Article ID: 1003－6326(2003)05－1145－04

Application of BP neural network to semi-solid apparent viscosity simulation①

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Abstract: Two-layer BP neural network was designed for the semi-solid apparent viscosity simulation. The apparent viscosity simulations of Sn-15% Pb alloy and Al-4.5% Cu-1.5% Mg alloy stirred slurries were carried out. The trained BP neural network forecast the curve of the apparent viscosity versus solid volume fraction of Sn-15% Pb alloy, under the condition of shear rate, $\dot{\gamma}= 150\ s^{-1}$, and cooling rate of $G= 0.33$ ℃/min. The simulation results are well agreement with the experimental values given in references. The fitted mathematical formula of Sn-15% Pb alloy apparent viscosity, under the condition of the cooling rate of $G= 0.33$ ℃/min, was obtained by optimization method. The results show that the precision of apparent viscosity simulation value by neural network is much better than that of its calculation value by fitted mathematical formula.

Key words: semi-solid; apparent viscosity; solid volume fraction; BP neural network
CLC number: TG 111.4 **Document code:** A

1 INTRODUCTION

Since the thixotropic properties of vigorously stirred tin-lead slurries were discovered by Spencer et al[1] at MIT, investigation and application of the semi-solid technology have been developed quickly. The study on the apparent viscosity is not only of theoretical but also of utilization significance. Many investigators have carried out a great deal of experimental research and put forward many mathematical models of the semi-solid apparent viscosity. Some of these models, which are related to popular exponential function and a classical power-law equation, are listed in the following.

A model of apparent viscosity related to the solid volume fraction is expressed by exponential function[2]:

$$\eta_a= A\exp(B\varphi_s) \qquad (1)$$

Another related to the shear rate is expressed by a classical power-law equation:

$$\eta_a= k\dot{\gamma}^n \qquad (2)$$

A combination model of Eqns. (1) and (2) is

$$\eta_a= A\exp(B\varphi_s)\dot{\gamma}^n \qquad (3)$$

A similar form of model (3) was used in Ref. [3]:

$$\eta_a= A\exp(B\varphi_s)\dot{\gamma}^{m\varphi_s+n} \qquad (4)$$

Other mathematical models of apparent viscosity can be found in Refs. [4－11].

Because there are many factors affecting the semi-solid apparent viscosity in a complicated way, and the present mathematical models usually consider only one or two factors, the error of semi-solid apparent viscosity is large between the experimental value and the computing value by the present fitted mathematical formulae. This not only reduces the fitting precision, but also limits its application. However, it is too difficult to improve the fitting precision of semi-solid apparent viscosity by adding more factors in a mathematical model.

In this article, the authors make an attempt to simulate the semi-solid apparent viscosity by BP neural network. According to the traits of neural network and the dominating factors affecting semi-solid apparent viscosity, two-layer BP neural network is designed for the semi-solid apparent viscosity simulation. And the apparent viscosity simulations are carried out on Sn-15% Pb alloy and Al-4.5% Cu-1.5% Mg alloy stirred slurries. The trained BP neural network is used to forecast the apparent viscosity curve of Sn-15% Pb alloy, related to solid volume fraction, under the condition of shear rate, $\dot{\gamma} = 150\ s^{-1}$, and cooling rate of $G= 0.33$ ℃/min.

2 DESIGN OF BP NEURAL NETWORK AND ITS IMPLEMENT

It is well known that three dominating factors affecting the semi-solid apparent viscosity are solid volume fraction φ_s shear rate $\dot{\gamma}$ and cooling rate G[11], and that two-layer nonlinear BP neural network should be adequate as universal approximations of any nonlinear function[12]. Based on these two points, two-layer nonlinear BP neural network (Fig. 1), is designed for semi-solid apparent viscosity simulation. The BP neural network has three node layers,

① **Received date:** 2002－11－21; **Accepted date:** 2003－03－26

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which are input nodes x_j (i e φ_s, $\dot{\gamma}$, G), hidden nodes y_i, and output node O_l(i e η_a).

