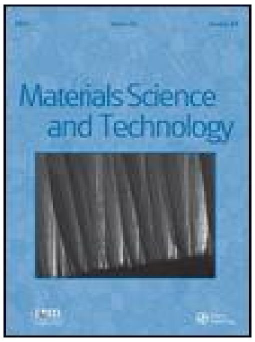

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Artificial neural network prediction on wear properties of high vanadium high speed steel (HVHSS) rolls

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Artificial neural network prediction on wear properties of high vanadium high speed steel (HVHSS) rolls

L.-J. Xu*[1], J.-D. Xing[1], S.-Z. Wei[2], Y.-Z. Zhang[2] and R. Long[2]

The present paper is dedicated to the application of artificial neural networks in the prediction of the wear properties of high vanadium high speed steel (HVHSS) rolls, including predictions of wear weight loss *W* according to carbon content *C* and number of revolutions *N*. Multilayer backpropagation networks were created and trained using comprehensive datasets tested by the authors. Very good performances of the neural networks were achieved. The prediction results show that the wear weight loss nearly linear increases with increasing number of revolutions at constant carbon content. The relative wear resistance of roll reaches the optimal value when the carbon content is ~2·55 wt-%. The prediction values have sufficiently mined the basic domain knowledge of wear process of HVHSS rolls. A convenient and powerful method of optimising the process parameters of abrasive resistant materials has been provided by the authors.

Keywords: High vanadium high speed steel, Roll, Neural network, Wear

Introduction

Recently, some high alloys cast iron rolls have been replaced by high speed steel rolls which possess superior wear properties. The research results have shown that the service lives of high speed steel rolls are three times longer than that of high chromium cast iron rolls.[1–4] But much tungsten element was often added into high speed steel rolls in previous research, which brought about two disadvantages. First, it is easy for tungsten element to segregate in the process of cast, especially centrifugal casting often used for making rolls, because the density of tungsten is far higher than that of Fe,[5–7] resulting in the deterioration of roll properties such as toughness and wear resistance. Second, a large amount of fishbone shape M_6C type carbides will form when tungsten content in high speed steel is high. Compared with grain shape MC type carbides with high hardness, fishbone shape M_6C type carbides possess not only low hardness but also poor morphology. So M_6C type carbides are easily to be crushed in the process of steel rolling.[2,5,8] This results in a decrease in wear resistance of high speed steel with high tungsten content. In order to solve the above problems, the present work regulated the chemical composition of the conventional high speed steel rolls by removing tungsten element and increasing vanadium element content (~9 wt-%) to manufacture six kinds of high vanadium high speed steel (HVHSS) rolls with different carbon contents. Via the roll wear simulation testing machine developed by authors,[9] the wear properties of new high speed steel rolls were tested.

Neural networks are a class of flexible non-linear models inspired by the way in which the human brain processes information. Given an appropriate number of hidden layer units, neural networks can approximate any non-linear function to an arbitrary degree of accuracy through the composition of a network of relatively simple functions.[10] The flexibility and simplicity of neural networks have made them a popular modelling and forecasting tool across different research areas in recent years. A variety of different neural network models have thus developed, among which the backpropagation (BP) network is the most widely adopted in the present study.[11–13] In the present work, the non-linear relationships model of the wear weight loss *W* of HVHSS rolls versus carbon content *C* and number of revolutions *N* were established by BP neural networks. And the effect of carbon content on wear properties of rolls was predicted via the well trained neural network model.

