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Modelling of tribological behaviours of composite PEEK-CF30 using BP neural networks

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A high performance of advanced composite PEEK-CF30 enables it to be utilized in many of the most critical areas in general industry such as automotive, electronics, medical and aerospace. In the present paper, a back propagation (BP) neural network was used to study the effects of the *pv* factor and sliding distance on the friction and wear behaviour of 30 wt. % carbon fibre reinforced poly(ether)–ether –ketone advanced composite (PEEK-CF30) at the contact temperature of 120 ºC. An experimental plan was performed on a pin-on-disc machine for obtained experimental results under unlubricated conditions. By the use of BP neural network, nonlinear relationship models of the friction coefficient (μ) and weight loss (W) of PEEK-CF30 vs. the *pv* factor and sliding distance (S) were built based on the experimental data. The test results show that the well-trained BP neural network models can precisely predict the friction coefficient and wear weight loss according to the *pv* factor and sliding distance. A new method of predicting wear behaviours of composite PEEK-CF30 has been provided by the authors.

Key words: *BP neural network; friction and wear; advanced composite (PEEK-CF30)*

1. Introduction

Preliminary investigations of neural networks techniques to predict tribological properties have been presented by Hutching's group at the University of Cambridge [1] and Jones et al. [2]. Subsequently, Friedrich et al. [3, 4] investigated the potential of artificial neural network techniques to predict and analyze the wear behaviour of short fibre reinforced plastics. Using multiple-layer feed-forward artificial neural network, the coefficient of friction and the specific wear rate have been predicted based on the measured data base for polyamide 4.6 composites. The predictive quality of the artificial neural network increased when enlarging the datasets and by optimising the net work construction.

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30 wt. % carbon fibre reinforced poly(ether)–ether–ketone (PEEK-CF30) is a relatively new semicrystalline polymer with high melting and glass transition temperatures |(T_m = 340 °C and T_g = 143 °C) [5]. The composite 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 extensively investigated in function of contact parameter and contact conditions (unlubricated or lubricated) [6–16]. Zhang et al. [10] tested PEEK composites blended with various contents of polytetrafuorethylene and/or graphite and reinforced with various amounts of short carbon fibres, against steel, using a block-on-ring tribometer under unlubricated conditions. According to these authors, the wear resistance of PEEK can be significantly improved by the use of various reinforcements (in particular, short carbon fibres, graphite flakes and PTFE particles), but at the cost of deterioration of some other mechanical properties in some degrees, e.g. toughness and strength. Davim et al. [15, 16] studied the friction and wear behaviour of PEEK-CF30 under dry conditions using statistical techniques.

The objective of the present study was the prediction of tribological behaviour (friction and wear) of PEEK-CF30 with the *pv* factor and sliding distance *S* using back propagation (BP) neural networks.

2. Algorithm and architecture of neural network models

In engineering, the BP algorithm is a kind of a generalized form of the least-mean-squares algorithm [17, 18]. The BP algorithm used in this work has been described elsewhere [19].

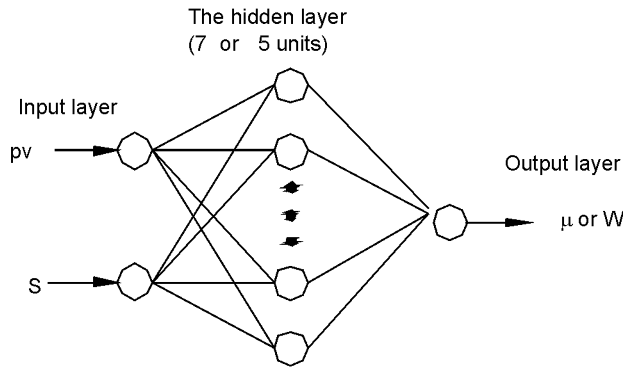

Fig. 1. Scheme of the BP network

The target of the research was to establish non-linear relationships between the input parameters (*pv*, *S*) and the output parameters (μ, *W*) using BP neural networks. Two three-layer neural networks were built and used for predicting the friction coefficient and wear weight loss, respectively, via the neural-network toolbox of Matlab 6.5® [18]. The quantity of nodes of hidden layers was determined by the 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, 5, 1}) of the two neural networks were obtained (Fig. 1). Sigmoid and pureline transfer functions were employed for hidden layers and output layers, respectively.

