Compressive Creep Prediction of Corundum-Mullite Refractories Based on BP Neural Network

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Abstract: Compressive creep of corundum-mullite refractories is an important performance to measure whether they can be used stably for a long time at high temperature. Therefore, a compressive creep prediction method of corundum-mullite refractory based on BP neural network is proposed. The inputs of the BP neural network are the content of Al2O3, SiO2, Fe2O3 and the time of high temperature whereas creep rate is the output. The results show that the predicted results can correspond well with the experimental results. The developed BP neural network model can efficiently and accurately predict the creep rate of corundum-mullite refractories.

1. Introduction
Corundum-mullite has been widely employed as a high quality refractory material because of its high mechanical strength, excellent corrosion resistance, high heat and creep resistance at high temperature, and so on [1-3]. The corundum-mullite refractory bricks have been widely applied in kiln furniture at high temperature [4-6]. In industrial applications, corundum-mullite refractories may undergo frequent thermal cycles under mechanical loads, and compressive loads at high temperatures may lead to creep of materials, thus changing their mechanical properties and performance. The creep deformation of the material will affect the lining design of the furnace [7], then affecting the service life of the furnace.

Corundum-mullite refractories will undergo frequent thermal cycles in the process of use. Long-term use under high temperature and load conditions will lead to creep deformation of materials, which will affect the mechanical properties and service life of materials. Compression creep test method for corundum mullite products follows the standard GB/T 5073-2005. It records the deformation of specimens of specified size with time under constant pressure and at specified test temperature. The creep curves and creep parameters obtained from the tests can be used to obtain the effects of time and chemical composition on the creep behavior of materials under high temperature and load conditions during service. The testing time is mostly 50 hours. Long time high temperature testing will cause aging and deformation of equipment components. At the same time, due to the different proportion of alumina and silica in corundum-mullite refractories, the creep behavior of corundum-mullite refractories is different. During long time high temperature testing, the creep of corundum-mullite may be too large. The excessive glass phase leads to the collapse of the testing material and damages the testing equipment at high temperature.

BP neural network has been widely used in prediction complex problems [8-10]. The relationship between experimental parameters and outputs has been built up. The most widely used of BP neural network is to modify weights between nodes in an iteration through error back propagation so as to
reduce in the next iteration the error between output of neural network and the expected output until error goal is met or iteration number is reached. It build up the relationship between the experimental data and the output targets. It can be used to continuously predict experimental data and obtain the predicted data in the whole experimental range. With the ability of processing nonlinear and complex system problems, BP neural networks have been widely used in regression, prediction and pattern recognition at present[11]. They build up the relationship between experiment parameters and output targets and avoid the time-consuming and cost-demanding task[12]. The most widely used BP neural networks type is a three layer neural network. It can be used to predict continuous experimental results and obtain the optimal value in all the results of the whole experimental range [13-14]. In the paper, BP neural network is a useful method to handle the complexity of influencing factors on creep rate.

Accurate creep prediction plays an important role in the protection of testing equipment. At present, there are few studies on the creep prediction of corundum-mullite refractory. In this paper, the BP artificial neural network is used to establish a model to study the effect of chemical composition and time on the creep of corundum-mullite. Thus, the accurate prediction of corundum-mullite refractories can be realized, and the method also shows guidance for creep detection for other refractories.

2. Experimental

The material studied was a commercially available corundum-mullite refractory brick. Chemical compositions of the materials were carried out by an X-ray fluorescence equipment (ZSX Primus II, Rigaku, Japan) according to the standard GB/T 21114-2007. Creep tests were carried out with refractory tester (RUL 421E, Netzsch, Germany) according to the standard GB/T 5073-2005. The schematic diagram of refractory tester is shown in Figure 1.

Cylindrical specimens with inner diameter of 12–13 mm, outer diameter and height of 50.0 mm were prepared for compression creep test. Platinum gaskets were placed at the top and bottom of corundum-mullite sample to prevent chemical reaction between the material and the top rod of equipment.

Figure 1. Schematic diagram of refractory tester.

In this paper, corundum-mullite specimens with different chemical compositions were loaded with 0.2 MPa to measure the creep of the specimens at 1500°C for 50 hours. The heating rate of the cylindrical specimens were at a constant rate of 5°C /min below 1000°C, and 3°C /min from 1000°C up to 1500°C. Creep properties of all corundum-mullite specimens were measured in air atmosphere.

3. BP neural networks

In this study, a three layer BP neural network model has been proposed for predicting the influence factors of the creep of corundum-mullite refractories. In the development of a multi-layer BP neural
network model, several decisions regarding number of neurons in the input layer, number of hidden layers, number of neurons in the hidden layers, and number of neurons in the output layer and optimum architectures have to be decided[15-16]. The chemical composition and creep time are highly influenced factors of creep rate.

