. It can be expected that the results of this work will extend the current research and pave a route for further in-depth studies of friction materials. © 2018 Wiley Periodicals, Inc. J. Appl. Polym. Sci. **2018**, *00*, 47157.

KEYWORDS: friction materials; monte carlo-based artificial neutral network; ultrasonic motor

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INTRODUCTION

Ultrasonic motors (USMs), new type microactuators, have received widespread attention in the field of aerospace, robotics, precision instruments, and various other applications due to high torque, exceptional start/stop feature, and fast response.[1–4] Nevertheless, driving efficiency and service lifetime of USMs are limited by friction materials, the heart of the motors. To enhance the properties of USMs, high-performance polymer-based friction materials still need to be optimized immediately. Taking into account the characteristics of friction materials including high and stable friction coefficient, antiwear, and no noise, great steps have been made during over the past decade.[5–9] The research results show multiphase composite friction materials are usually imperative since single material has difficulty in satisfying reliable and comfortable requirements.[10–13] Hence, friction materials are fabricated with a lot of different constituents. In addition, tribological properties are influenced by distinct conditions,[14–16] particle sizes,[17] and types of functional fillers[18,19] owing to nonlinear relationship between ingredients and tribological properties. Therefore, formulation optimization and tribological properties prediction of friction materials depend primarily on a trial and error method. This approach is time-consuming and laborious and gets relatively acceptable products rather than the best products. As aforementioned, the main problem for friction materials is how to optimize raw materials and predict friction and wear behavior.

For enhancing tribological performance of composites effectively and efficiently, many optimization methods have been proposed in the last years, such as uniform design,[20] orthogonal design,[21,22] Taguchi experimental design,[23,24] golden section approach,[25] and so on. These endeavors have greatly enhanced performance of friction materials. However, there is an obstacle that is lack of ability to predict tribological characteristic preventing the further application of friction materials to a wider range. Prediction of tribological properties exerts a key role in endowing exceptional capability and compensating for drawbacks with change in content of constituents. Herewith, the artificial neural network (ANN), a cogent mathematical methodology, is introduced into the field of materials science to address above problem and optimize friction materials formulation.

ANN is of importance method to simulate the relationship of complex polymer composites because it can be learned and

Table I. List of Detailed Information of Raw Materials

Raw material	Size	Supplier
PTFE	75 μm	Daikin Fluorochemicals Co., Ltd., Jiangsu
PTW	0.5–2.5 μm	Shanghai Whiskers Composite Material Co., Ltd.
Nano-SiO_2	20 nm	Beijing DK Nano technology Co., Ltd.
Cu	5 μm	Beijing DK Nano technology Co., Ltd.
Aramid pulp	800–1350 μm 29–193 μm	Teijin aramid Trade Co., Ltd., Shanghai
Mica	<15 μm	Shenzhen Haiyang Powder Technology Co., Ltd.

PTFE, polytetrafluoroethylene.

trained to settle matters.[26–29] In the present ANN model, back propagation-based ANN (BP-ANN) is one of the most popular models. Xu *et al.*[30] predicted the nonlinear relationship between friction coefficient and wear loss by virtue of BP-ANN model. Simultaneously, the prediction of wear loss and microhardness values by means of this model was proved to be reasonably good.[31] In addition, mechanical property of PA 6.6 composites was also predict by Jiang *et al.*[32] However, there are some disadvantages which hinder the development of BP-ANN model, including slow simulated speed, large number of samples, etc. Therefore, Monte Carlo-based ANN (MC-ANN) model is implemented because of good fitting effect to the samples, strong nonlinear mapping ability and accurate and fast prediction.[33,34] This method is great progress in forecasting which has been widely used in financial engineering, macroeconomics, biomedicine, computational physics, and so on. Nonetheless, according to our best knowledge, the application of MC-ANN model in the field of tribology community has been rarely reported yet.

