

# An improved neural network model for prediction of mechanical properties of magnesium alloys

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**An improved neural network model was developed for prediction of mechanical properties in the design and development of new types of magnesium alloys by refining the types of input variables and using a more reasonable algorithm. The results showed that the improved model apparently decreased the prediction errors, and raised the accuracy of the prediction results. Better preprocessing parameters were found to be [0.15, 0.90] for the tensile strength, [0.1, 0.9] for the yield strength, and [0.15, 0.90] for the elongation. When the above parameters were used, the relativity for prediction of strength was bigger than 0.95. By using improved ANN analysis, more reasonable process parameters and composition could be obtained in some magnesium alloys without addition of strontium.**

magnesium alloys, neural network model, composition, mechanical properties

## 1 Background

Because of their low density, magnesium alloys have attracted an increasing interest in transportation, aeronautical and aerospace industries for the past decade, but their mechanical properties and processing performances still could not meet the needs of some important parts in vehicles and other important application fields<sup>[1–4]</sup>. Many new types of magnesium alloys are being developed in the world in order to further improve the mechanical properties and processing performances of the magnesium alloys<sup>[5–7]</sup>. However, conventional methods for developing new alloys need a lot of experimental work and take long time.

Prediction of mechanical properties of engineering alloys is important for scientists and engineers, which can save not only cost but also time. However, due to the complex interconnections among chemical compositions and materials properties, conventional mathematical models are sometimes very complex to handle by the numerical techniques. In recent years, neural network models have been widely used in different metallurgical operations. Efforts have been made to use this technique

for predicting the hot extrusion processes of AZ31 and AZ61 magnesium alloys and for investigating the influence of Y and Zn additions on the mechanical properties of Mg-Zn-Zr-Y alloys<sup>[8–12]</sup>. However, significant prediction errors in some cases call for further improvement of the neural network model for more accurate predictions. In the present work, an improved neural network model was developed for prediction of mechanical properties in the design and development of new types of magnesium alloys by refining the types of input variables and using a more reasonable algorithm.

## 2 Database and the artificial neural network model (ANN model)

### 2.1 Data collection and database construction

The performance of an ANN model depends upon the dataset used for its training. Therefore, for a reliable

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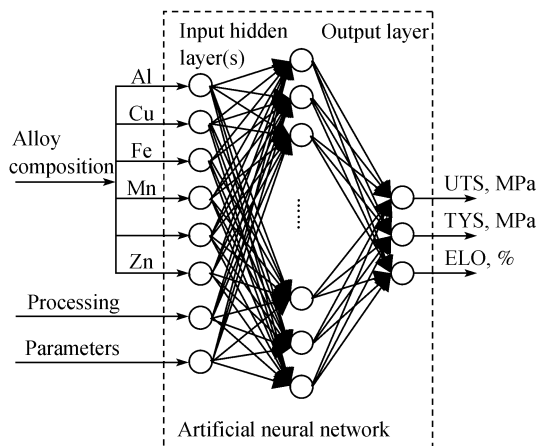
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neural network model a significant amount of data as well as powerful computing resources are necessary. An amount of data on mechanical properties of magnesium alloys at different conditions are currently available in the literature [7–12]. However, these data are rather disorder and confusing for use of engineering practice. Moreover, in Mg-system, the experimental data in the literature are very sparse compared to Al-alloys and steels. In order to make full use of the neural network model, an effective database for magnesium alloys has been set up in the National Engineering Research Center for Magnesium Alloys in China.

## 2.2 ANN model

Following the main aim of the present work, a general scheme of the model as well as a full connected multi-layer feed forward neural network is given in Figure 1. The input parameters of the neural network are processing parameters and alloy compositions, including the commonly used alloying elements in magnesium alloys, namely Ag, Al, Be, Cu, Fe, Mn, Nd, Ni, RE, Si, Th, Y, Zn, Zr, etc. The outputs of the ANN are the mechanical properties including ultimate tensile strength (UTS,  $\sigma_b$ ), yield strength (YS,  $\sigma_{0.2}$ ), elongation (ELO,  $\delta$ ), and so on. The general model consists of separate networks for each mechanical property in the present work. This is because the data available for each individual output property are different. In the present work, the neural network models were designed and trained using the MATLAB 6.1® package [13].