Building neural network model

Algorithm

A BP algorithm is a kind of generalised form of the least mean squares algorithm usually used in engineering. But the basic BP algorithm is too slow for most practical applications. In order to speed up the algorithm and make it more practical, several modifications have been proposed by researchers. The research on faster algorithm falls roughly into two categories. One involves the development of heuristic techniques such as the use of

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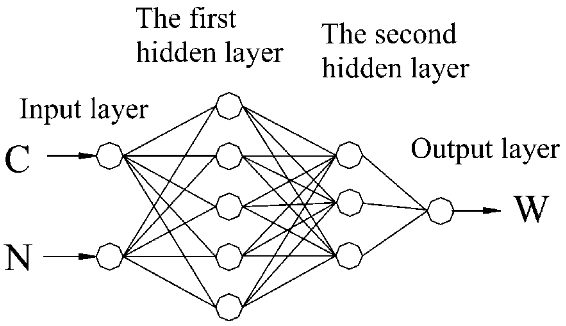


1 Scheme of BP neural network

momentum and variable learning rates. The other has focused on standard numerical optimisation techniques such as the conjugate gradient algorithm and the Levenberg–Marquardt algorithm.[14,15] Among these algorithms, Levenberg–Marquard algorithm is most rapid for medium networks. But it is difficult to get excellent composite of high training precision and good generalisation capability when Levenberg–Marquardt algorithm is employed in the present work. In order to enhance the generalisation capability of networks, two methods, including regularisation and early stop, are often employed. Regularisation constrains the size of the network parameters,[16] the idea of which is that the true underlying function is assumed to have a degree of smoothness. When the parameters in a network are kept small, the response of the network will be smooth. Thus any modestly oversized network should be able to sufficiently represent the true function, rather than capture the noise. With regularisation, the objective function becomes

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

where 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 emphasise parameter size reduction at the expense of network errors, thus producing a smoother network response. The optimal regularisation parameter can be determined by Bayesian techniques.[17] So the present work adopted Bayesian regularisation in combination with Levenberg–Marquardt.

Architecture of model

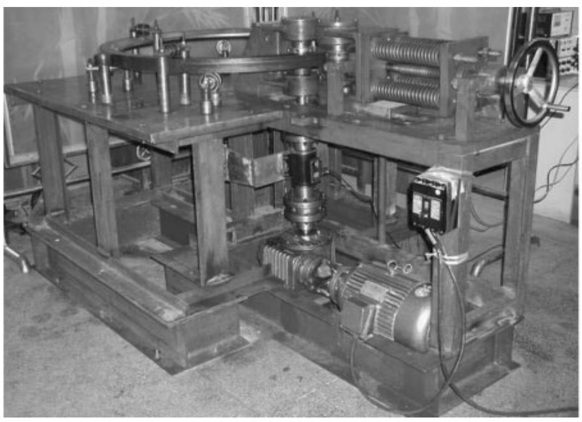
The target of the present research is to establish non-linear relationships between the input parameters C and N and the output parameters W using BP networks. A lot of computational instances show that two hidden layers neural networks are suitable.[11] In the present paper, two hidden layer networks are built and used for predicting wear properties of rolls via the neural network toolbox of matlab6·5.[18] If N is the quantity of nodes in output layer and N_1, N_2 are the quantity of nodes in the first and the second hidden layer respectively, $N_2 = N + 1$ or $N_2 = N + 2$. Adjusting N_1 ensures both the generalisation performance and the rate of the convergence satisfactory. After trial and error computation for many times by the artificial neural network programme, the perfect topologies ({2, 5, 3, 1} of two hidden layer neural networks were obtained (Fig. 1). Sigmoid and pureline transfer function was employed for hidden layers and output layer respectively.