In this study, MC-ANN model was applied to predict tribological properties of friction materials. In order to optimize and explore the effect of each ingredient on tribological performance, the grey relational analysis (GRA) was employed to analyze correlation between components and performance taking into account six ingredients in different contents of the constituents. In addition, the BP-ANN and MC-ANN models were compared with the experimental and simulated results to test the accuracy of the model. Simultaneously, it is expected that this work can provide useful indications for design and optimization of new polymer tribomaterials.

EXPERIMENTAL

Formulation and Preparation of Friction Materials

In the present work, the friction materials including six ingredients were composed of polytetrafluoroethylene (PTFE) resin, fibers, friction modifiers, and functional fillers, and detailed information was summarized in Table I. The fillers were added and mixed in shredding machines for 3 min. The composites were fabricated by cold pressed (40 MPa, 20 min) and then materials were sintered in an oven (375 °C, 120 min). In order to choose representative formulations, the orthogonal table L_{18} (3^7) was chosen to schedule the test programs presented in Table II.

Tribological Tests

The friction tests were implemented using a quasi-static test rig (see Figure 1). The friction materials with a dimension of Φ 60×0.3 mm^2 were adhered on the surface of the dynamic rotor, aluminum alloy, sliding against the stationary phosphor bronze stator (QSn6.5-0.4 and R_a = 0.2–0.3 μm).

During of the tribological tests, the sliding velocity and contact load were 180 rpm (0.523 m s^{-1}) and 350 N, respectively, and each test for a duration of 120 min at ambient temperature. Each friction measurement at least three times was repeated under each condition in order to evaluate average friction coefficient and specific wear rate. The friction coefficient was dynamically measured during the entire test using a torque sensor, and the value of specific wear rate Ws [mm^3 (Nm^{-1})] was calculated according to the following formula:

$$Ws = \frac{\Delta M}{\rho F L} \tag{1}$$

where ΔM is the wear mass loss after the sliding test in g, ρ is the density of the friction material in g cm^{-3}, F is the normal load in N, and L is the total sliding distance in m.

ANN Model

The ANN as promising model has enormous potential in scientific and practical application because its capacity to solve multivariable nonlinear problem.[35] According to the nature and complexity of problem, the model is divided into different layers. Generally speaking, ANN model has three-layer architecture including input layer, hidden layer, and output layer, and each layer needs to accomplish specific role. The input of large amounts of data is completed in the input layer, and then the data are processed in the hidden layer. Finally, output layer processes and generates the ultimate results. Data processing and calculation require a nonlinear transformation with the help of transfer functions.

In the ANN model, BP-ANN is one of the most widely used models nowadays. It is a feedforward model that forwards information and backpropagates the error. The schematic description and training flowchart of this model are shown in Figures 2 and 3(a). Input $\{X_1, X_2, X_3, \ldots, X_M\}$, X is the input data vector, the number of input layer, hidden layer, output layer is M, N, and P, respectively.

$$\text{hidden layer} = H_j = f\left(\sum_{i=1}^{M} w_{ji} \cdot x_i\right) \tag{2}$$

$$\text{output layer } Y_p = \sum_{j=1}^{N} w_{pj} \cdot H_j \tag{3}$$

Table II. Formulations of Friction Materials Based on Orthogonal Experimental Table

Test	PTFE	Aramid pulp	PTW	Mica	Cu	Nano-SiO$_2$
F1	84.5	2.9	4.2	5.6	1.4	1.4
F2	72.7	4.9	7.3	9.7	3.6	1.8
F3	63.8	6.4	9.6	12.8	5.3	2.1
F4	79.5	2.3	3.4	9.1	3.4	2.3
F5	71.5	4.1	6.1	12.2	5.1	1
F6	76.5	6.6	9.8	4.4	1.1	1.6
F7	70	10	8.6	7.6	1	2.8
F8	81.2	2	6.1	4.1	5.1	1.5
F9	66	8.7	8.7	7.7	4	4.9
F10	76.2	5.7	2.9	11.4	2.9	0.9
F11	68.8	2.3	10.3	13.7	3.2	1.7
F12	60	12	13.8	5.2	6.4	2.6
F13	73.2	7.3	7.3	9.8	1.2	1.2
F14	75.3	2.2	6.5	12.9	1.1	2
F15	65.9	15.4	9.9	4.4	3.3	1.1
F16	84.5	2.9	4.2	5.6	1.4	1.4
F17	78.9	3.9	2.9	11.8	1	1.5
F18	70.1	11.9	11.8	2.2	2.1	1.9