**Figure 1** Schematic diagram of the ANN model for prediction of mechanical properties of magnesium alloys.

## 3 Improvement of the ANN Model

### 3.1 Effects of different preprocesses on the predicted results

Different preprocess parameters have important influences on the predicted results. The effort has been made for improving preprocesses of the ANN model. Part of results for different preprocesses are shown in Tables 1–3 and in Figures 2 and 3. It can be seen that the very good results can be obtained for the prediction of the tensile strength, and acceptable results can be predicted for the elongation. The better preprocessing parameters are [0.15, 0.90] for the tensile strength, [0.1, 0.9] for the yield strength, and [0.15, 0.90] for the elongation.

**Table 1** Effects of different processing parameters on the predicted tensile strength

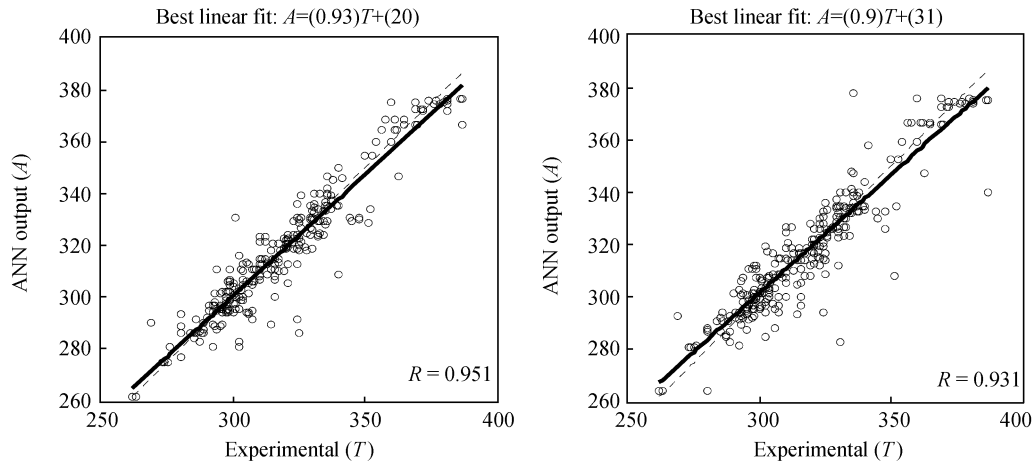
Processing parameters	Relativity	Error (%)	Evaluation
[0, 1]	0.954	2.80	Very good
[0.01, 0.99]	0.951	2.85	Very good
[0.10, 0.90]	0.942	3.09	Good
<b>[0.15, 0.90]</b>	<b>0.950</b>	<b>2.76</b>	<b>Very good</b>

