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Prediction of Mechanical Properties of 6061 aluminum Alloy After Heat Treatment Based on GA-BP Neural Network

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ABSTRACT

To study the influence of the heat treatment process on the mechanical properties of 6061 aluminum alloy, a prediction model of the mechanical properties of 6061 aluminum alloy after heat treatment based on the GA-BP neural network was established. Based on this model, a set of simple and easy-to-operate built-in data prediction systems was designed. The correlation coefficient R of the GA-BP model was 0.98869, 0.98282, 0.93975, and 0.95657, respectively, and the prediction effect was good. Comparing the predicted value with the experimental value in the prediction system, it is concluded that the prediction accuracy reaches 95.6%, which proves that the model and system have certain stability and feasibility. In addition, this study provides an empirical reference for exploring the effects of solution temperature, cooling rate, aging temperature, and aging duration on the properties of aluminum alloys.

KEYWORDS

6061 aluminum alloy; Heat treatment process; GA-BP neural network; Mechanical properties

1. INTRODUCTION

In recent years, scholars have established a prediction model for the mechanical properties of aluminum alloys using artificial neural networks. Natrayan et al. [1] predicted the hardness and tensile strength of AA6061 aluminum alloy by artificial neural network, and the prediction accuracy was as high as 95 %. Zhang et al. [2] established a data set of 6061 aluminum alloy and TiC-reinforced 6061 aluminum alloy. They compared the accuracy of three prediction models: back propagation neural network (BP), particle swarm optimization BP neural network (PSO-BP), and genetic algorithm optimization BP neural network (GA-BP). Results Compared with the BP and PSO-BP models, the GA-BP prediction model had better accuracy. Among them, GA-BP has good prediction accuracy. Wei Meng [3] used the optimized BP neural network to establish a network model for the forging performance of aluminum alloy for automobiles. The results show that the relative average training errors of the tensile strength and wear volume of the model output are 3.89 % and 4.04 %, respectively. The relative average prediction errors are 3.86 % and 3.67 %, respectively. The model has small prediction errors and high prediction accuracy. These studies have shown that artificial neural networks have the advantages of strong computing power and good generalization potential, and are more suitable for predicting the material properties of aluminum alloys [4-6].

At present, many studies on the prediction of mechanical properties of aluminum alloys based on artificial neural networks focus on conventional solid solution aging parameters as input data. However, the prediction of how the cooling rate, a key factor in the quenching stage, affects the properties of aluminum alloys is relatively scarce. Therefore, in this paper, through the combination of an artificial neural network and genetic algorithm, the solid solution temperature, solid solution time, aging temperature, aging time, and cooling rate are taken as the input parameters of the model, and the tensile strength, hardness, and grain size are taken as the output parameters. The strength prediction model (GA-BP model) and prediction system of 6061 aluminum alloy were constructed to guide the actual production and theoretical research of 6061 aluminum alloy.

2. ESTABLISHMENT OF MACHINE LEARNING MODEL

2.1. Data Processing

Through literature research and JMatPro calculation, the data of solid solution temperature, aging temperature, aging time, and mechanical properties of 34 groups of 6061 aluminum alloy were obtained [7- 13]. Some data sets are shown in Table 1. The data set is preprocessed, including noise reduction and bin smoothing, to obtain a high-quality data set. The data set is divided into two independent parts: the training set and the test set. The two parts account for 8:2, of which the training set is 28 groups and the test set is 6 groups. Due to the different dimensions of the input parameters, to avoid the influence of the large numerical input parameters during the training process, the data is normalized by the normalized function, so that the input data changes from 0 to 1. The linear normalization formula used is:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

In Equation (1), x' is the normalized data set, x is the original data set, max (x) and min (x) are the maximum and minimum values of the normalized data set, respectively.

Table 1. Initial data set

NO.	Solution temperature/°C	Solution time/h	Aging temperature/°C	Aging time/h	Cooling rate/°C/s	Tensile strength/MPa	Hardness/hv	Grain size/μm
1	535	2.5	180	0.5	176	265	80	212.4
2	535	2.5	180	1	156	290	90	218.56
3	540	3	170	2	156	289	120	97.66
…	…	…	…	…	…	…	…	…
34	595	1.5	180	6	248	325	98	126.89

2.2. BP Neural Network Model

Backpropagation is generally composed of the input layer, output layer, and hidden layer. The input layer receives the external input data and passes it to the next layer; the hidden layer passes the results to the output layer by performing a series of nonlinear transformations and feature extraction on the input data. The output layer generates the final output according to the results of the hidden layer. In the training process of the BP neural network, according to the error between the current output and the expected output, the weight value in the network is continuously adjusted through the backpropagation algorithm to gradually optimize the performance of the network.