PTFE, polytetrafluoroethylene.

where w_{ji} and w_{pj} are weights from input layer to hidden layer and hidden layer to output layer, respectively. $f(\cdot)$ is a monotonically increasing differentiable transfer function such as sigmoid function, threshold function, linear function, piecewise-linear function, and so on.

In the present study, MC-ANN, a new type ANN model, is introduced into field of tribology whose training flowchart and schematic construction can be seen in Figures 3(b) and 4. It is capable of building a learning model with limited amount of data based on repeated random sampling. MC-ANN model also has great flexibility in the selection of transfer functions. In this article, the transfer function combined with eqs. (4)–(7) is used. Generally speaking, the single transfer function has relatively limited ability to express complex relationship. However, combination of transfer functions is provided with excellent nonlinear expression ability and can achieve more accurate results.[36]

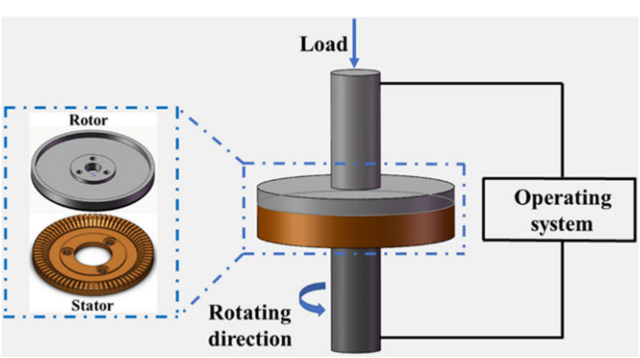

Figure 1. Schematic diagram of the tribological tests. [Color figure can be viewed at wileyonlinelibrary.com]

Sigmoid function

$$y=\frac{1}{1+e^{-x}} \tag{4}$$

Polynomial function

$$y=x^3+x^2+x+1 \tag{5}$$

Tanh function

$$y=\frac{e^x-e^{-x}}{e^x+e^{-x}} \tag{6}$$

Gauss function

$$y=e^{-x^2} \tag{7}$$

$$\text{hidden layer}\begin{cases}\bar{h}_n=\sum_{i=1}^{M}\omega_{\text{in}}\cdot x_i+b_n\\ h_n=f_i\left(\beta_n\cdot\bar{h}_n\right)\end{cases} \tag{8}$$

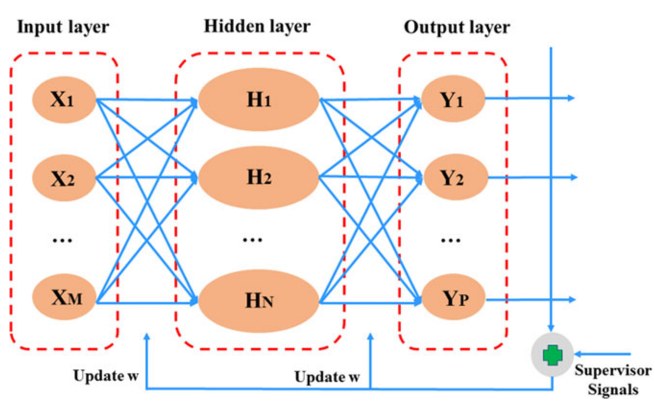

Figure 2. Schematic construction of a BP-ANN. [Color figure can be viewed at wileyonlinelibrary.com]