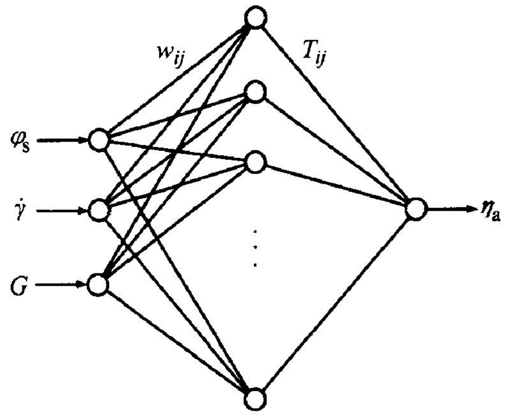

Fig. 1 BP neural network for semi-solid apparent viscosity simulation

The training of the BP neural network is to update its weighted interconnections (w_{ij}, T_{ij}) and threshold values θ, in order to reduce the value of sum-squared network error function along with negative gradient direction. Let w_{ij} be weighted interconnections between input nodes and hidden nodes, and T_{ij} be weighted interconnections between hidden nodes and the output node. As the desired response of the output node is t_l, the computing formulae of the BP neural network are as follows[13].

The outputs of hidden nodes are

$$y_i = f_1(net_i) \tag{5}$$

where $net_i = \sum_j w_{ij} x_j - \theta_i$, and f_1 is a transfer function.

The computing output of the output node is

$$O_l = f_2(net_l) \tag{6}$$

where $net_l = \sum_i T_{li} y_i - \theta_l$, and f_2 is a transfer function.

The sum-squared network error function of the output node is

$$E = \frac{1}{2} \sum_l (t_l - O_l)^2 \tag{7}$$

The equations for updating weighted interconnections are

$$\left.\begin{array}{l} w_{ij}(k+1) = w_{ij}(k) + \eta \delta_i x_j \\ T_{li}(k+1) = T_{li}(k) + \eta' \delta'_l y_i \end{array}\right\} \tag{8}$$

where η and η′ are learning rates.

Transfer functions usually used are the linear function and sigmoid function as follows:

$$f(x) = x \tag{9}$$

$$f(x) = 1/(1 + e^{-x}) \tag{10}$$

3 SIMULATION RESULTS

The authors make use of experimental data of Sn-15% Pb alloy apparent viscosity in Ref. [11], which were obtained in the solid volume fraction range between 0.10 and 0.61, the shear rate range between 115 s^{-1} and 750 s^{-1}, and the cooling rate of 0.33 ℃/min and 25 ℃/min, respectively, and perform the neural network simulation. Firstly, the parameters of the BP neural network are determined. Let the number of hidden nodes be 20, and learning rates $\eta = \eta' = 0.0008$, transfer function f_1 be sigmoid function, and transfer function f_2 be linear function, and the maximum training times of the BP neural network be 80 000. Secondly, input data are normalized. Thirdly, the BP neural network is trained. Finally, the trained BP neural network obtains the simulation results of the Sn-15% Pb alloy apparent viscosities as following:

1) The curve of the output node sum-squared error versus training times (Epoch) of the BP neural network is shown in Fig. 2, in which the dashed line presents the given error value for terminating training the BP neural network. The sum-squared network error of the output node is 20.237 8, after the BP neural network is trained.

2) Fig. 3 indicates that the apparent viscosity simulation value of Sn-15% Pb alloy slurries sheared continuously, at cooling rate of G = 0.33 ℃/min, increases with increasing solid volume fraction.

3) Some of the apparent viscosity simulation values and experimental values are listed in Table 1, in which the data in bracket are experimental values in Ref. [11].