3. Training and verifying

3.1. Experimental data

The experimental tests were conducted on a pin-on-disc tribometer. 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 experimental tests were performed with contact temperature of 120 °C. The composite tested in this investigation was the PEEK reinforced with 30 wt. % of carbon fibres (PEEK-CF30) manufactured by Erta®. The counterfaces tested were made of carbon steel Ck45K (DIN) with the arithmetic mean roughness value *Ra* of ca. 0.5 μm. All pins were weighed in a balance with 0.1 mg precision.

To ensure a reasonable distribution and a sufficient information content of the dataset, 30 experimental values of the friction coefficient and wear weight loss were collected, respectively, corresponding to various *pv* factors and sliding distances. 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 importance of each parameter during the training process, the examination 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

$$P_n = 0.1 + (0.9 - 0.1) \times \frac{P - P_{\min}}{P_{\max} - P_{\min}} \tag{1}$$

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 in the way corresponding to the normalization. The unnormalizing method is

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

where P is the unnormalized value of P_n.

3.3. Training and verifying

After about 10 and 12 cycles of training, the training errors of two networks attained stabilization, reaching about 0.064 and 0.097, respectively, as shown in Figs. 2 and 3.

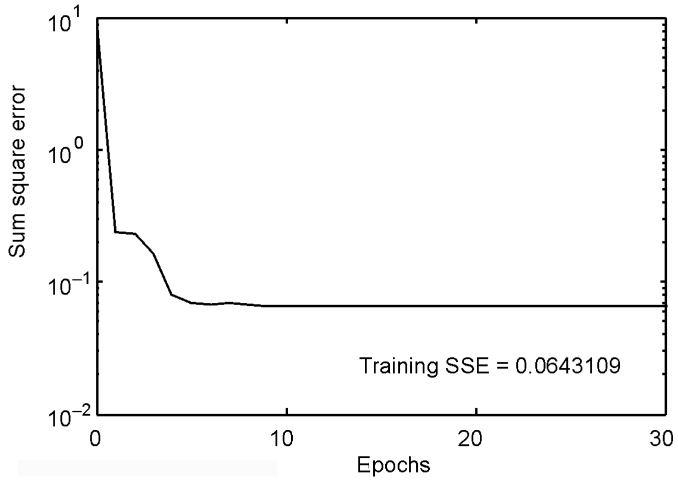

Fig. 2. The training error curve of friction coefficient network

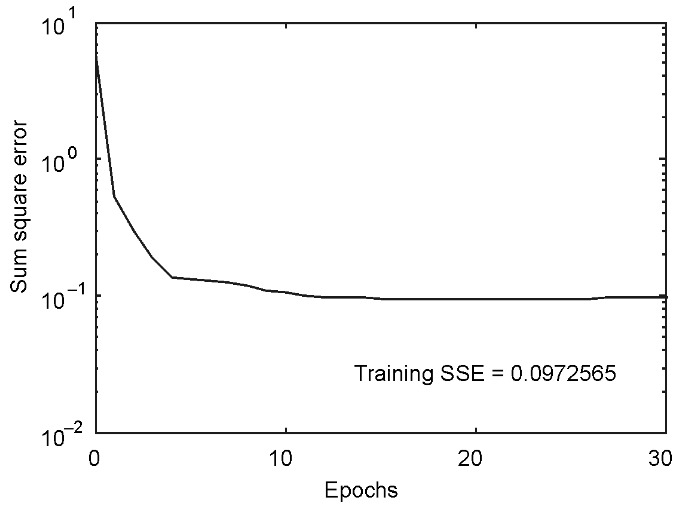

Fig. 3. The training error curve of wear weight loss network

The verifying results of trained data are shown in Figs. 4 and 5. The test results are shown in Table 1; the relative error of all the test data is lower than 15%.