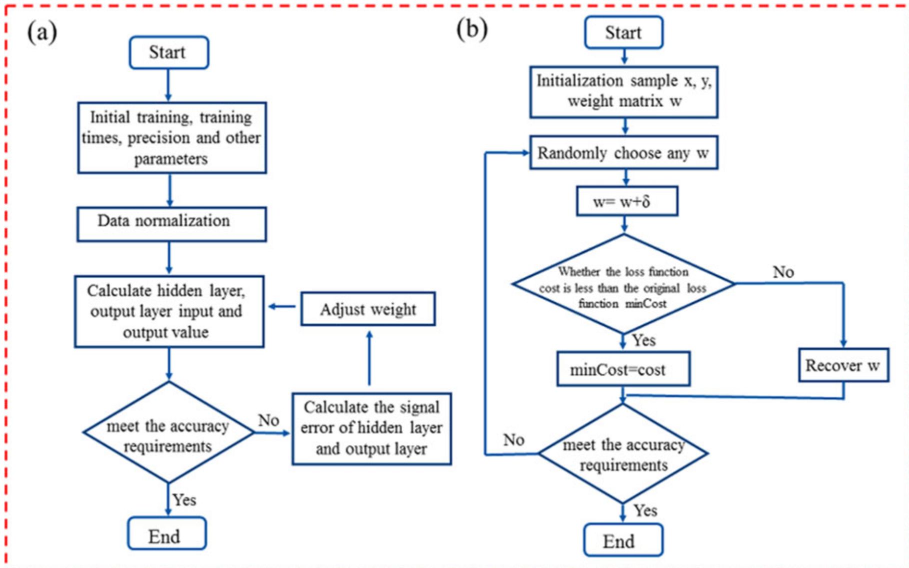

Figure 3. The training flowchart of learning method (a) BP-ANN model and (b) MC-ANN model. [Color figure can be viewed at wileyonlinelibrary.com]

$$\text{output}\quad \text{layer}\; y_p = \sum_{j=1}^{N} \mu_{\text{jl}} \cdot h_p \tag{9}$$

where x_i, h_n, y_p f_i, $\overline{h}_n$, β_n, and b_n represent the input vector, the output value of the nth node of the hidden layer, the output value of the pth node of the output layer, neuron transfer function, local field, the coefficient, and offset of the nth hidden node, respectively. The ω_{in} is the connection weight between $x_i$and nth node of the hidden layer, μ_{jp} is the connection weight between pth node of the output layer and jth node of the hidden layer.

The GRA

Grey system (GS) is a research method for studying systems with less data and uncertainty. The aims of GS are to provide theory, techniques, notions, and ideas for resolving (analyzing) latent and intricate systems. The GRA is an important analytical method of GS and has characteristics of no need for large samples and obvious distribution. According to this method, all factors are normalized to remove the influence of different dimensions of the system, and then the correlation analysis is performed on the observed objects.[37] The results are in good agreement with the qualitative analysis, and the GRA is introduced to calculate correlation coefficient $\xi(k)$:

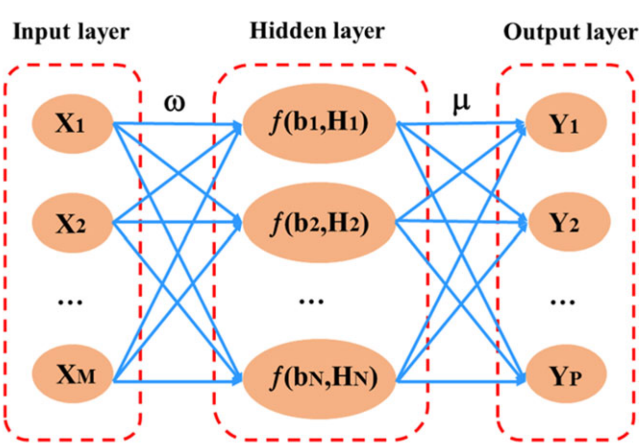

Figure 4. Schematic construction of an MC-ANN. [Color figure can be viewed at wileyonlinelibrary.com]

$$\xi(k) = \frac{\min_i \min_k |X_0(k) - X_i(k)| + \rho \max_i \max_k |X_0(k) - X_i(k)|}{|X_0(k) - X_i(k)| + \rho \max_i \max_k |X_0(k) - X_i(k)|} \tag{10}$$

where $i = 1, 2, \ldots, m$, $k = 1, 2, \ldots, n$ and ρ is the distinguishing coefficient.

