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Prediction on tribological behaviour of composite PEEK-CF30 using artificial neural networks

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Abstract

In the present article artificial neural networks (ANN) were used to study the effects of *pv* factor and contact temperature on the dry sliding tribological behaviour of 30 wt.% carbon-fibre-reinforced polyetheretherketone composite (PEEK-CF30). An experimental plan was performed on a pin-on-disc machine for obtained experimental results. By the use of back propagation (BP) network, the non-linear relationship models of friction coefficient and weight loss of PEEK-CF30 versus *pv* factor and contact temperature were built. The test results show that the well-trained BP neural network models can precisely predict friction coefficient and wear weight loss according to *pv* factor and contact temperature. The obtained results show that friction coefficient was mainly influenced by the *pv* factor (mechanical factor), and the weight loss was mainly influenced by the contact temperature (thermal factor).

Keywords: Artificial neural network (ANN); Tribology; Composites (PEEK-CF30)

1. Introduction

The high performance of composites PEEK-CF30 enables it to be utilized in many of the most critical areas in general industry, such as: automotive, electronics, medical and aerospace.

The PEEK-CF30 exhibits outstanding wear resistance and relatively low friction for several ranges of pressure, sliding velocity and contact temperature. The tribological behaviour of PEEK-CF30 composite/steel pair was investigated as a function of contact parameter extensively [1–4].

Zhang et al. [5] reported an experimental study of the wear of PEEK composites related to their mechanical performances. The wear rates of PEEK composites show slightly dependence on the material composites, modulus density and impact resistance, opposite to the flexural properties and toughness, which are not so influential.

Davim and co-workers [6,7] studied the tribological behaviour of PEEK-CF30 under lubrication conditions. The effect of counterface roughness, sliding velocity and contact stress of PEEK-CF30 when slid against steel under dynamic conditions was studied. It was been observed that the counterface roughness and sliding velocity exert a great effect on the friction coefficient of PEEK-CF30/steel pair. The contact stress showed little effect on the friction coefficient. Subsequently, Davim and Cardoso [8,9] studied the friction and wear behaviour of PEEK-CF30 under dry conditions using statistical techniques.

The preliminary investigations of neural networks techniques to predict friction and wear have been presented by Hutching's group at the University of Cambridge (1996) [10] and Jones et al. [11]. Subsequently, Friedrich and co-workers [12,13] investigated the potential of artificial neural net works techniques to predict and analyzed the wear behaviour of short fibre reinforced plastics. Using multiple-layer feed-forward ANN, the coefficient of friction and the specific wear rate have been predicted based on a measured database for polyamide 4.6 composites. The predictive quality of the ANN increased when enlarging the datasets and by optimising the network construction.

The objective of the present study is the prediction of tribological behaviour (friction and wear) of PEEK-CF30 with the *pv* factor and contact temperature, using artificial neural networks. The *pv* factor in tribology is the product of the nominal contact pressure on a load surface and the relative surface velocity between the load material and its counterface.

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2. Algorithm and architecture of neural network model

The ANN is inspired by the biological nerve system and is used to solve a wide variety of complex scientific problems. In engineering a BP (back propagation) algorithm is a kind of generalized form of the least-mean-squares algorithm. In order to speed up the algorithm and make it more practical, several modifications have been proposed. The research on faster algorithm falls roughly into two categories [14]. The first involve the development of heuristic techniques such as the use of momentum and variable learning rates. The second has focused on standard numerical optimization techniques such as the conjugate gradient algorithm and the Levenberg–Marquardt algorithm. Among these algorithms, Levenberg–Marquardt algorithm is most rapid for medium networks. But it is difficult to get excellent composite of high training precision and good generalization capability when Levenberg–Marquardt algorithm is employed in this work. In order to enhance the generalization capability of networks, two methods, including regularization and early stop, are often employed [14]. Regularization constrains the size of the network parameters [15], the idea of which is that the true underlying function is assumed to have a degree of smoothness. If parameters in a network are kept small, the network response will be smooth. According [14] any modestly oversized network should be able to sufficiently represent the true function, rather than capture the noise. With regularization, the objective function becomes:

$$F = \gamma E_D + (1-\gamma)E_W \tag{1}$$

being, E_W is the sum of squares of the network parameters and γ is the performance ratio, the magnitude of which dictates the emphasis of the training. If γ is very large, then the training algorithm will drive the errors to be small. But if γ is very small, then training will emphasize parameter size reduction at the expense of network errors, thus producing a smoother network response. The optimal regularization parameter can be determined by Bayesian techniques [16]. The present work adopted Bayesian regularization in combination with Levenberg–Marquardt.