**Table 2** Effects of different processing parameters on the predicted yield strength

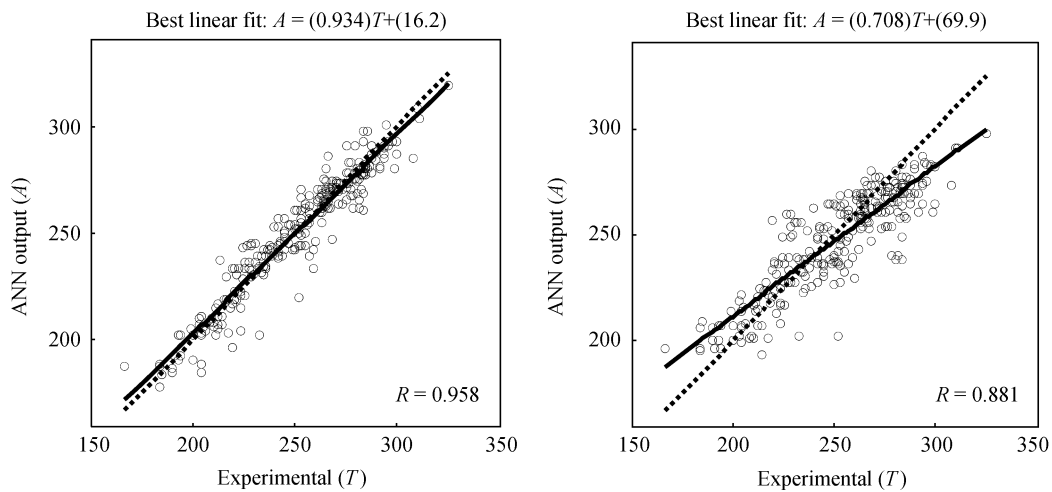
Processing parameters	Relativity	Error (%)	Evaluation
[0, 1]	0.901	6.26	Good
[0.01, 0.99]	0.863	7.02	/
<b>[0.10, 0.90]</b>	<b>0.970</b>	<b>2.07</b>	<b>Very good</b>
[0.15, 0.90]	0.920	5.45	Good

**Table 3** Effects of different processing parameters on the predicted elongation

Processing parameters	Relativity	Error (%)	Evaluation
[0, 1]	0.770	22.0	Bad
[0.01, 0.99]	0.814	22.0	Bad
<b>[0.15, 0.90]</b>	<b>0.901</b>	<b>14.33</b>	<b>Good</b>
[0.10, 0.90]	0.795	22.0	Bad



**Figure 2** Predicted ultimate tensile strengths (MPa) for magnesium alloys by the ANN model with different processing parameter values vs. experimental data.



**Figure 3** Predicted yield strengths (MPa) for magnesium alloys by the ANN model with different processing parameter values vs. experimental data.

### 3.2 Effects of different hidden layer structures on the predicted results

The structure of hidden layer structure also has important influence on the predicted results. The effects of hidden layers and neurons on the predicted tensile strength, yield strength and elongation were calculated, and it was found that the number of neurons had a more obvious influence on the predicted values. Parts of research results are shown in Table 4 and Figure 4. It can be seen that the best predicted results for the tensile strength can be obtained when single hidden layer and the neurons of 19 are used.