2.3. GA-BP Model

Since the initial weights and thresholds of the BP neural network are often set to 0 by default, these weights and thresholds can be carefully adjusted and optimized by specific algorithms, and a new network model can be successfully constructed. Compared with the unoptimized network, the optimized GA-BP network model usually has higher prediction accuracy. The flow of the algorithm is shown in Figure 1. The initial neural network is a three-layer structure, in which the number of input neurons in the hidden layer is 5, the number of output neurons is 1, and the number of hidden layer neurons is 6 ~ 12. The learning rate is set to 0.01, the error threshold is 10 − 4, the momentum factor is 0.01, and the number of iterations is 1000. The increase in the number of nodes in the network will make the model easy to overfit, but too few nodes will lead to poor generalization ability of the model. After multiple trainings, the number of hidden layer nodes is 10, and the mean square error is 0.0016. On this basis, the genetic algorithm is combined with the BP neural network, and the main parameters of the BP neural network are optimized by GA. The initial population size is 10, the maximum evolution algebra is 200, the crossover rate is 0.8, and the mutation rate is 0.2.

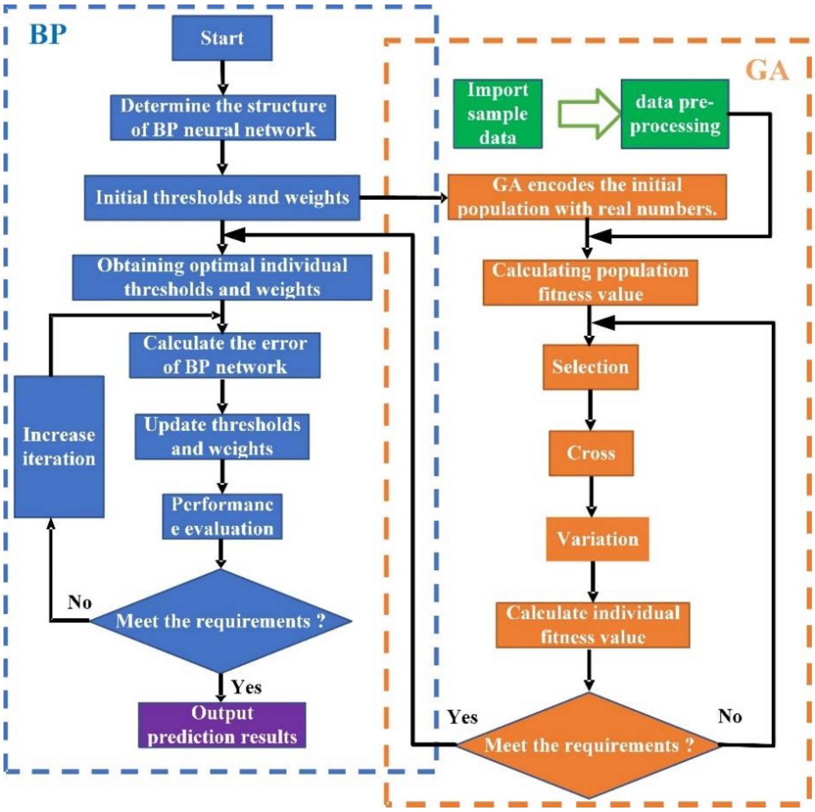

Figure 1. GA-BP algorithm flow chart

2.4. Evaluation Indicators

To evaluate the prediction accuracy of the model on the training set and the test set, the root mean square error (RMSE), mean absolute error (MAE), regression coefficient (R^2), and correlation coefficient (R) were used. These metrics help to gain insight into the performance and accuracy of the model. The magnitude of RMSE and MAE values indicates the degree of closeness between the predicted results of the model and the true values. Regression coefficient (R^2) and correlation coefficient (R) are indicators to measure the goodness of fit of the model, indicating the degree of interpretation of the model to the dependent variable [14]. In summary, the smaller the MAE and the smaller the RMSE and the closer to 0 ; when R^2 and R are larger and closer to 1, the performance of the model is better and the prediction accuracy is higher. The four error calculation models are shown in formula (2) ~ (5) [15].

$$E_{\mathrm{RMSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$E_{\mathrm{MAE}} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{4}$$

$$R = \rho(y_i, \hat{y}_i) = \frac{cov(y_i, \hat{y}_i)}{\sigma_{y_i}\sigma_{\hat{y}_i}} \tag{5}$$

In the formula: E_{RMSE} is root mean square error; E_{MAE} is the average absolute error. R^2 is the regression coefficient; R is Correlation coefficient; n is the number of samples; y_i and $\hat{y}_i$ is the experimental value and the predicted value of the i th sample are respectively the experimental value and the predicted value. $\bar{y}$ is the average value of the experimental value. $cov(y_i, \hat{y}_i)$ is the covariance of $\hat{y}_i$ and y_i; σ_{y_i} and $\sigma_{\hat{y}_i}$ are the standard deviations of y_i and $\hat{y}_i$ respectively.