The target of this research is to establish non-linear relationships between the input parameters (pv, T) and the output parameters (μ, W) using BP networks. In this paper, two 3 layers networks are built and used for predicting friction coefficient and wear weight loss, respectively, via the neural-network toolbox of Matlab 6.5® [17]. The quantity of nodes of hidden was determined by trial-and-error method. After trial-and-error computation for many times by the artificial neural network program, the perfect topologies ({2, 7, 1}, {2, 8, 1}) of two-hidden-layer neural networks were gotten, respectively (Fig. 1). Sigmoid and pureline transfer function was employed for hidden layers and output layer, respectively.

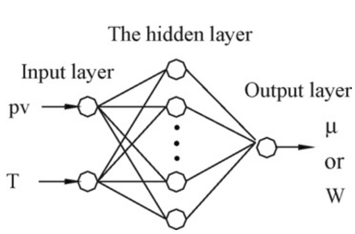

Fig. 1. Scheme of BP network.

3. Training and verifying

3.1. Experimental data

The composite tested in this investigation was the PEEK reinforced with 30% (weight) of carbon fibres (PEEK-CF30) manufactured by ERTA®. The counterface tested were made of carbon steel (Ck45K-DIN) with an arithmetic mean roughness value, $R_a \approx 0.5\,\mu$m.

The tribological tests were conducted on a pin-on-disc machine PLINT® TE67HT. The pin was fixed to the load arm with a chuck. The pin stayed over the disc with two degrees of freedom: a vertical one, which allows normal load application by a pneumatic system, causing direct and permanent contact with the surface of the disc, and a horizontal one, for friction measurement. The temperature on contact was measured in steel disc boundary with an optical pyrometer. All samples were weighed in a Mettler H78AR balance with 0.1 mg precision. Tribological tests were performed with a long distance of 10 km.

To ensure reasonable distribution and enough information containing of the dataset, 30 experimental data of friction coefficient and wear weight loss were collected, respectively, corresponding to different pv factors and contact temperatures. Among these, 25 data were selected as training data of neural network, and the residuals were used to verify the predicted results.

3.2. Normalization

In order to relieve the training difficulty and balance the important of each parameter during training process, the examinational data were normalized. It is recommended that the data be normalized between slightly offset values such as 0.1 and 0.9. One way to scale input and output variables in interval [0.1, 0.9] is as

$$P_n = 0.1 + (0.9-0.1) \times \frac{P - P_{min}}{P_{max} - P_{min}} \tag{2}$$

being, P_n is the normalized value of P, and P_{max} and P_{min} are the maximum and minimum values of P, respectively.

After the neural network was trained, tested and simulated, it is necessary for the simulating data to be unnormalized corresponded with normalization. The unnormalized method is as

$$P = (P_n - 0.1) \times \frac{P_{max} - P_{min}}{0.9 - 0.1} + P_{min} \tag{3}$$

being, P is the unnormalized value of P_n.

3.3. Training and verifying

After about 33 and 56 cycles of training, the training errors of two networks reach stabilization values, which are about

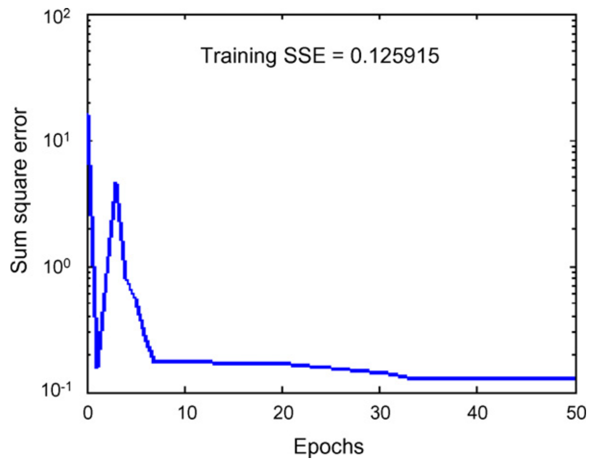

Fig. 2. The training error curve of friction coefficient network.

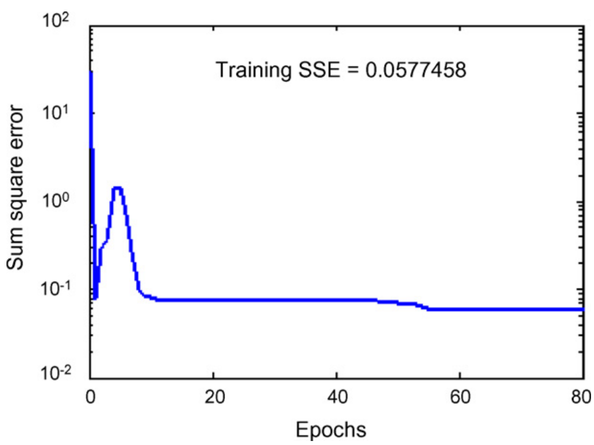

Fig. 3. The training error curve of wear weight loss network.