Full Sequence of Research Flow Steps

Figure 5 displayed the full sequence of research flow steps. The orthogonal table L_{18} (3^7) was adopted to schedule the test programs and then corresponding experimental results were obtained. Afterward, the BP-ANN as a comparison model was used to verify the accuracy of the MC-ANN model by comparing experimental and simulated values. According to MC-ANN model, tribological behaviors of friction materials could be predicted. The GRA was applied to study weight of factors, optimize formulation design, and calculate nonlinear dependency of ingredients. Therefore, guidance for the design of friction materials could be provided on the basis of major and minor factors. In a word, combination of MC-ANN model and GRA had the ability to optimize formulation and predict the performance of friction materials.

RESULTS AND DISCUSSION

Friction and Wear Behavior

The tribological properties of 18 tests are shown and listed in Figure 6 and Table III. The experimental results are divided into a training and test dataset. Here, 15 formulations are chosen randomly to train the network and then adjust the parameters. Afterward, the remaining three groups abbreviated as 1, 2, and 3 are used to test the accuracy of the forecast results. For avoiding the accident error, the training process is repeated as far as

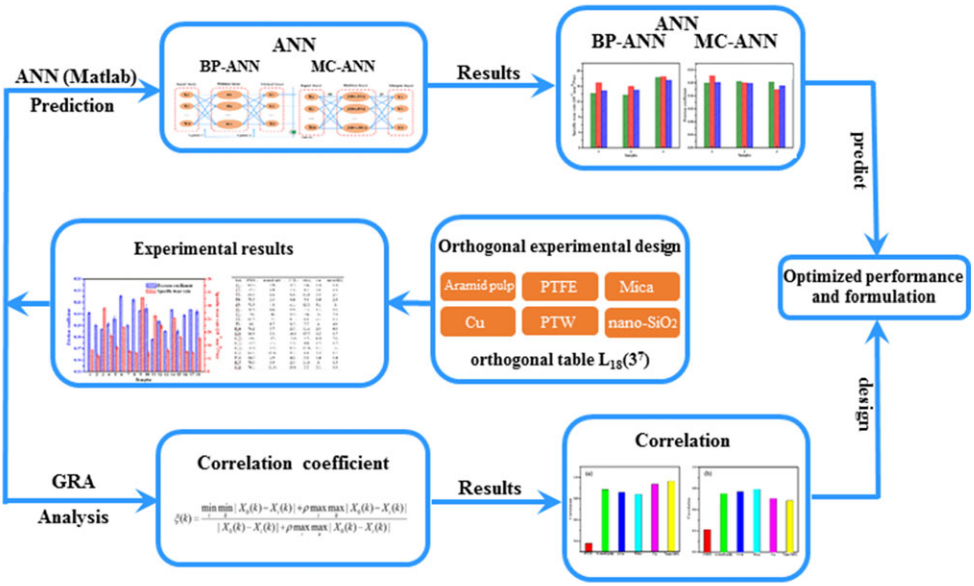

Figure 5. The full sequence of research flow steps. [Color figure can be viewed at wileyonlinelibrary.com]

possible. The root-mean-squared error (RMSE) is applied to assess quality of two models in this study.

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i-Y_i')^2} \tag{11}$$

where Y_i and $Y_i^{'}$ are observed values and predicted values, respectively. n is the number of samples. The smaller the value of RMSE, the higher predictive accuracy.

In order to ensure comparability, the implementation of two algorithms runs on the same platform shown in Table IV. The detailed modeling process can be found in Figure 7. The content of ingredients, friction, and wear data are trained as input data and target, respectively. When a well-trained ANN is completed, the results of prediction can be obtained by inputting test data without having to perform long-lasting experiments. In the following sections, computational efficiency and accuracy of MC-ANN and BP-ANN models are explored.