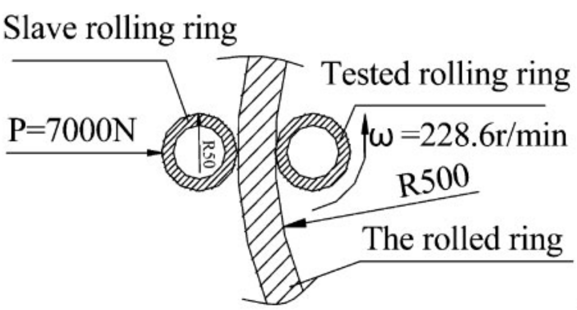
Training and verifying

Collection of experimental data

Six kinds of HVHSS rolls were manufactured via open sand casting. The carbon contents of six rolls are 1·58, 1·90, 2·23, 2·58, 2·82 and 2·92 wt-% respectively. The contents of other elements are designed as follows: 8·50–9·50 wt-%V, 3·80–4·50 wt-%Cr, 2·70–3·40 wt-%Mo, 0·5–0·8 wt-%Si, 0·8–1·0 wt-%Mn and the actual chemical composition satisfies the above requirement. All the rolls samples were austenised at 1050°C, air quenched and then tempered at 550°C. The rolled material was conventional high chromium cast iron with 20%Cr. After the roll samples were machined, the wear properties were tested via the roll wear simulation testing machine developed by authors, as shown in Fig. 2. And the tested size of the samples and tested conditions were listed in Table 1. The wear weight loss was measured when the rolls worked for 27432, 54864, 82296, 109728 and 137160 cycles respectively. So the total data of wear weight loss reach 30, corresponding to different carbons and number of revolutions.

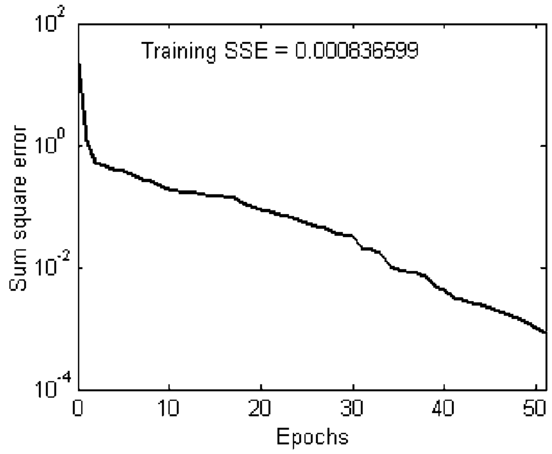
In this section, the 30 experimental data of wear weight loss were used for building the neural network models. Among these, 25 data were selected as training data and the others were used to verify the predicted results.


(a)

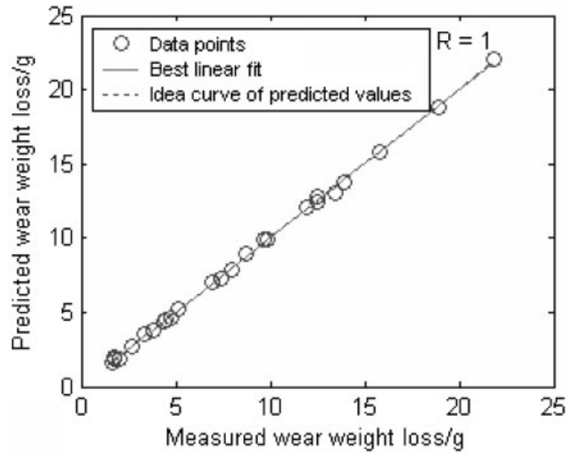


(b)

2 *a* photo and *b* diagram of rolling simulation testing machine



3 Error curve of training



4 Verifying results of wear weight loss of training specimens using BP neural network

Normalisation

In order to relieve the training difficulty and balance the importance of each parameter during training process, the experimental data were normalised. It is recommended that the data be normalised 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

$$P_n = 0{\cdot}1 + (0{\cdot}9 - 0{\cdot}1)(P - P_{min})/(P_{max} - P_{min}) \quad (2)$$

where P_n is the normalised 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 unnormalised corresponded with normalisation. The unnormalised method is as

$$P = (P_n - 0{\cdot}1)(P_{max} - P_{min})/(0{\cdot}9 - 0{\cdot}1) + P_{min} \quad (3)$$

where P is the unnormalised value of P_n.

Training and verifying

After about 52 cycles of training, the sum square error of network reach 0·001, as show in Fig. 3. The verifying results of trained data are shown in Fig. 4. To test the generalisation performance of the trained network, the relationships between the predicted values from the trained neural network and the tested data are shown in Table 2. The verifying results in Table 2 show that the well trained network models take on optimal generalisation performance, and have great accuracy in predicting wear weight loss of HVHSS rolls according to carbon content and number of revolutions.