4) Fig. 4 gives the curve of apparent viscosity forecasted by the trained BP neural network versus solid volume fraction, under the condition of shear rate $\dot{\gamma}$ = 150 s^{-1}, and cooling rate of G = 0.33 ℃/min. For comparison, Fig. 4 also shows the two experimental curves of apparent viscosity, with shear rate $\dot{\gamma}$ = 115 s^{-1} and $\dot{\gamma}$ = 230 s^{-1} respectively, at the same cooling rate.

In order to compare the precision of neural network simulation with that of the fitted mathematical formula, the authors choose Eqn. (4) as the representative of the fitted mathematical equa-

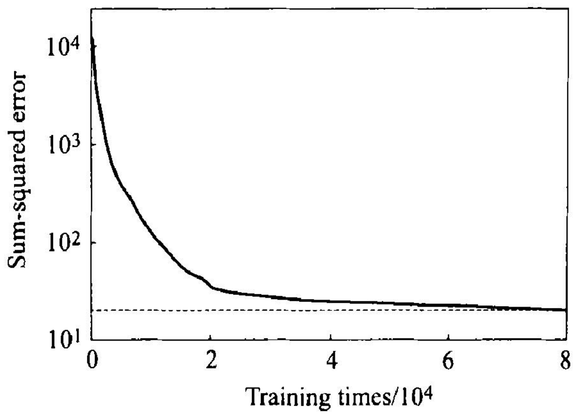

Fig. 2 Curve of sum-squared network error vs training times (Epoch)