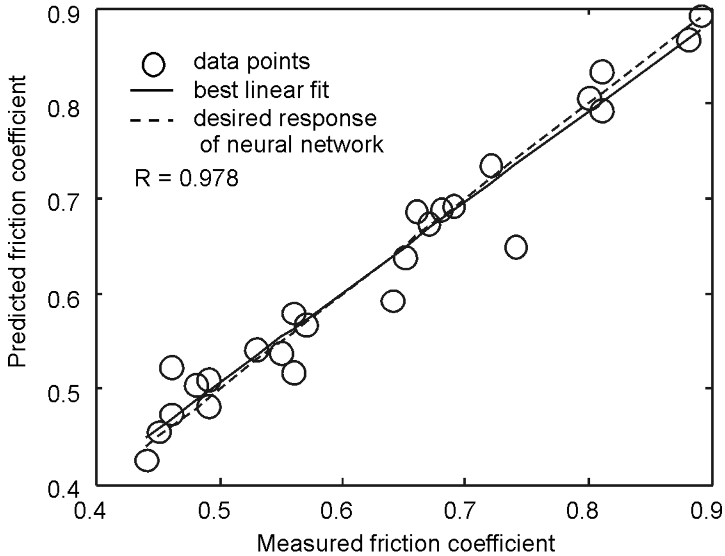

Fig. 4. Verifying results of the friction coefficient of training specimens using the BP neural network

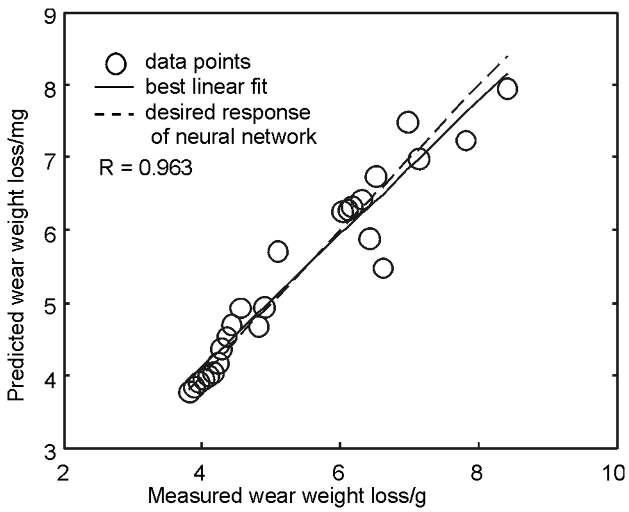

Fig. 5. Verifying results of wear weight loss of training specimens using the BP neural network

These results show that a well-trained network model takes on optimal generalization performance, and has a great accuracy in predicting the friction coefficient and wear weight loss.

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}	Sliding distance/m	Tested data	Predicted values	Relative error/%	Tested data	Predicted values	Relative error /%
0.5	8000	0.83	0.83	0	6.4	6.5	1.8
1.0	3500	0.60	0.59	–2.5	4.5	4.8	7.9
1.5	8000	0.76	0.78	2.1	6.2	6.4	2.3
2.0	5000	0.59	0.62	4.9	5.0	5.2	5.6
2.5	10000	0.77	0.75	–3.1	6.9	7.7	12.2

4. Prediction and discussion

After neural networks have been successfully trained, all domain knowledge extracted out from the existing samples is stored as digital form in weights associated with each connection between neurons. Results shown in Figs. 6–9 were obtained making a full use of the domain knowledge stored in the trained networks. The figures show the dependences of tribological properties (friction coefficient and weight loss) on the *pv* factor and sliding distance.

4.1. Friction coefficient analysis

Figures 6–8 show the prediction of the coefficient of friction of PEEK CF30 against steel in function of the *pv* factor and sliding distance. The friction coefficient increased upon increasing the sliding distance and decreased upon increasing the *pv* factor. It is important to refer that all the results were obtained for temperatures below the glass transition temperature (T_g = 143 ºC) of the PEEK matrix of the composite. At the contact temperature, approximately 120 ºC, the increase of the *pv* factor facilitates

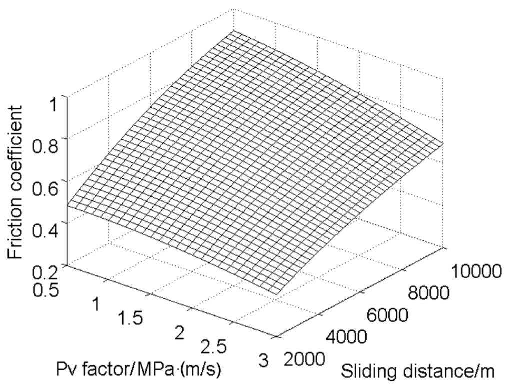

Fig. 6. Prediction for the relationship of the friction coefficient vs. *pv* and sliding distance using the BP neural network