The data of measured chemical composition and creep time are used as input data of BP neural network. The function relationship between input and output is established, and the BP neural network model is established. The networks with four inputs, one output and a hidden layer of 9 nodes are used in this work. The alumina content, silica content, ferric oxide content and creep time are used as input to the network, and the values of creep rate are used as output to the network under the corresponding conditions. The diagram is indicated in Figure 2.

![Figure 2. A three layer BP neural network model for predicting the creep rate of corundum-mullite refractories.](image)

Firstly, the experimental data are divided into two sets. One is the training set (6 data sets, sample 1–6 in Table 1), which is used for training until the network has learned the relationship between the inputs and outputs. The training set is used to establish the BP neural network model. The other is the testing set (1 data set, sample 7 in Table 1), which verifies the generalization ability of the BP neural network as an independent data set. The testing set is to test the accuracy of the BP neural network model. After training and testing, the prediction of a new set of data can be accomplished by the trained and tested networks.

4. Results and discussion

4.1. Chemical composition and the creep rate of corundum-mullite refractories

The chemical composition of the corundum-mullite refractories is shown in Table 1. Under the pressure of 0.2 MPa, the specimens shrink during compressive creep testing. The creep rate of corundum-mullite refractories with time is shown in Table 2.

| Table 1. The chemical composition of the corundum-mullite refractories. |
|-------------------------------------------------------------|
| Composition       | 1    | 2    | 3    | 4    | 5    | 6    | 7    |
| Al₂O₃            | 94.94| 83.99| 84.61| 82.75| 88.91| 89.28| 87.44|
| SiO₂             | 4.12 | 15.15| 14.65| 16.36| 10.25| 9.24 | 11.63|
| Fe₂O₃            | 0.11 | 0.14 | 0.093| 0.11 | 0.11 | 0.099| 0.11 |
| Other components | 0.83 | 0.72 | 0.647| 0.78 | 0.73 | 1.381| 0.82 |
Table 2. The creep rate of corundum-mullite refractories.

| Creep time (h) | 1    | 2    | 3    | 4    | 5    | 6    | 7    |
|---------------|------|------|------|------|------|------|------|
| 5             | 0.407| 0.072| 0.063| 0.017| 0.315| 0.154| 0.051|
| 10            | 0.639| 0.117| 0.081| 0.020| 0.464| 0.179| 0.133|
| 15            | 0.829| 0.150| 0.095| 0.021| 0.559| 0.209| 0.203|
| 20            | 0.999| 0.177| 0.098| 0.022| 0.624| 0.247| 0.262|
| 25            | 1.150| 0.195| 0.099| 0.023| 0.681| 0.289| 0.311|
| 30            | 1.293| 0.212| 0.100| 0.024| 0.733| 0.335| 0.354|
| 35            | 1.422| 0.234| 0.111| 0.025| 0.779| 0.391| 0.393|
| 40            | 1.545| 0.250| 0.123| 0.026| 0.823| 0.428| 0.432|
| 45            | 1.658| 0.265| 0.129| 0.034| 0.859| 0.459| 0.465|
| 50            | 1.752| 0.277| 0.133| 0.036| 0.896| 0.478| 0.498|

At constant pressure of 0.2 MPa, the creep rate increases with test time. It shows that the creep rate increases with time, and the range of creep rate is different for each sample, indicating that the influence of chemical composition on creep rate is different.

Corundum-mullite specimens with high silica content have little creep. Corundum-mullite specimens with high alumina content have high creep. It shows that different chemical compositions of alumina, silica and ferric oxide affect the creep properties of corundum-mullite refractories.

4.2. Prediction of creep rate by BP neural networks

In order to study the influence of these various factors on creep properties, BP neural networks model can be used to predict. First, the BP neural networks need to training. Data of the first 6 sets in Table 1 and Table 2 need to be normalized and then trained.

The BP neural networks were composed of four neurons in the input layer and one neuron in the output layer. In the three layer BP neural networks, the relationship between the number of neurons in the hidden layer $q$ and the number of neurons in the input layer $M$ is generally similar to the following: $q=2M+1$. In the network, the hidden layer was set to nine neurons.

![Best Training Performance is 6.49e-05 at epoch 215](image)

**Figure 3.** Training mean squared error at epoch 215.

Tangent sigmoid transfer function (tansig) was used as activation function for the hidden layer meanwhile S-logarithmic function (logsig) for the output layer. The training results are shown in Figure 3. After 215 training cycles, the mean squared error is less than the value of $10^{-10}$, training
The process stopped at epoch 215 with the best validation performance. Thus, the BP neural networks model can well learn the relationship between input and output of the training data of the corundum-mullite refractory specimens.

The comparison of developed model prediction creep rate values of experimental data of training was shown in Figure 4. The solid line represented the best fit linear regression line between outputs and targets. The relationship between the output and targets was indicated by the correlation coefficient (R) value. There is an exact linear relationship between outputs and targets, if R equal one. As can be seen from the Figure 4, the training data signified an excellent fit. Its correlation coefficient is 0.9995. It shows that the BP neural network can be used to predict creep rate of corundum-mullite refractory specimens.