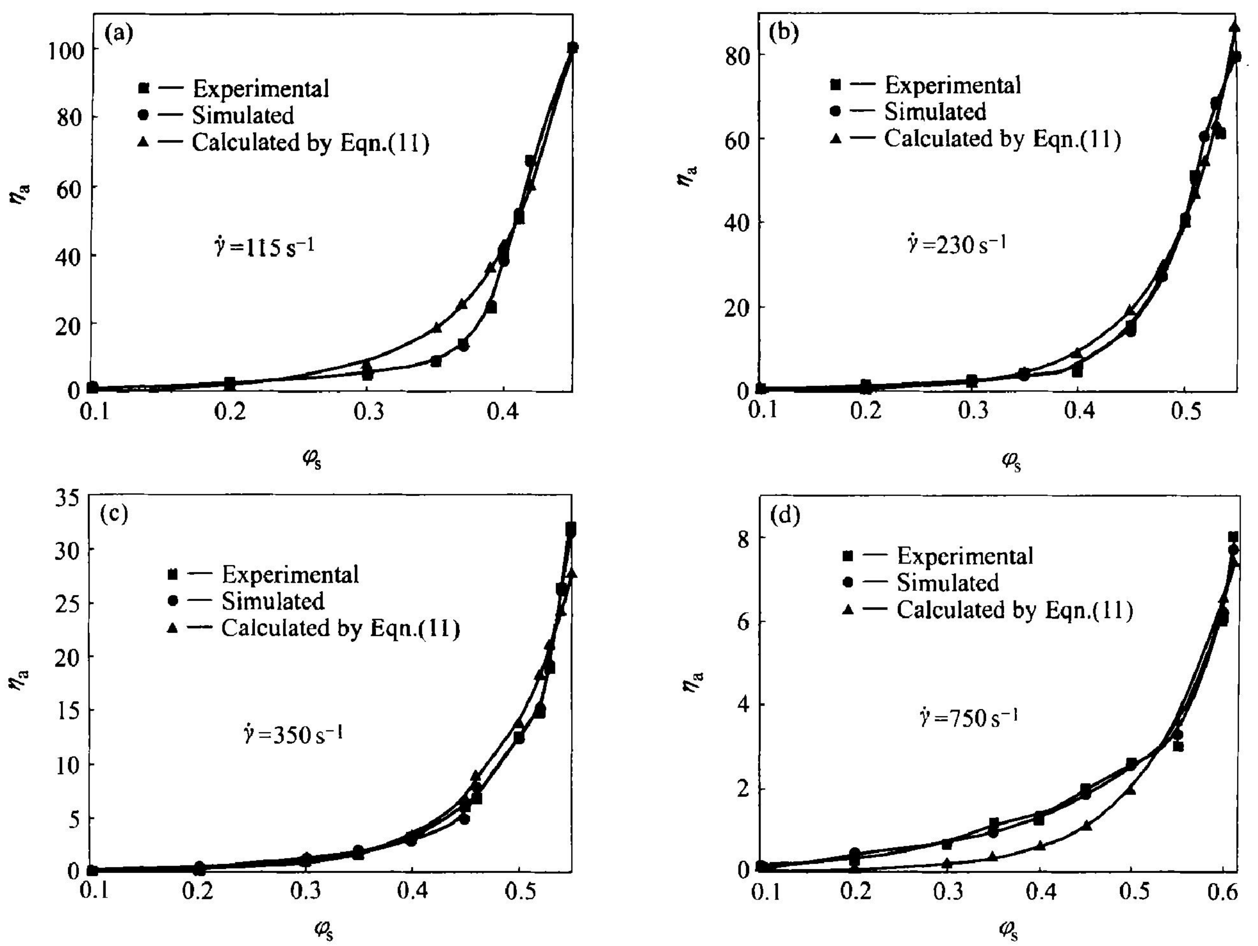

Fig. 3 Apparent viscosity vs solid volume fraction of Sn-15% Pb alloy sheared continuously at cooling rate G = 0.33 ℃/min

Table 1 Comparison between apparent viscosity simulation values and experimental values

φ_S	Initial shear rate, $\dot{\gamma}_0/s^{-1}$ (cooling rate, G = 0.33 ℃/min)				Initial shear rate, $\dot{\gamma}_0/s^{-1}$ (cooling rate, G = 25 ℃/min)			
	115	230	350	750	115	230	450	750
0.20	2.42(2.5)	1.08(1.2)	0.47(0.4)	0.47(0.3)	1.16(1.2)	1.10(1.2)	0.34(0.2)	0.01(0.1)
0.30	5.09(5)	2.20(2.5)	1.26(1)	0.72(0.7)	2.34(2.5)	2.55(2.5)	1.02(1.2)	1.03(1.0)
0.35	8.90(8.7)	3.32(3.5)	1.94(1.7)	0.95(1.2)	4.49(4.5)	4.36(4.5)	4.03(4)	2.52(2.5)
0.40	37.78(40)	5.70(5)	2.84(3)	1.31(1.3)	12.80(13)	9.98(10)	8.03(8)	5.90(6)
0.45	99.81(100)	14.01(15)	4.98(6.2)	1.84(2)	39.83(40)	36.88(37)	17.82(18)	11.98(12)
0.50	-	41.20(40)	12.30(12.5)	2.52(2.6)	84.79(85)	99.59(100)	41.54(42)	29.82(30)
0.55	-	79.83(80)	31.54(32)	3.26(3)	-	-	-	79.58(80)

tion. With the experimental data of Sn-15% Pb alloy apparent viscosity[11], under the condition of the cooling rate G = 0.33 ℃/min, the parameters of Eqn.(4) are determined by the optimization method[14] and the fitted mathematical formula of Sn-15% Pb alloy apparent viscosity becomes

$$\eta_a = 10.7621\exp(30.4537\varphi_S)\dot{\gamma}^{-2.74092\varphi_S - 1.16792} \quad (11)$$

The apparent viscosity curves from Eqn.(11) are also shown in Figs. 3 and 4. The maximum absolute error between the calculation values by Eqn.(11) and the experimental values is 11.57.

In order to prove that BP neural network is applied to semi-solid apparent viscosity simulation of other metals, the authors also perform the apparent viscosity simulation of Al-4.5% Cu-1.5% Mg alloy stirred slurries. The B-spline curves of its apparent viscosity simulation values and the experiment values in Ref. [5] are given in Fig. 5. It also shows that the simulation results are well consistent with experimental values.