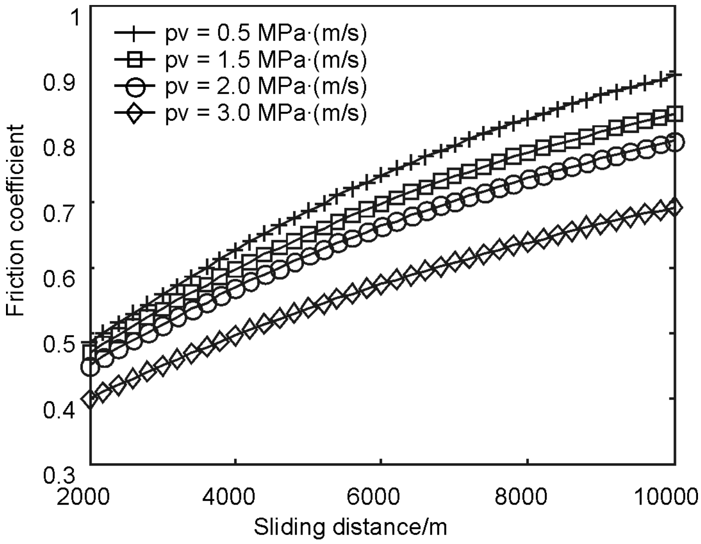

Fig. 7. Prediction for the effect of sliding distance on the friction coefficient using the BP neural network

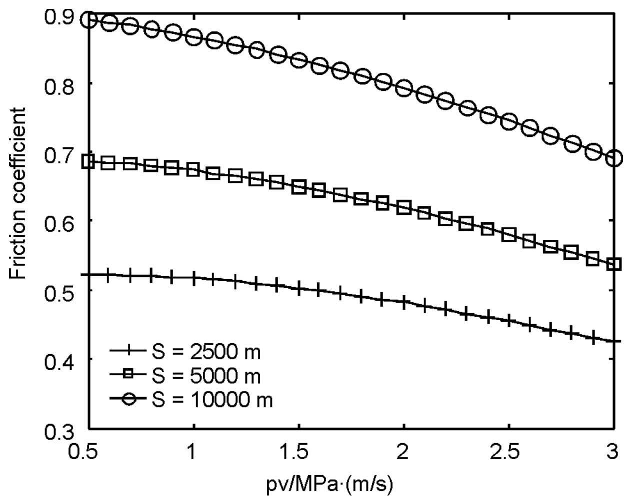

Fig. 8. Prediction for the effect of *pv* factor on the friction coefficient using the BP neural network

the transference of the PEEK film for the steel counterface. With the increase of the *pv* factor this transfer film formed a uniform and continuous layer on the steel track. In general the increase of sliding distance damages the contact surface, resulting in increasing the friction coefficient. The friction coefficient is highly influenced by sliding distance and in a smaller degree by the *pv* factor.

4.2. Wear analysis

Figures 9 and 10 show the prediction of weight loss of PEEK CF30 against steel in function of the *pv* factor and sliding distance.

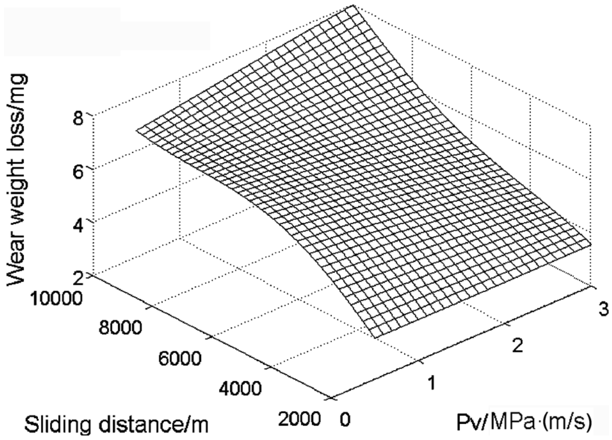

Fig. 9. Prediction for the relationship of wear weight loss vs. *pv* factor and sliding distance using BP neural network

