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# Optimization of heat treatment technique of high-vanadium high-speed steel based on back-propagation neural networks

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**Abstract**

This paper is dedicated to the application of artificial neural networks in optimizing heat treatment technique of high-vanadium high-speed steel (HVHSS), including predictions of retained austenite content ($A$), hardness ($H$) and wear resistance ($\varepsilon$) according to quenching and tempering temperatures ($T1$, $T2$). Multilayer back-propagation (BP) networks are created and trained using comprehensive datasets tested by the authors. And very good performances of the neural networks are achieved. The prediction results show residual austenite content decreases with decreasing quenching temperature or increasing tempering temperature. The maximum value of relative wear resistance occurs at quenching of 1000–1050 °C and tempering of 530–560 °C, corresponding to the peak value of hardness and retained austenite content of about 20–40 vol%. The prediction values have sufficiently mined the basic domain knowledge of heat treatment process of HVHSS. A convenient and powerful method of optimizing heat treatment technique has been provided by the authors.


*Keywords:* High speed steel; BP neural network; Heat treatment temperature; Retained austenite; Hardness; Wear resistance

## 1. Introduction

High-vanadium high-speed steel (HVHSS) is one kind of new abrasive resistant material used for making steel rollers in some countries [1–4]. Recently, researchers have paid more attention to the applications of HVHSS in crush industry such as hammer, jaw, rotor, etc. for abrasive wear [5,6]. The research results have shown that wear resistance of HVHSS applied for roll and crush industry is about 3–5 times higher than that of high chromium cast iron [3–7]. The excellent wear property of HVHSS depends on its microstructure, i.e. carbides and matrix. At a certain chemical composition, heat treatment technique plays a crucial role in changing matrix microstructure, such as retained austenite content and characteristics of martensite, resulting in significantly influencing on wear resistance. The previous research mainly focused on the effect of alloys on carbides and wear properties of HVHSS [1,2,8,9], but neglected the effect of heat treatment conditions on microstructure and wear properties. This work tested the retained austenite content, harnesses and wear properties after HVHSS containing about 10%V was treated by different heat treatment techniques, and then predicted the effect of heat treatment temperatures on retained austenite content in matrix, hardness and wear resistance according to the test data using artificial neural networks. So that the users can get proper heat treatment technique for controlling retained austenite content and improving wear resistance of HVHSS.

Neural networks are a class of flexible nonlinear 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 nonlinear function to an arbitrary degree of accuracy through the

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composition of a network of relatively simple functions [10,11]. The flexibility and simplicity of neural networks have made them a popular modeling and forecasting tool across different research areas in recent years. A variety of different neural network models have thus developed, among which the back-propagation (BP) network is the most widely adopted in the present study [12–14]. In this work, the nonlinear relationships of the retained austenite content ($A$), hardness ($H$) and abrasive wear resistance ($\varepsilon$) vs. quenching temperature and tempering temperature ($T1$, and $T2$) were established, respectively, by the use of BP networks.

## 2. Building the neural network model

### 2.1. Algorithm

A BP algorithm is a kind of generalized 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 momentum and variable learning rates. The other 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 in this work when Levenberg-Marquardt algorithm is employed because the data of hardness and wear resistance are very dispersive and complicate. In order to enhance the generalization capability of networks, two methods, including regularization and early stop, are often employed. 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. When the parameters in a network are kept small, the network response will be smooth. Thus any modestly oversized network should be able to sufficiently represent the true function, rather than capture the noise. With regularization, the objective function ($E_D$) becomes

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

where $F$ is the objective function after $E_D$ is regularized, $E_W$ is the sum of squares of the network parameters, and $\gamma$ is the performance ratio, the magnitude of which dictates the emphasis of the training. If $\gamma$ is very large, then the training algorithm will drive the errors small. But if $\gamma$ 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]. So this work adopted Bayesian regularization in combination with Levenberg-Marquardt.

### 2.2. Architecture of model

Quenching temperature ($T1$) and tempering temperature ($T2$) play important roles in influencing retained austenite content ($A$), hardness ($H$) and relative wear resistance ($\varepsilon$) of HVHSS when chemical composition is certain. The target of this research is to establish nonlinear relationships between the input parameters ($T1$, and $T2$) and the output parameters ($A$, $H$, and $\varepsilon$) by use of BP networks. A lot of computational instances show that two hidden layer neural networks are suitable [13]. In this paper, three four-layers BP neural networks, includes one input layer, two hidden layers and one output layer, are used for predicting retained austenite content, hardness and relative wear resistance, respectively (Fig. 1). If $N1$ and $N2$ are the quantity of nodes in the first and the second hidden layer respectively, $N2 = N + 1$ or $N2 = N + 2$. Adjusting $N1$ ensures both the generalization performance and the rate of the convergence satisfactory. After many times of trial-and-error computation by the artificial neural network program, the perfect topologies ({2, 5, 2, 1}, {2, 5, 3, 1} and {2, 15, 2, 1}) of three neural networks were gotten, respectively. Sigmoid and pureline transfer function was employed for hidden layers and output layer, respectively.

## 3. Training and verifying

### 3.1. Collecting the experimental data

The chemical composition of tested HVHSS is listed in Table 1. The knowledge of a specific field is implicated in the existing training samples, so an appropriate dataset with good distribution is significant for reliable training and performance of neural networks. To ensure reasonable distribution and enough information containing of the dataset, heat treatment techniques of HVHSS are covered with different quenching temperatures and tempering temperatures, as shown in Table 2. The total samples reach 30.

The alloy ingot was produced by melting the raw materials in a 50 kg intermediate frequency induction melting furnace. To improve the absorptivity of vanadium, liquid steel was deoxidized preliminarily before adding ferrovanadium, which is added in liquid steel in the final stage of melting. At the same time, the residence time of high temperature liquid steel was shortened to enable the absorptivity of vanadium reach 90%. The final deoxidation was conducted by adding 0.1% pure aluminum. The modifying

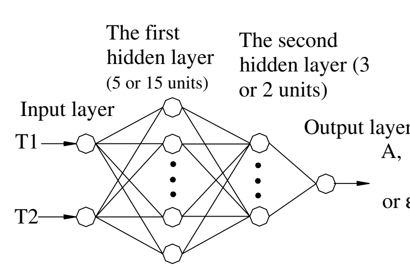


Fig. 1. Scheme of BP network.