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Mathematical simulation experiment based on optimisation of heat treatment process of aluminium alloy materials

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Abstract

The paper establishes a related differential equation model about changes in financial interest rates. It uses information related to liquidity to feedback the law and stability of differential equations in interest rate changes. The article applies stochastic processes and partial differential equations to complex financial networks to confirm node yields in financial market networks. It confirms the existence of interest rate stickiness in Chinese financial markets. The advantage of this interest rate model is that when the external economic environment changes, the state of interest rates will also change accordingly.

Keywords: neural network, aluminium alloy, heat treatment, process optimisation, wear performance, numerical simulation.

AMS 2010 codes: 92B20

1 Introduction

Aluminium alloy has a wide range of application prospects in aerospace, automotive, transportation, civil and other fields due to its advantages of low density, high strength, and excellent welding performance and processing performance. In recent years, with the development of the economy and the needs of the people, the automobile industry has become a pillar industry of the Chinese national economy. And because of increasing emphasis on environmental protection, this also places higher demands on the automotive industry [1]. As a result, the automobile industry is attempting to introduce innovations in low energy consumption, measures to attenuate environmental pollution and crafting lightweight products. For automobiles, compared with steel materials, aluminium alloy has the advantages of low density, high specific rigidity, high specific strength, good

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elasticity and high recovery rate. Therefore, the use of aluminium alloys in automobiles has become more and more widespread in recent years. Automotive aluminium alloys mainly include cast aluminium alloys and forged aluminium alloys [2]. Forged aluminium alloys have been widely used because of their excellent cold and hot processing performance, producing automobile parts with better performance. However, forging automotive aluminium alloy requires complicated processes such as thermal deformation processing, and its raw materials and processing costs are high.

Therefore, we only rely on experimental methods to optimise the process, which is not conducive to improved enterprise production efficiency. A neural network is a new type of data processing system that simulates the human brain neural network structure. It has sound application effects in modelling, prediction, estimation, diagnosis, composition and process optimisation [3]. Some scholars have researched the optimisation of the aluminium treatment process based on the BP neural network gradient descent algorithm. Some scholars have predicted the mechanical properties of A357 alloy based on an artificial neural network. Some scholars have predicted the secondary ageing performance of 7055 aluminium alloy based on an artificial neural network. However, few studies are still focusing on the use of neural networks to optimise the heat treatment process of forging automotive aluminium alloys. Therefore, this article uses a neural network to build a neural network model with a $7 \times 35 \times 2$ three-layer topology structure and deeply researches the forging process of automotive aluminium alloy. We hope to find the best automotive aluminium alloy forging process to optimise the heat treatment process for forging automotive aluminium alloy.

2 Construction of neural network optimisation model

To construct a neural network optimisation model for the heat treatment process of aluminium alloy for automobiles, we adopted a $7 \times 35 \times 2$ three-layer topology structure. Figure 1 is a schematic diagram of this structure. This model includes three levels: input layer, hidden layer and output layer. There are seven parameters in the input layer. These are forged aluminium alloy grades, annealing temperature, annealing time, solution temperature, ageing temperature, solution time and ageing time. Their respective values are as follows: Forged aluminium alloy grades are 2017, 2018, 2024, 2218, 2618. The annealing temperature is 250–450 °C, and a value is taken every 10 °C. The annealing time is 1–10 h, and a value is taken every 0.5 h. The solid solution temperature is 450–600°C, and a value is taken every 10°C. The solution time is 3–10 h, and a value is taken every 0.5 h. The aging temperature is 120–220°C, and a value is taken every 10°C. The ageing time is 5–25 h, and a value is taken every 0.5 h. There are two output parameters of the neural network optimisation model: wear resistance and impact performance. The transfer function of the output layer is represented by a pure function [4]. The transit function represents the transfer function of the hidden layer. This article uses the normalisation method to process each input parameter, and we use the inverse operation of the normalisation method when processing the output parameters.

The gradient descent method will be used to derive an error rotation calculation formula suitable for optimising the 7003 aluminium alloy heat treatment process [5]. In the learning optimisation process, we set the desired output of the k output neuron and the network output Q_{pk} . Then the average error of the system is

$$E_n(\tau) = \frac{1}{2} \sum_{p=1}^P \sum_{k=1}^n (O_{dk} - O_{pk})^2 \quad (1)$$

According to the gradient descent method, we find that the weight change term ΔW_{ji} is proportional to $\partial E / \partial W_{ji}$,

$$\Delta W_{ji} = -\eta \frac{\partial E_n}{\partial W_{ji}} \quad (2)$$

In this article, the BP algorithm has a slower convergence rate [6]. To speed up the convergence of BP, the

Fig. 1 The structure of the neural network optimisation model.