## 4 Predictions of the mechanical properties of magnesium alloys

The improved ANN model was used to predict the me-

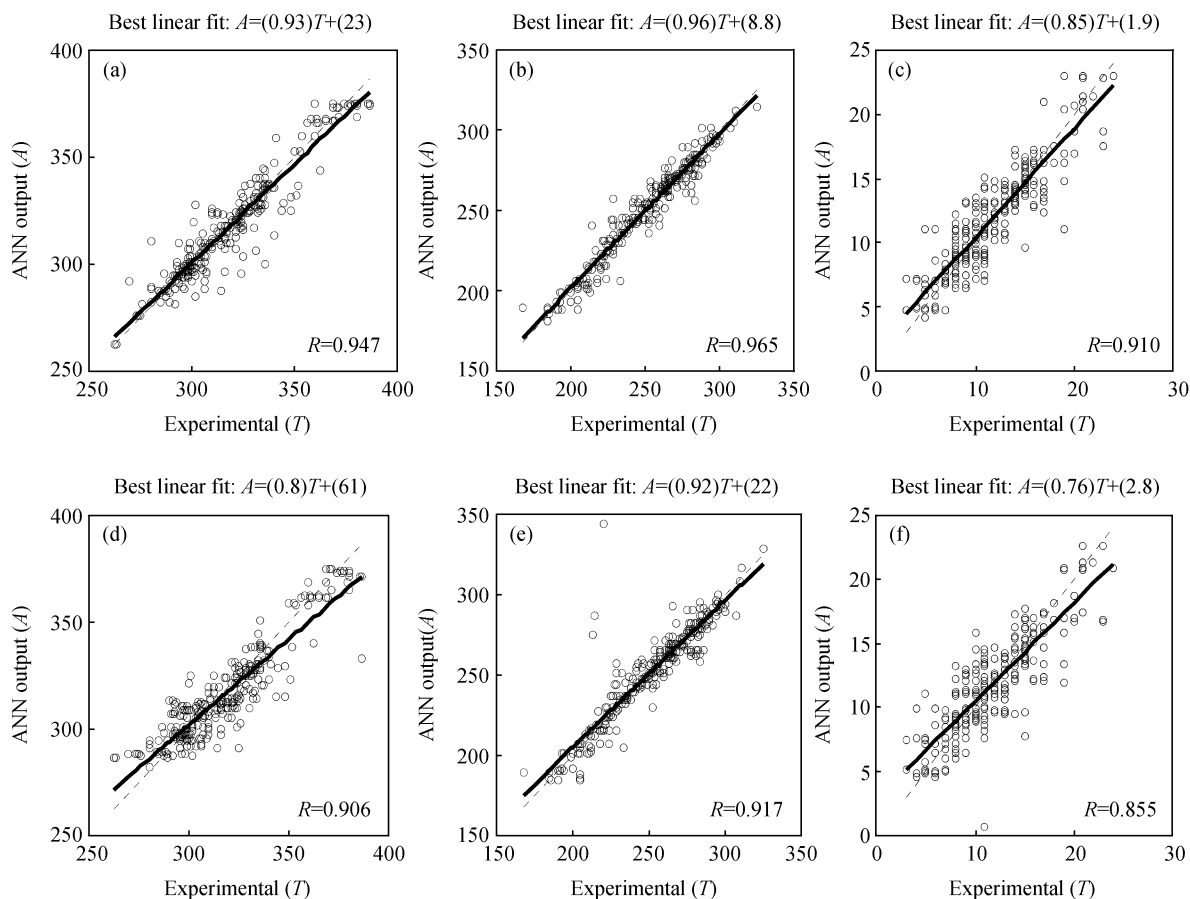
chanical properties of Mg-Zn-Zr alloys, Mg-Zn-Zr-Y alloys, Mg-Al-Zn alloys, Mg-Zn-Y alloys, and Mg-Mn-Ce alloys without addition of strontium by using different processing parameters. Figures 5 and 6 are some research results by the ANN model as well as experimental work. Figure 7 is the predicted elongation values for Mg-Zn-0.6Zr-Y alloys. It can be seen from Figures 5 and 6 that the predicted mechanical properties are consistent with the experimental data, which reveals that the improved ANN model can be used to develop new types of magnesium alloys and to optimize process parameters of magnesium alloys.