Prediction and discussion

After neural networks are trained successfully, all domain knowledge extracted out from the existing samples is stored as digital forms in weights associated with each connection between neurons. Making full use of the domain knowledge stored in the trained networks, Figs. 5–7 were obtained, which show the relationship of wear properties versus carbon content. Obviously, Figs. 5–7 exhibit much more professional knowledge.

The prediction results show that:

(i) at constant carbon content, the wear weight loss of HVHSS rolls linear increases with the increasing number of revolutions (Figs. 5 and 6)

(ii) at carbon content of <2·25 wt-%, the relative wear resistance increase slightly with increasing carbon content. But the relative wear resistance rapidly increases after carbon content is >2·25 wt-%. When carbon content is ~2·55 wt-%, the wear weight loss reaches the least and the relative wear resistance reaches optimal. With further increasing carbon, the relative wear resistance decreases rapidly (Figs. 5 and 7).

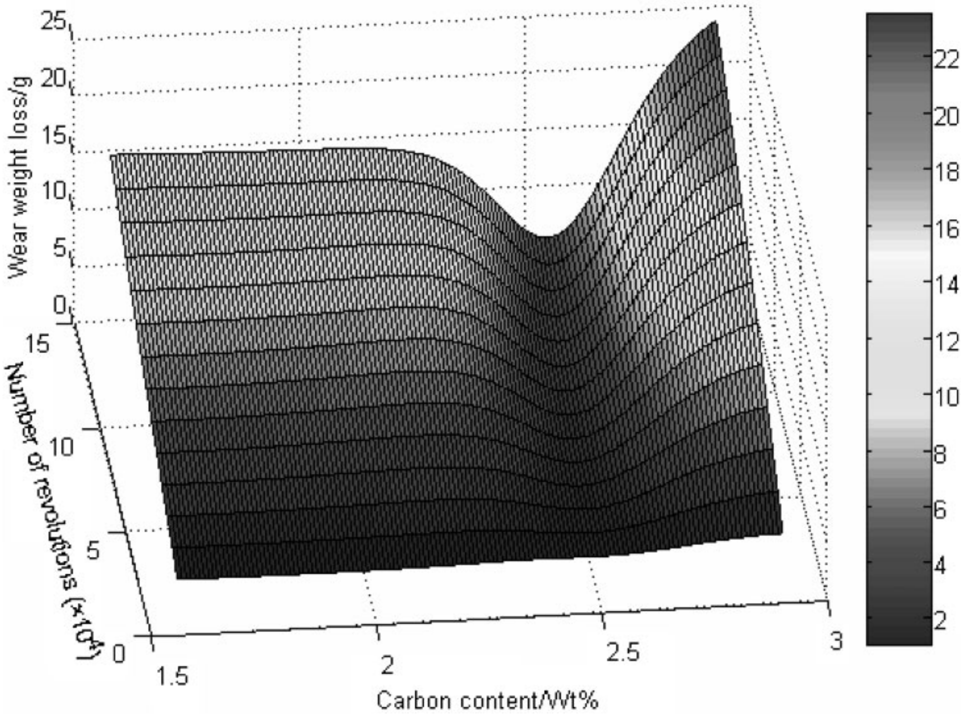
The wear failures of high speed steel rolls are caused by the composition factors, such as fatigue, sliding and abrasive wears.[17,19,20] The carbon content has obvious

Table 1 Conditions of simulating experiment

Tested HVHSS or high chromium cast iron rolling ring				Rolled ring			Rolling pressure
External diameter d_1, mm	Inner diameter d_2, mm	Thick b, mm	Rotating speed ω, rev min^{-1}	External diameterD_1, mm	Inner diameteD_2, mm	Thick B, mm	P, N
Φ100	Φ69	70	228·6	Φ1150	Φ1000	10	7000