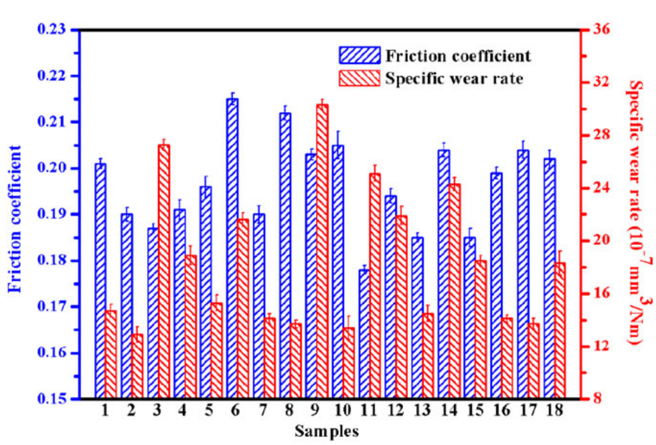

Figure 6. The results of the experimental formulations. [Color figure can be viewed at wileyonlinelibrary.com]

Correlation Analysis

The GRA is researched to determine the important order of the influential factors, and the bigger the correlation coefficient, the greater the impact degree. This method main role is to find the factors that have a high correlation degree with the target results. Figure 8 gives a bar chart for comparing the influence on the specific wear rate and friction coefficient, respectively. For the specific wear rate, the magnitude of factors in the order is mica, potassium titanate whisker (PTW), aramid pulp, nano-SiO_2, Cu, and PTFE in Figure 8(a). In the meantime, Figure 8(b) reveals that the highest

Table III. The Experimental Results of Different Formulations of Friction Materials

Test	Friction coefficient	Specific wear rate (10^{-7} mm^3 Nm^{-1})
F1	0.201	14.7
F2	0.190	12.9
F3	0.187	27.3
F4	0.191	18.9
F5	0.196	15.3
F6	0.215	21.6
F7	0.190	14.1
F8	0.212	13.7
F9	0.203	30.3
F10	0.205	13.4
F11	0.178	25.1
F12	0.194	21.9
F13	0.185	14.5
F14	0.204	24.3
F15	0.185	18.5
F16	0.199	14.1
F17	0.204	13.7
F18	0.202	18.3

Table IV. List of Experimental Environments

Processor	Intel(R)Core(TM)i3-2350M CPU@ 2.30-2.3 GHz
RAM	8 G
System	Windows 7
Test environment	MATLAB R2016a

correlation factor is nano-SiO_2 indicating it has the strongest influence on the friction coefficient. According to correlation coefficient of various factors, main factors are prioritized to optimize the formulation of the friction materials without considering secondary factors. It can be seen that GRA has an instructive role to predict dependency between ingredients and design polymer tribomaterials.

Friction and Wear Analysis

From previous studies, it is identified that relationship between tribological properties and ingredients is complex and nonlinear.[38–40] Therefore, two ANN models are adopted to analyze and address above complicated question. Figure 9 compares the difference of tribological properties of predicted and measured values. It is clear that two models are excellent match to the real results and have quite good performance in prediction. However, the MC-ANN model has better performance in predicting and fitting effect and shows excellent RMSE results of 0.97 and 0.007, while in BP-ANN model results are 2.08 and 0.019. This indicates that MC-ANN model demonstrates more accurate results and has a better agreement with the results of experiments. This may be assumed that variation and volatility of data are predicted by MC algorithm after giving an overall trend. Thus, it can be seen that MC-ANN model possesses a high predictive quality, and the prediction results can be well acceptable. According to this model, as long as the content of each component is input, the corresponding friction coefficient and wear rate can be obtained without experiments. Therefore, this method can greatly improve the design efficiency of friction materials.