method of adding momentum is used to achieve

$$\Delta W_{ji}(\tau) = \alpha W_{ji}(\tau - 1) - \eta \frac{\partial E_n}{\partial W_{ji}} \quad (3)$$

$$\frac{\partial E_n}{\partial W_{ji}} = \sum_{k=1}^n \left(\frac{\partial E_n}{\partial O_{kp}} \circ \frac{\partial O_{kp}}{\partial I_{kp}} \circ \frac{\partial I_{kp}}{\partial O_{jp}} \right) \circ \frac{\partial O_{jp}}{\partial I_{jp}} \circ \frac{\partial I_{jp}}{\partial W_{ji}} \quad (4)$$

Make

$$\delta_p = (O_{dk} - O_{kp}) f'(I_{kp}) \quad (5)$$

$$\delta_p = \sum_{k=1}^n \delta_p w_{kj} f'(I_{jp}) \quad (6)$$

Derived

$$\Delta W_{ji}(\tau + 1) = \frac{\eta}{p} \sum_{k=1}^n \delta_p O_{jp} \quad (7)$$

Neuron threshold

$$\Delta \theta_j = -\eta \frac{\partial E_n}{\partial \theta_j} \quad (8)$$

$$\frac{\partial E_n}{\partial \theta_j} = \sum_{k=1}^n \left(\frac{\partial E_n}{\partial O_{kp}} \circ \frac{\partial O_{kp}}{\partial I_{kj}} \circ \frac{\partial I_{kj}}{\partial O_{jp}} \right) \frac{\partial O_{jp}}{\partial I_{jp}} \circ \frac{\partial I_{jp}}{\partial \theta_j} \quad (9)$$

Finally got

$$\Delta \theta_j(\tau + 1) = \frac{\eta}{p} \sum_{p=1}^p \delta_p \quad (10)$$

We programme the above BP model in MATLAB7.0, and the four input parameters of the network in the programming are solid solution temperature Z_1 , solid solution time Z_2 , ageing temperature Z_3 and ageing time Z_4 . The output parameter is the hardness value O_1 , and the middle hidden layer is 10 neurons. We use the transit transfer function for hidden layer neurons [7]. The output neuron adopts a pure type transfer function. In the training algorithm, we use the gradient descent method. According to Eqs (7) and (10), we can control the BP network's weights and thresholds to realise the BP network's training. After the requirements are met, the interconnection weights between the nodes of the network are completely determined. At this point, we can identify and predict unknown samples. The prediction results are shown in the last six groups of data in Table 1.

Table 1 Artificial neural network prediction points and verification points

Sample	Heat treatment process				HRB hardness		
	$\theta 1/^{\circ}\text{C}$	t1/h	$\theta 2/^{\circ}\text{C}$	t2/h	Actual value	Predictive value	Relative value/%
1	460	0.5	110	20	41.2	40.9	0.71
2	460	1	120	48	55.7	55.6	0.18
3	460	1	130	75	61.2	61	0.32
4	460	1.167	110	100	60.3	60.5	-0.33
5	460	1.167	120	30	45.2	45.3	-0.22
6	460	1.167	130	50	51.3	51.3	0
7	470	0.5	120	100	62.5	62.4	0.16
8	470	0.5	130	125	54.3	53.9	0.73
9	470	1	110	20	38.7	37.8	2.3
10	470	1	120	48	55.7	55.9	-1.4
11	470	1	130	75	49.5	48.7	1.6
12	470	1.167	110	100	59.8	60.2	-0.67
13	470	1.167	120	30	41.7	42.1	-0.95
14	470	1.167	130	75	56.8	57	-0.35
15	480	0.5	110	45	53.9	54.2	-0.55
16	480	1	120	40	50.8	50.6	0.39
17	480	1	120	20	53.2	52.9	0.56
18	480	1.167	130	30	55.6	56.3	-1.23
19 ¹⁾	460	1	120	55	57.5	57.9	-0.69
20 ¹⁾	470	1	110	50	56.8	56.9	-1.7
21 ¹⁾	470	1.617	110	55	58.3	58.3	0
22 ¹⁾	470	1.617	120	50	62.5	61.9	0.96
23 ¹⁾	480	1	120	45	60.1	59.8	0.49

1) indicates the test sample; the others are all training samples.

3 Test materials and methods

The material used in the experiment is forged aluminium alloy. The forging process parameters are randomly selected parameters in the input layer. Through integration, 30 sets of required data are obtained. The forging test was carried out on a 3MN hydraulic press, and 24 samples of forged aluminium alloy were obtained.

We used a PG18 metallurgical microscope and EVO18 scanning electron microscope to observe the sample's microstructure [8]. We also used a THT type high-temperature friction and wear tester to test its wear resistance. For carrying out tests at room temperature, we choose the grinding wheel speed of 250 r/min, the wear time of 20 min, the relative sliding speed of 90 mm/min and the load of 100 N. The wear volume is tested with the ContourGT type non-contact three-dimensional optical profiler.

We use the JK-KC impact testing machine for testing. The test temperature is room temperature, and the EVO18 scanning electron microscope observes the morphology of the impact fracture.