Table 2 Tested data, predicted values of BP neural network and relative errors

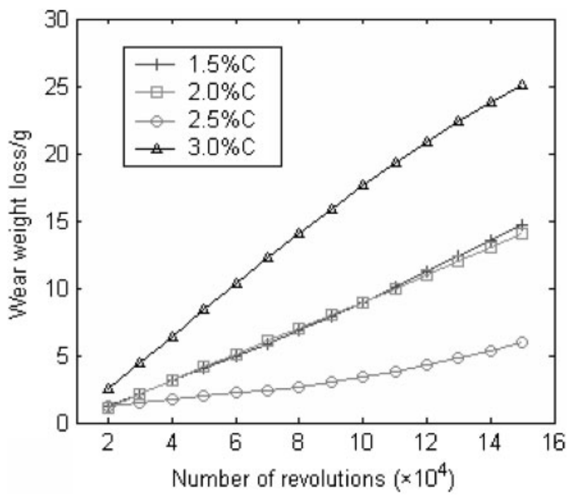
Carbon content, wt-%	Number of revolutions N	Tested data, g	Predicted values, g	Relative errors
1·58	54 864	4·476	4·418	−1·30
1·90	82 296	7·038	7·111	1·04
2·23	109 728	10·014	9·878	−1·36
2·82	27 432	3·741	3·409	−8·87
2·92	109 728	18·612	18·229	−2·06



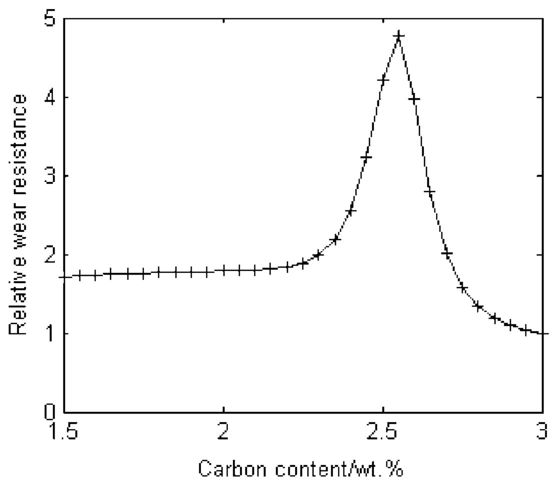
5 Prediction on relation between wear weight loss versus carbon content and number of revolutions using BP neural network

effects on microstructures of HVHSS rolls, and therefore affects the wear resistance. According to the method of definite proportion of carbon,[21] ferrite matrix, with low microhardness and high toughness, will form when the carbon content of HVHSS is under ~2·25 wt-% (Fig. 8*a*). So the rolls with ferrite microstructure cannot availably resist the sliding wear and abrasive wears although they can resist fatigue wear effectively, resulting in poor wear resistance. With this understanding, sliding wear and abrasive wear are the main factors to determine wear resistance of HVHSS rolls, and therefore the relative wear resistance only increases slightly with increasing carbon content because there is ferrite in matrix of HVHSS.