3. RESULTS AND DISCUSSION

3.1. Prediction Results of the GA-BP Model

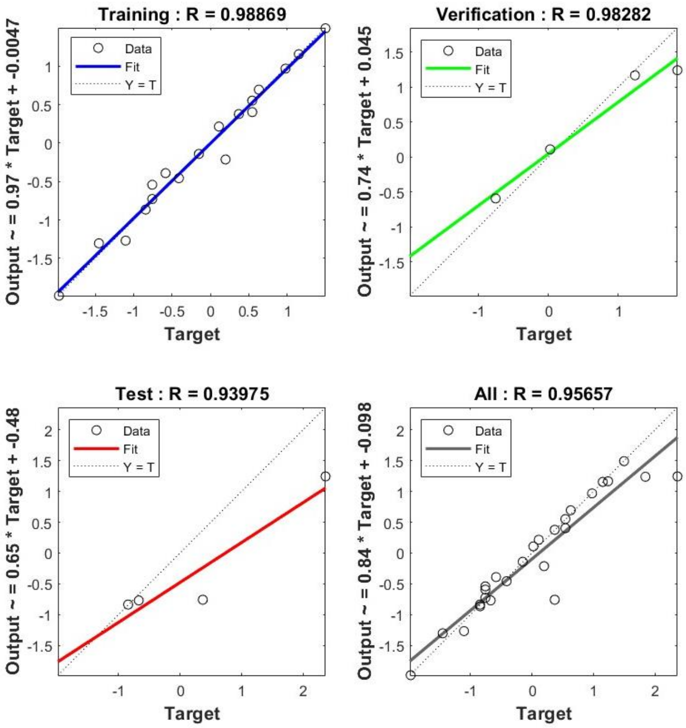

Figure 2. Regression ability analysis

The evaluation results of the GA-BP model are E_{RMSE}=0.01349, E_{MAE}=0.10039, R^2=0.97152, R=0.95657, as shown in Table 2. The regression ability analysis of the GA-BP model is shown in Fig. 2. The correlation coefficients R of the training subset, the validation subset, the test subset, and the training set are 0.98869, 0.98282, 0.93975, and 0.95657, respectively. It can be seen that the r values of the validation set, the training set, and the test set have good performance and can achieve better prediction results, indicating that the established network model can achieve accurate prediction of the mechanical properties of aluminum alloys. The results of comparing the training set and test set of the prediction model with the real value are shown in Figure 3 and Figure 4. The coincidence rate of the two broken lines in Fig. 3 and Fig. 4 is high, indicating that the prediction effect is good. According to the analysis of the index values in Table 2 and Fig. 2, the prediction error of the GA-BP model is small, and it has high accuracy in predicting the mechanical properties of 6061 aluminum alloy.

Table 2. GA-BP model evaluation index results

Evaluating indicator	E_{RMSE}	E_{MAE}	R^2	R
GA-BP model	0.01349	0.10039	0.97152	0.95657