0.126 and 0.058, respectively, as shown by Figs. 2 and 3. The verifying results of trained data are shown in Figs. 4 and 5. The test results were shown in Table 1, which show that the relative error of each test datum is lower than 10%. These results show that the well-trained network model takes on optimal generalization performance, and has great accuracy in predicting friction coefficient and wear weight loss.

4. Prediction and discussion

After neural networks are trained successfully, all domain knowledge extracted out from the existing samples is stored

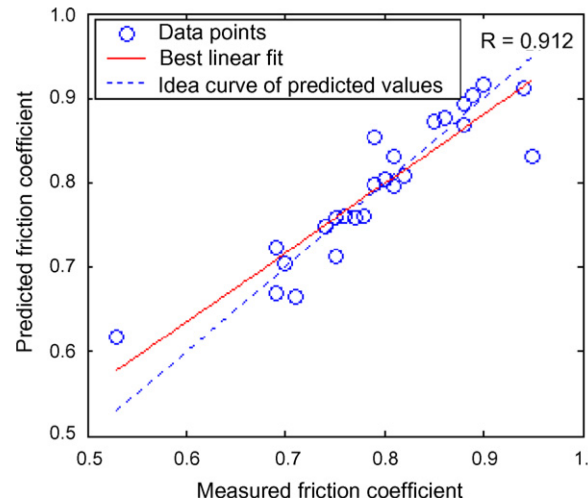

Fig. 4. Verifying results of friction coefficient of training specimens using the BP neural network.

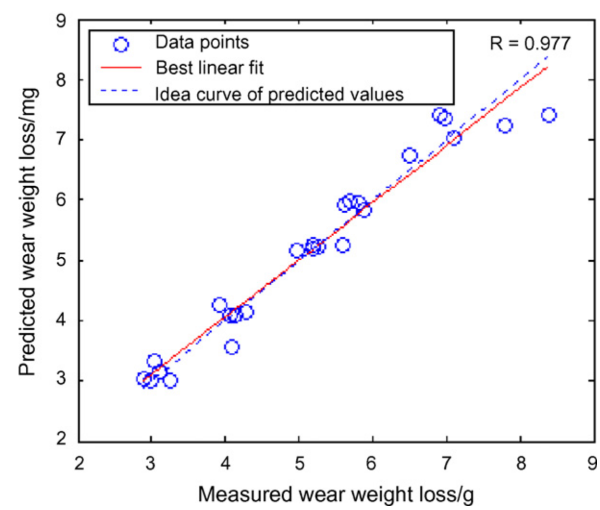

Fig. 5. Verifying results of wear weight loss of training specimens using the BP neural network.

as digital forms in weights associated with each connection between neurons. Making full use of the domain knowledge stored in the trained networks, Figs. 6–9 were gotten, which show the relationship of tribological properties (friction coefficient and weight loss) versus *pv* and contact temperature.

Table 1
The tested data, predicted values of BP neural network and error

Inputs		Friction coefficient			Wear weight loss (mg)		
pv (MPa m s^{-1})	Temperature (°C)	Tested data	Predicted values	Relative error (%)	Tested data	Predicted values	Relative error (%)
1.0	75	0.84	0.85	1.07	4.2	4.1	−2.07
1.5	100	0.82	0.84	2.20	5.7	5.0	4.02
2.0	90	0.78	0.79	1.15	5.6	5.2	−6.87
2.5	75	0.73	0.72	−2.05	4.0	4.1	3.60
3.0	100	0.71	0.72	1.27	5.5	5.9	6.52

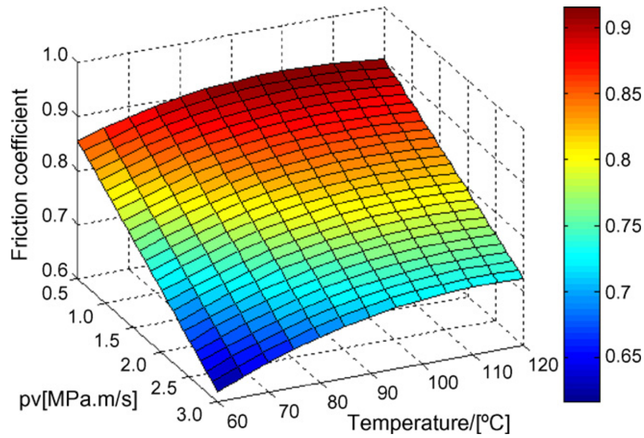

Fig. 6. Prediction for the relationship of friction coefficient vs. pv and temperature using BP neural network.