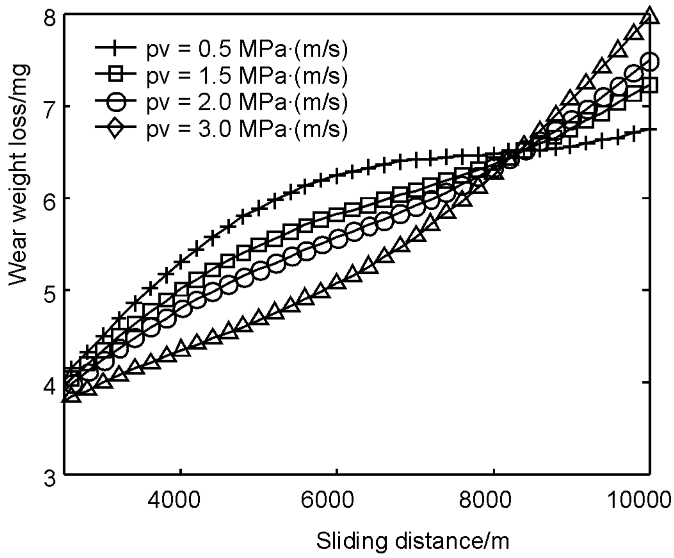

Fig. 10. Prediction for the effect of sliding distance on wear weight loss using neural network

At a small *pv* factor (0.5), the weight loss increases slowly above the sliding distance of 5000 m. On the other hand, at high *pv* values (1.5; 2.0 and 3.0), the increase of the weight loss is slower and nearly linear at small sliding distances, and much steeper above ca. 7000 m. SEM examinations of the worn surface of PEEK CF30 revealed an increase of fibre breakage and fibre removal from PEEK matrix with the increasing of mechanical action *pv* factor (Fig. 11). The weigh loss is highly influenced by the sliding distance.

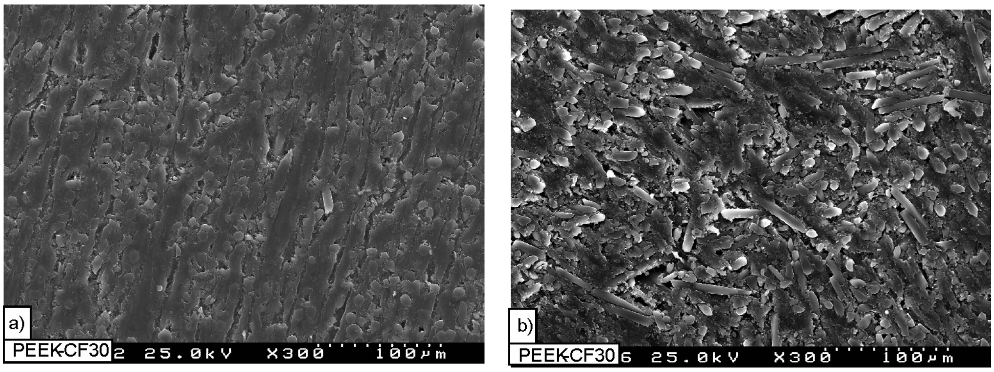

Fig. 11. Worn surface examples of PEEK-CF30 (sliding distance 10 km):
a) $pv = 0.5$ MPa·m·s^{-1}; b) $pv = 3$ MPa·m·s^{-1}

5. Conclusions

The following conclusions can be drawn from friction and wear behaviour of PEEK-CF30 using BP neural networks:

• Non-linear models of the friction coefficient and weight loss of PEEK-CF30 vs. the *pv* factor and sliding distance have been built. The test results show that the well-trained BP neural network models can precisely predict the friction coefficient and wear weight loss according to the *pv* factor and sliding distance.

• The friction and wear is highly influenced by sliding distance and in a smaller degree by the *pv* factor.

• The BP neural networks should be used for modelling the behaviour of the friction and wear in complex tribological systems with care and enough data. The degree of complexity of the investigated material and number of the factors affecting its properties do not allow considering the present results as generally true for all PEEK-based systems.

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