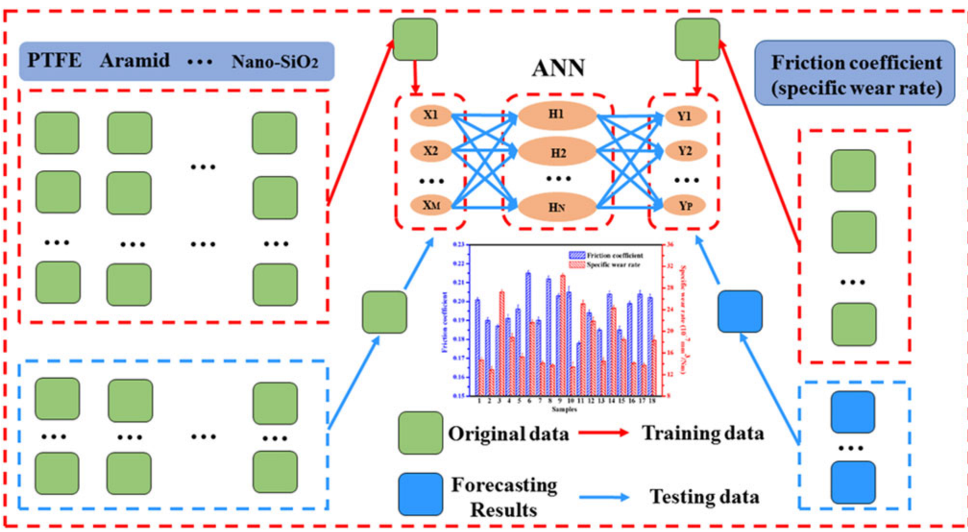

Figure 7. Modeling method of ANN model. [Color figure can be viewed at wileyonlinelibrary.com]

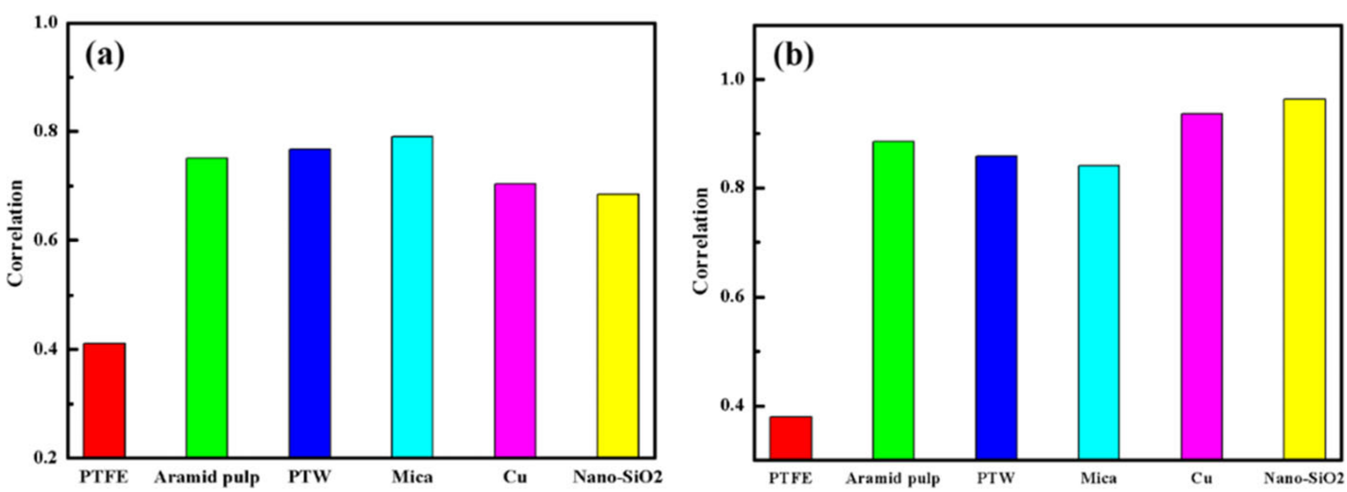

Figure 8. Influence of different ingredients on the correlation of (a) specific wear rate and (b) friction coefficient. [Color figure can be viewed at wileyonlinelibrary.com]