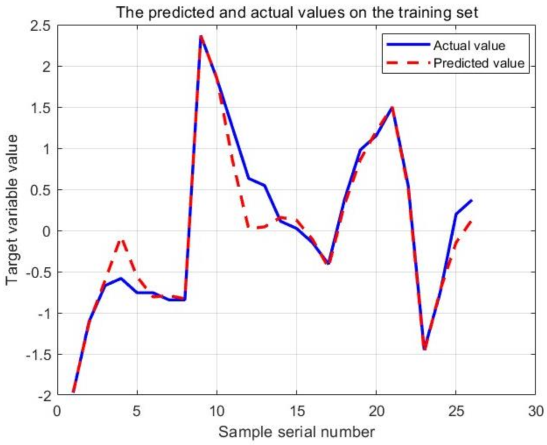

Figure 3. Comparison of prediction results of training set

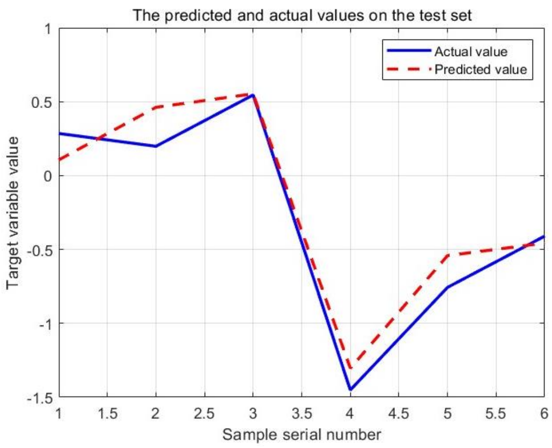

Figure 4. Comparison of testing set prediction results

3.2. GA-BP Model Application and System Application Verification

Using the above-mentioned GA-BP model with significant effect, the system is designed by MATLAB language and Matlab App Designer. The data is built into the code in this system, which saves the steps and time of importing sample data. The system interface is shown in Figure 5, where there are 5 input variables and 3 output variables, and the scope of application of each input variable is shown. After filling in, the user only needs to click the 'Prediction' button below the interface, and the system will predict the algorithm model according to the input variable value. The predicted results will be generated immediately and displayed in the corresponding output predicted value area so that users can quickly understand the mechanical properties of the material. The design of the system is easy for users to view and operate. Once the user completes the prediction task, just click the ‘Quit’ button on the system interface, and the system will close the prediction system. This simple and intuitive interaction design enables users to complete the prediction of mechanical properties without tedious operations, which improves the ease of use and user experience of the system.

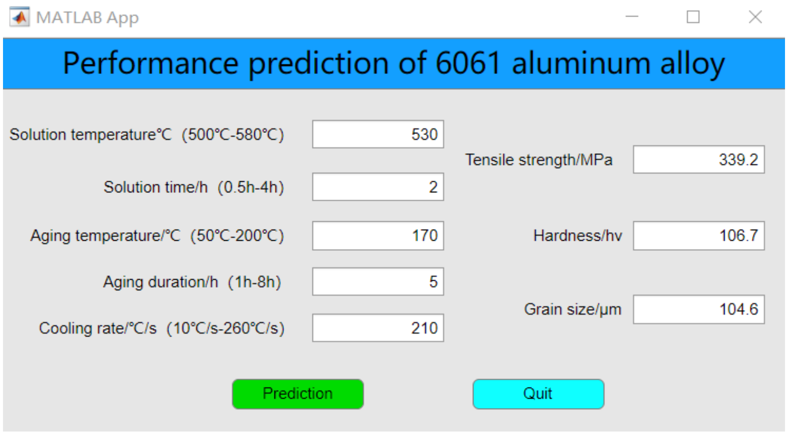

Figure 5. 6061 aluminum alloy performance prediction system

Five heat treatment parameters of 6061 aluminum alloy in the experiment were input into the system interface based on the trained GA-BP model as the prediction set, and the predicted tensile strength is 339 MPa. The predicted values are compared with the experimental values, as shown in Figure 6. By comparing the prediction error of only 4.77 %, it is proved that the prediction model and prediction system have certain stability and feasibility.

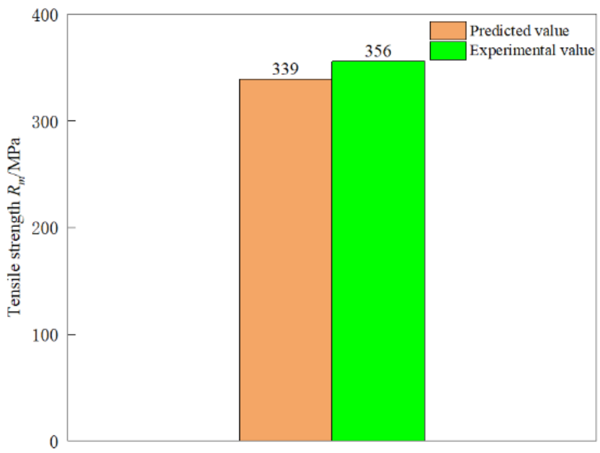

Figure 6. Comparison of predicted and experimental values

4. SUMMARY

(1) A GA-BP model with good generalization ability and high prediction accuracy was established to predict the properties of 6061 aluminum alloy after heat treatment. The correlation coefficients R of the GA-BP model were 0.98869, 0.98282, 0.93975, and 0.95657, respectively. The GA-BP model had a good prediction effect on the tensile strength.

(2) A set of 6061 aluminum alloy heat treatment mechanical properties prediction systems was designed and developed by using the GA-BP model. The predicted tensile strength value was compared with the experimental tensile strength value, and the prediction error was 4.77 %. The effect is good, which proves that the prediction model and prediction system have certain stability and feasibility. This prediction system saves R & D and experimental costs and provides theoretical support for studying the effects of solid solution temperature, solid solution time, aging temperature, aging time, and cooling rate on the properties of 6061 aluminum alloy.

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