4 Training, prediction and verification of neural network optimisation model

4.1 Model training

The training sample data of this model is 22 sets of parameters freely selected from the above 30 sets of

data. In this model training, we use the trail function as the function to be trained. The training rate is 0.02, the expected error is 1×10^{-5} and the momentum factor is 0.8. Figure 2 shows the performance curve of this model training. It can be seen from Figure 2 that after 7962 pieces of training, the training performance curve of this model generally shows a smoother trend, with more minor fluctuations. This shows that the model has better stable performance [9]. Therefore, the neural network model can better map the input parameters (annealing temperature, annealing time, forged aluminium alloy grades, solution temperature, solution time, ageing temperature and ageing time) and output parameters (impact and wear resistance). The relationship between the people.

Fig. 2 Training performance curve of the model.

4.2 Model prediction and verification

To optimise the forging process of automotive aluminium alloys, in addition to model learning and training, it is also necessary to verify its predictive ability and accuracy. Therefore, we will verify that the eight groups of parameter data that have not been trained and learned are marked as 23–30. Figure 3 is the result of the verification [10]. It can be seen from Figure 3 that the relative error range of the prediction of wear resistance (wear volume) output by the model is 2.8–4.3%, and the average relative error of the prediction is 3.4%. The predicted relative error of the impact performance (impact absorption energy) output by the model is 2.8–4.1%. The average relative error of the forecast is only 3.3%. This data series shows that this neural model is highly predictive and has very high prediction accuracy. It can objectively express the relationship between input parameters (annealing temperature, annealing time, forged aluminium alloy grade, solution temperature, solution time, ageing temperature and ageing time) and output parameters (impact performance and wear resistance). Therefore, it can improve and optimise the forging process.

5 Production line application of neural network optimisation model

After completing the prediction and verification, we applied the model to the actual forging aluminium alloy process. We applied it to the automotive aluminium alloy production line of a particular company [11]. Table 2 shows the process parameters of 2618 aluminium alloy for automobiles.

After comparing the production line's traditional process parameters, we can significantly use the model process parameters to reduce the wear volume. It has been reduced from the original $59 \times 10^{-3} \text{ mm}^3$ to $37 \times 10^{-3} \text{ mm}^3$. This reduces it by 22% and improves its wear resistance. Figure 4 shows the surface morphology after wear and according to the traditional process parameters of the production line and the parameters optimised

Fig. 3 Predictive verification results of the model.

Table 2 Process parameters of 2618 aluminium alloy for automobiles

Process parameters	Production line tradition	Neural network model optimisation
Annealing temperature/°C	360	330
Annealing time/h	7	5.5
Solution temperature/°C	530	510
Solution time/h	4.5	6
Aging temperature/°C	180	160
Aging time/h	17	14

by the neural network. From Figure 4(a), it can be seen that the aluminium alloy for automobiles treated with the traditional process parameters of the production line has relatively coarse wear marks on the surface after being worn out. At the same time, there are more peeling and peeling phenomena. Therefore, the aluminium alloy undergoes a significant amount of wear [12]. It can be seen from Figure 4(b) that through the process parameter processing optimised by the neural network model, there is no large wear scar on the surface of the forged aluminium alloy after the wear test. The wear scar is relatively small, and there is no significant peeling and shedding. Therefore, we conclude that it has minor wear. This result is the same as the conclusion of the wear volume of forged aluminium alloys for automobiles.

Fig. 4 Wear surface morphology of specimens heat-treated with different processes.

The impact absorption energy of the forged aluminium alloy specimens subjected to heat treatment using

the neural network model to optimise the process parameters is significantly higher than the impact absorption energy of the traditional production line process. The data decreased from 29 J to 52 J, an increase of 79%. This significantly improves the impact performance. It can be seen from Figure 5(a) that the impact fracture of the forged aluminium alloy prepared by the traditional process parameters of the production line has a small number of dissociation steps in addition to dimples and tearing edges [13]. This is manifested as a relatively prominent mixed fracture feature with ductile fracture as the main component and brittle fracture as the supplement. Figure 5(b) shows that the impact fracture of the automotive aluminium alloy prepared by using the neural network model to optimise the process parameters is composed of small dimples and a small amount of tearing edges, and there is no obvious dissociation step. These observations indicate a better impact performance for the aluminium alloy prepared by using the neural network model in comparison with the heat treatment samples of the traditional process of the production line. This is consistent with the test results of the impact absorption energy of the sample.

Fig. 5 SEM photos of the impact fractures of heat-treated samples of different processes.

6 Conclusion

The relative prediction error of the wear resistance performance (wear volume) output by the neural network optimisation model of the $7 \times 35 \times 2$ three-layer topology established in the article is 2.8–4.3%. The average relative error of the forecast is 3.4%. The predicted relative error of the impact performance (impact absorption energy) output by the model is 2.8–4.1%. The average relative error of the forecast is 3.3%. As a result, the wear volume of forged aluminium alloys for automobiles to which we applied the neural network treatment process reduced by 22% compared with the traditional process. The impact absorption energy increased by 79%, and the wear resistance and impact performance have been significantly improved.

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