## 5 Conclusions

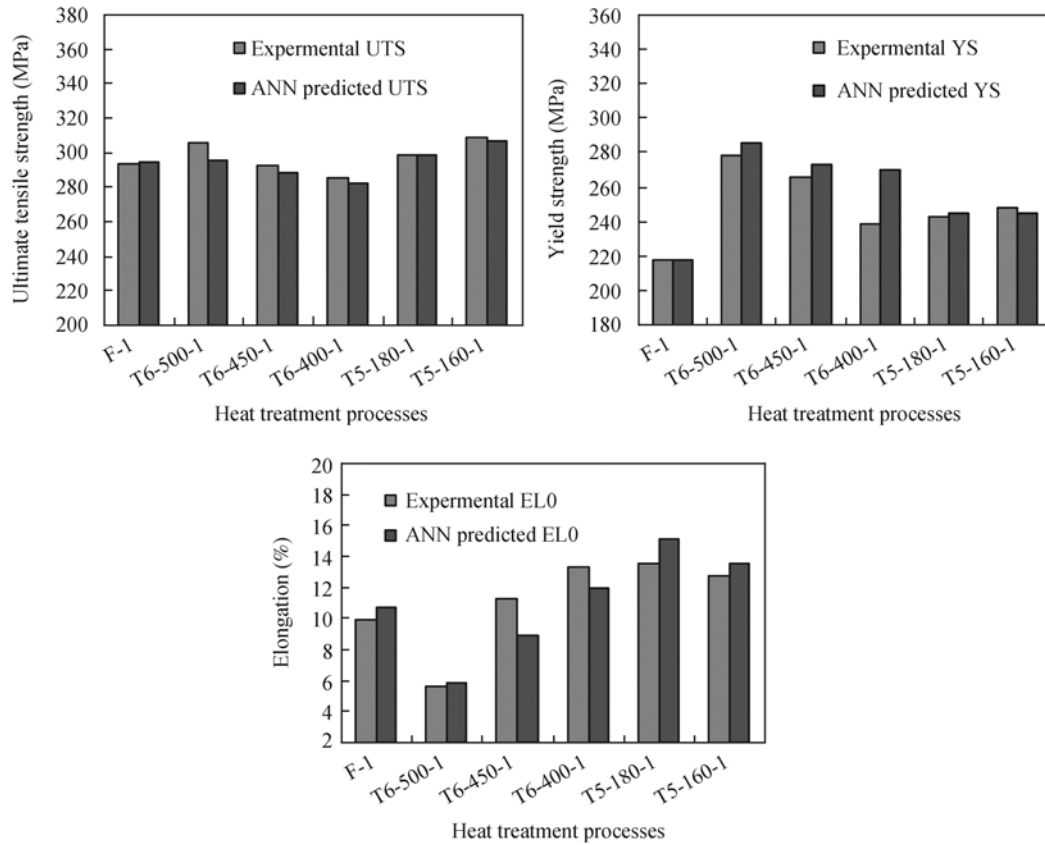
1) The artificial neural network model (ANN model) for predicting mechanical properties of magnesium alloys

**Table 4** Effect of neurons in the hidden layer structure on the predicted results

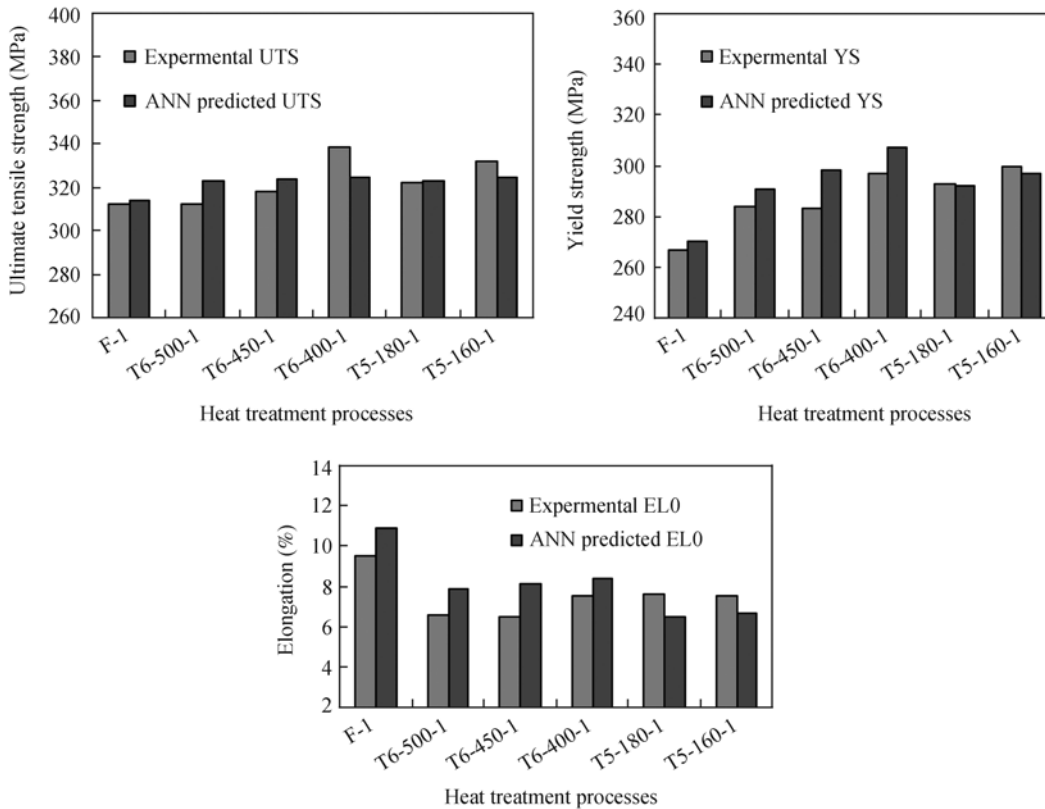
Number of neurons	Relativity	Error (%)	Evaluation
	UTS/YS/ELO	UTS/YS/ELO	
3	0.881/0.894/0.669	2.74/3.99/25.3	Good for ELO
4	0.873/0.921/0.870	2.65/3.30/16.0	
5	0.893/0.941/0.894	2.39/3.05/15.2	
6	0.889/0.930/0.911	2.73/2.95/14.6	
7	0.920/0.944/0.883	2.24/2.63/14.9	
8	0.874/0.940/0.895	2.47/2.77/15.3	Very good for YS
9	0.931/0.919/0.829	2.04/3.46/16.7	
10	0.920/0.967/0.858	2.22/2.10/16.1	
11	0.910/0.923/0.850	1.94/3.19/18.1	
12	0.888/0.938/0.847	2.57/2.53/15.9	
13	0.896/0.936/0.863	2.49/2.56/16.6	Very good for UTS
14	0.942/0.875/0.875	1.87/3.96/15.3	
15	0.911/0.920/0.857	1.83/3.38/16.0	
16	0.925/0.920/0.780	2.21/3.35/20.0	
17	0.942/0.955/0.784	1.61/2.68/18.8	
18	0.901/0.940/0.881	1.93/2.90/13.3	
19	0.950/0.943/0.881	1.80/2.80/15.3	
20	0.932/0.944/0.855	2.26/2.21/16.1	