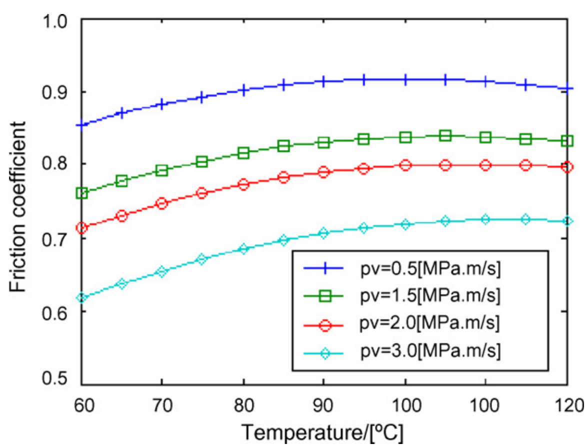

Fig. 7. Prediction for the effect of contact temperature on friction coefficient using BP neural network.

4.1. Friction coefficient analysis

The prediction of friction coefficient of pair (PEEK-CF30/steel) as function of pv factor and contact temperature can be seen in Figs. 6 and 7. At constant pv factor, the friction coefficient gradually increases to maximum with increasing temperature to about 90–100 °C, and the friction coefficient decreases with further increasing temperature. At constant temperature, the friction coefficient decreases rapidly with increasing the pv value. It can be observed transfer of pin material (PEEK-CF30) to the steel counterface at all testing temperatures. After the near contact temperature region 90–100 °C this transfer film formed is a uniform and continuous layer on the steel surface responsible for decreasing of friction coefficient in the contact.

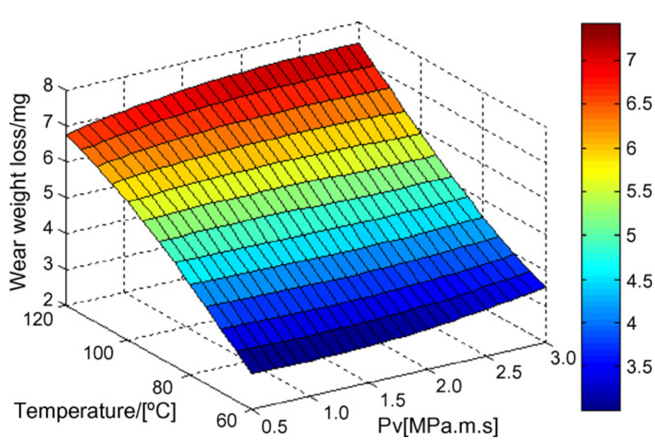

Fig. 8. Prediction for the relationship of wear weight loss vs. pv and temperature using BP neural network.

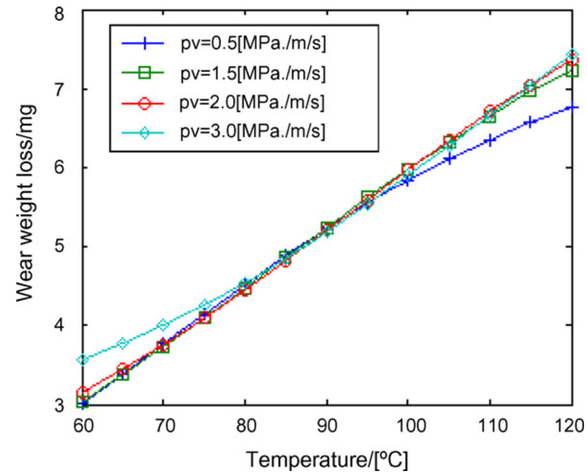

Fig. 9. Prediction for the effect of temperature on wear weight loss using BP neural network.

4.2. Wear analysis

The prediction of weight loss of pin (PEEK-CF30) as function of pv factor and contact temperature can be seen in Figs. 8 and 9. The weight loss for each constant pv value rapidly increases with the increase of contact temperature (Fig. 9). But the wear weight loss varies slightly with the increase pv value under constant contact temperature conditions. With the increasing of contact temperature transfer film formed is a uniform and continuous layer on the steel surface responsible for increasing of weight loss of pin.

5. Conclusions

Based on the results presented, the following conclusions can be draw from tribological behaviour of PEEK-CF30 using artificial neural networks:

(A) The non-linear relationship models of friction coefficient and weight loss of PEEK-CF30 versus pv factor and contact temperature were built. The test results show that the well-trained BP neural network models can precisely predict friction coefficient and wear weight loss according to pv factor and contact temperature.
(B) The friction coefficient was mainly influenced by the pv factor (mechanical factor), and the weight loss was mainly influenced by the contact temperature (thermal factor).

(C) The artificial neural networks should be used for modelling tribology behaviour with care and enough data.

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