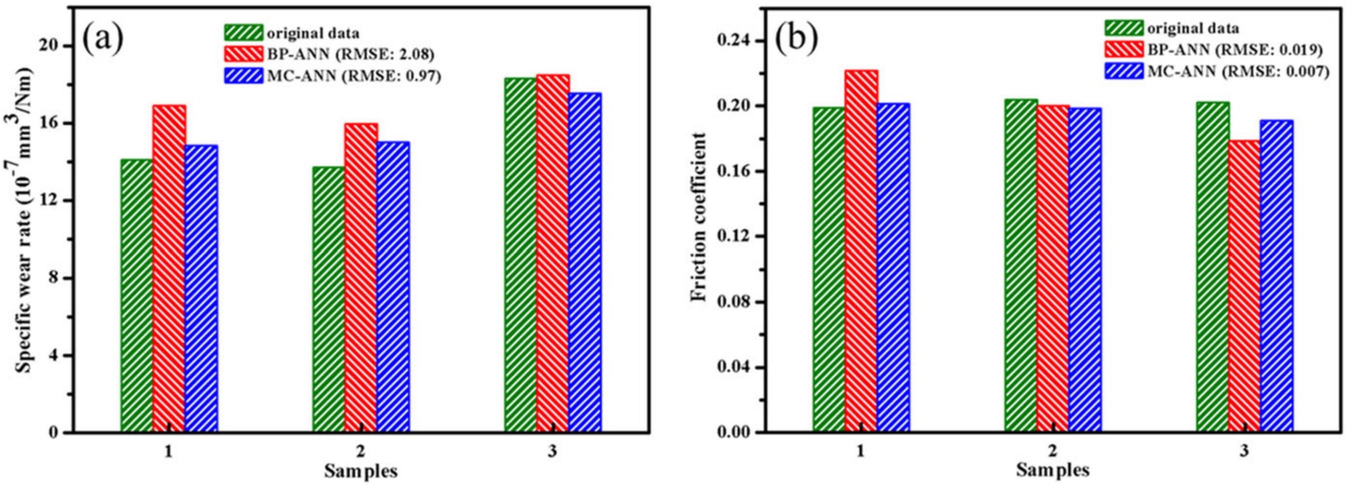

Figure 9. Comparison of the (a) specific wear rate and (b) friction coefficient of predicted and measured values. [Color figure can be viewed at wileyonlinelibrary.com]

CONCLUSIONS

In the present study, the correlation between ingredients and performance is analyzed. The friction and wear characteristics of friction materials are predicted. Based on comprehensive investigates, following conclusions can be obtained:

1. The correlations between various factors and tribological properties are obtained by GRA which provides guidance for the design of friction materials according to major and minor factors.
2. For friction coefficient and specific wear rate, the important order of the factors is nano-SiO_2 > Cu > aramid pulp > PTW > mica > PTFE and mica > PTW > aramid pulp > Cu > nano-SiO_2 > PTFE, which indicates that nano-SiO_2 and mica play a dominated role in improving tribological properties.
3. Tribological characteristics of friction materials are predicted by using a novel MC-ANN model which has been rarely reported in the field of tribology. This model is used to account for the nonlinear dependency of the friction and wear behavior on ingredients with a limited number of dataset.
4. By comparing BP-ANN and MC-ANN models, the latter shows better performance with RMSE (0.97 and 0.007) than the former (2.08 and 0.019) in predicting and fitting effect. This may be due to MC algorithm possesses high predictive quality for variation and volatility of data.

In the future work, this model can be applied to predict nonlinear relationships of system parameters (velocity, load, surface geometry, etc.), mechanical, and tribological properties. Furthermore, this simulated method can also predict tribological performance in different conditions such as vacuum, high and low temperatures, proton irradiation, lubrication, and other aspects.

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