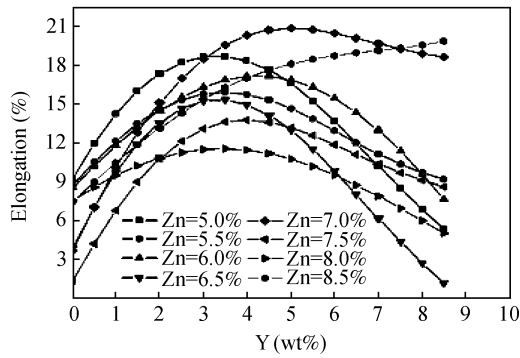
**Figure 4** Predicted mechanical properties for magnesium alloys ANN model with different hidden layer structures vs. experimental data. (a) and (d) Tensile strength (MPa); (b) and (e) yield strength (MPa); (c) and (f) elongation (%).



**Figure 5** The predicted and experimental values of the mechanical properties of Mg-6Zn-1.2Y alloys for different conditions.



**Figure 6** The predicted and experimental values of the mechanical properties of Mg-6Zn-0.5Zr alloys for different conditions.



**Figure 7** The predicted elongation values for Mg-Zn-0.6Zr-Y alloys with different contents of Zn and Y.

was improved by refining preprocessing variables and using a more reasonable structure of hidden layers.

2) The results show that the improved model could apparently decrease the prediction errors, and raise the accuracy of the prediction results.

3) The better preprocessing parameters were [0.15, 0.90] for the tensile strength, [0.1, 0.9] for the yield strength, and [0.15, 0.90] for the elongation. When the above parameters were used, the relativity for prediction of strength was bigger than 0.95.

4) The improved ANN model was used to predict the mechanical properties of Mg-Zn-Zr alloys, Mg-Zn-Zr-Y alloys, Mg-Al-Zn alloys, Mg-Zn-Y alloys, and Mg-Mn-Ce alloys without addition of strontium. The predicted results were found to be in good agreement with the experimental data.

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