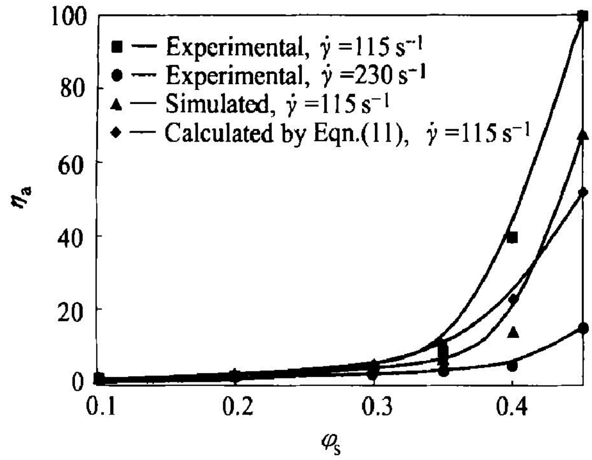

Fig. 4 Apparent viscosity simulation curve of Sn-15% Pb alloy sheared continuously at cooling rate G= 0.33 ℃/ min

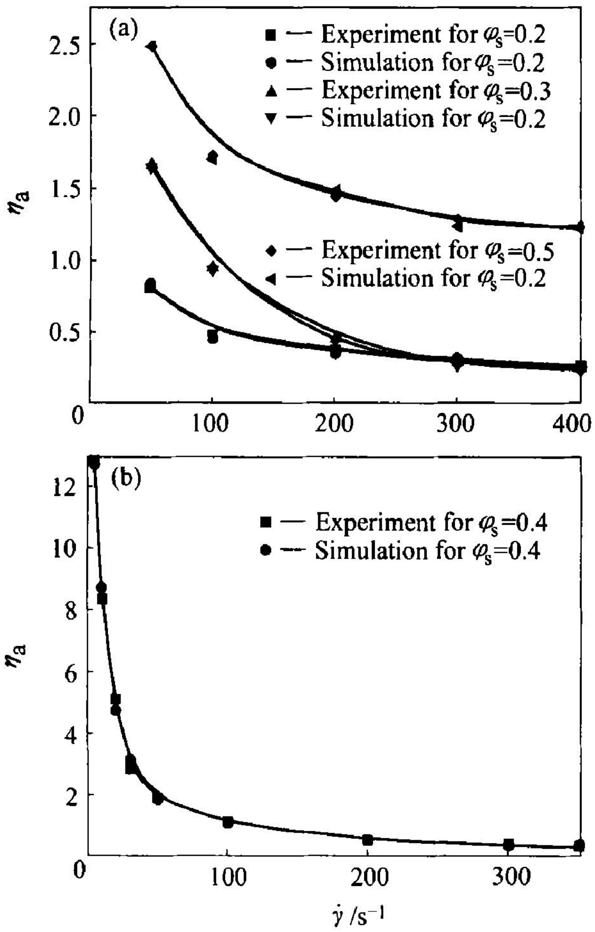

Fig. 5 Apparent viscosity vs shear rate of Al-4. 5% Cu-1. 5% Mg alloy

4 ANALYSIS OF SIMULATION RESULTS

From Figs. 3, Fig. 5 and Table 1, it is easy to know that the apparent viscosity simulation values of these two alloys by the BP neural network are well agreement with experimental values. For Sn15% Pb alloy, the maximum absolute error between the simulation values by the BP neural network and experimental values is 2.22, which is much less than that between the calculation values by Eqn. (11) and the experimental values. From Fig. 4, we know that the curve of apparent viscosity predicted by the BP neural network, with shear rate $\dot{\gamma}$= 150 s^{-1}, lies between the curves composed of experimental values, with shear rate $\dot{\gamma}$= 115 s^{-1} and $\dot{\gamma}$= 230 s^{-1}. This accords with the fact that the apparent viscosity decreases with increasing shear rate.

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(Edited by YUAN Sai-qian)