![Regression plots of BP neural networks predicted model for creep rate.](image)

**Table 3.** Comparison between experimental creep rate and predicted creep rate.

| Time/h | Experimental creep rate/% | Predicted creep rate/% | Absolute value of error/% |
|--------|---------------------------|------------------------|--------------------------|
| 5      | 0.051                     | 0.053                  | 4.71                     |
| 10     | 0.133                     | 0.129                  | 3.23                     |
| 15     | 0.203                     | 0.205                  | 0.97                     |
| 20     | 0.262                     | 0.263                  | 0.28                     |
| 25     | 0.311                     | 0.311                  | 0.06                     |
| 30     | 0.354                     | 0.357                  | 0.76                     |
| 35     | 0.393                     | 0.399                  | 1.45                     |
| 40     | 0.432                     | 0.437                  | 1.12                     |
| 45     | 0.465                     | 0.471                  | 1.36                     |
| 50     | 0.498                     | 0.504                  | 1.21                     |

**4.3. Training of creep rate by BP neural networks**

In order to confirm the accuracy of the BP neural networks model, the seventh data of the Table 1 and Table 2 which were not included in the training data sets were tested.
The comparison of creep rate predicted by BP neural network with actual creep rate is shown in Table 3. It can be seen that the predicted creep rate of the neural network is close to the actual creep rate. The errors of creep rate are found to be in the range of 0.06% ~ 4.71%. The creep rate error is small, which shows that BP neural network model can predict the creep performance of corundum-mullite refractories well.

4.4. The experimental data verified by BP neural networks

After the training of creep rate is completed, the established model by BP neural networks is used to calculate the experimental data. The contents of Al$_2$O$_3$, SiO$_2$, Fe$_2$O$_3$ in the experimental data are 89.23%, 9.87% and 0.094%, respectively. The creep rate is shown in Table 4.

| Time/h | 5   | 10  | 15  | 20  | 25  | 30  | 35  | 40  | 45  | 50  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| creep rate/| 0.327 | 0.450 | 0.526 | 0.578 | 0.627 | 0.669 | 0.707 | 0.742 | 0.772 | 0.794 |

The creep data obtained by the model and the experimental data are shown in Figure 5. It is seen that the predicted data agree with the experimental data. This signifies that the BP neural network can be effectively used to predict creep rate distribution of any input variable within in the training range.

5. Conclusion

In this study, an important method for studying the creep rate of the corundum-mullite refractories is provided. A three layer BP neural network model is developed for the prediction of corundum-mullite refractories. The results from predicted creep rate data match well with the experimental ones, and the error is less than 5%. The results showed that the BP neural network model approach give quite encouraging predictions for the performances of corundum-mullite refractories, which indicate that BP neural network model is an accurate tool for performances analysis of refractories. It can be concluded that the method in this paper can be acted as a reference for further research on the creep rate of other refractories. At the same time, the BP neural network model can help us prevent equipment damage caused by excessive creep.
References

[1] Medvedovski E 2006 Ceram. Int. 32 369-375.
[2] Schneider H, Schreuer J, Hildmann B 2008 J. Eur. Ceram. Soc. 28 329-344.
[3] Zhang F C, Luo H H, Roberts S G 2007 J. Mater. Sci. 42 6798-6802.
[4] Olivas-Ogaz M A, Antti M L, Ion J C, Lindblom B 2013 Ceram. Int. 39 791-800.
[5] Tripathi H S, Das S K, Mukherjee B, Ghosh A, Banerjee G 2001 Ceram. Int. 27 833-837.
[6] Kong X, Tian Y, Chai Y, Zhao P, Wang K, Li Z 2015 Ceram. Int. 41 4294-4300.
[7] Li K M, Pan C C, Xie J L, Li C Y, Li L P, Xue F, Lin G W, Zhang L L 2016 Key Eng. Mater. 680 352-357.
[8] Zhang H, Du S, Cao Y, Lu L, Zhang S 2014 Ceram. Inter. 40 2287-2293.
[9] Lucon P A, Donovan R P 2007 Compos. Part B-Eng. 38 817 – 823.
[10] Wang Y R, Gibson G E 2010 Automat. in Constr. 19 341-346.
[11] Inal F 2006 Fuel Process. Technol. 87 1031 – 1036.
[12] Sahoo B K, De S, Meikap B C 2017 International Journal of Mining Science & Technology 27 379-386.
[13] Altiparmak F, Gen M, Lin L, Paksoy T. 2006 Comput. Indus. Eng. 51 196–215.
[14] Zhou C C, Yin G F, Hu X B. 2009 Mater. Des. 30 1209–1215.
[15] Sarkar A, Sinha S K, Chakravartty J K, Sinha R K 2014 Ann. Nucl. Energy 69 246-251.
[16] Lucon P A, Donovan R P 2007 Compos. Part B-Eng. 38 817-823.