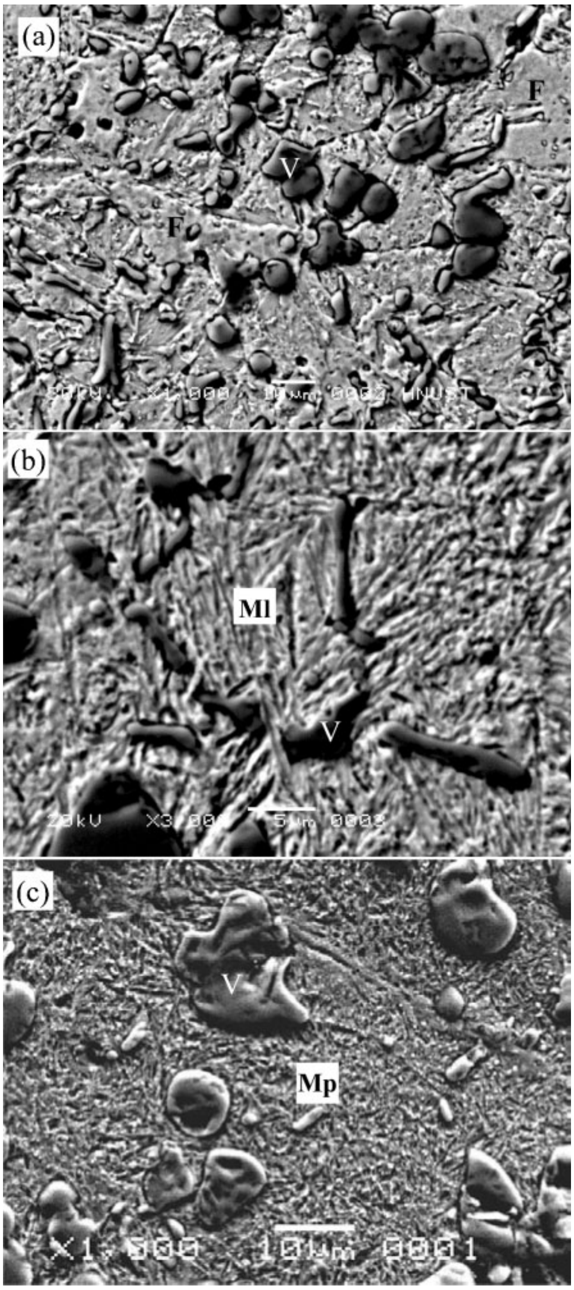
At carbon content of >2·25 wt-%, the carbon content is higher than the stoichiometric carbon equivalent forming VC, the microstructure of matrix varies from ferrite to martensite and austenite with high microhardness because there is some carbon dissolving in matrix after forming carbides. So the rolls possess stronger abilities to resist sliding wear and abrasive wears, resulting in increasing wear resistance. Besides, there are large amounts of VC with very high microhardness in the microstructure of HVHSS. These VC can effectively resist sliding wear and abrasive wear if there is high hardness matrix to support it availably. When the carbon content reaches ~2·55 wt-%, the microstructure of HVHSS roll is characterised by VC distributing in large amounts of lath martensite with high microhardness and good toughness (Fig. 8*b*). So the rolls can effectively resist not only fatigue wear but also sliding wear and abrasive wear, resulting in optimal wear resistance.



6 Prediction for effect of number of revolutions on wear weight loss using neural network



7 Prediction on relative wear resistance using neural network after rolls work for 150 000 cycles



a sample 1; *b* sample 2; *c* sample 4

8 Microstructure of HVHSS with different carbon contents etched in etchant of 5 g $FeCl_3$+10 mL HNO_3+3 mL HCl+87 mL ethyl alcohol: V – vanadium carbides (VC); F – ferrite; M1 – lath martensite; Mp – plate martensite

But if the carbon content is further increased to ~2·80 wt-%, there is >1% carbon dissolving in matrix after forming carbides, which leads to the formation of excessive amounts of plate martensite with poor toughness in matrix (Fig. 8*c*). Because fatigue cracks tend to propagate along the plate of martensite to cause peeling on the surface of roll,[2,19,22] the relative wear resistance decreases rapidly. With this understanding, fatigue wear is the main factor to determine the wear resistance of HVHSS roll.

Conclusions

1. The non-linear relationship between wear weight loss W and carbon contents C, number of revolutions N could be built by BP neural network. The tested results show that the well trained BP neural network can precisely predict the wear properties of HVHSS rolls according to the carbon contents.

2. The prediction results show that the optimal carbon content is ~2·55 wt-% for HVHSS rolls. And the prediction results have sufficiently mined the basic domain knowledge of the relation between wear property and chemical composition of alloys. Therefore, a new way to optimise the chemical composition of abrasive resistant material has been provided by the authors.

Acknowledgements

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