# Predicting model on ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foam filter based on BP neural network

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**Abstract:** In present study, BP neural network model was proposed for the prediction of ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foam filter prepared by centrifugal slip casting. The inputs of the BP neural network model were the applied load on the epispastic polystyrene template ($F$), centrifugal acceleration ($v$) and sintering temperature ($T$), while the only output was the ultimate compressive strength ($\sigma$). According to the registered BP model, the effects of $F$, $v$, $T$ on σ were analyzed. The predicted results agree with the actual data within reasonable experimental error, indicating that the BP model is practically a very useful tool in property prediction and process parameter design of the $Al_2O_3$-$ZrO_2$ ceramic foam filter prepared by centrifugal slip casting.

**Key words:** $Al_2O_3$-$ZrO_2$ ceramic foam; centrifugal slip casting; BP neural network; process parameters; ultimate compressive strength

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Porous ceramics are widely used as filters for molten metal and hot gases, membranes for chemical processes, thermal insulation, catalyst supports and chemical sensors, due to their unique three-dimensional skeleton structure, high porosity, low density, high thermal stability and resistance to chemical attack [1-3]. Alumina matrix ceramic foams with the special properties of chemical inertness and high-temperature stability are mainly used in filtering molten metal. There are several ways of producing ceramic foams [4]. A common method used to produce ceramic foams, known as 'replication process,' involves the impregnation of a polymer sponge with a thixotropic ceramic slurry [5, 6]. One of the drawbacks of this method is the tendency to leave a hollow strut after pyrolysis. The presence of hollow strut defect is critically influential to the mechanical properties. So a simple and efficient method is urgently needed to improve the density of cell strut and to achieve higher strength.

In the present research, centrifugal slip casting the ceramic slurry into the interstitial spaces of pre-arrayed epispastic polystyrene (EPS) template was used to produce $Al_2O_3$-$ZrO_2$ ceramic foams. The general procedure is as follows: forming a close-packed template with EPS spheres, and filling the interstitial spaces with ceramic slurries by centrifugal slip casting, then removing the mold, drying and sintering at special temperatures to obtain a porous inverse replica. The centrifugal slip casting can avoid holes and cracks resulted from the pyrolysis of organic sponges, so the sintered products have dense cell struts and good mechanical properties. It is known that the ultimate compressive strength of ceramic foam filter is very important, and can affect the service life of the products. In centrifugal slip casting process, the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foams is closely associated with the process parameters such as the load applied on the EPS template ($F$), centrifugal acceleration ($v$) and sintering temperature ($T$). Therefore, by controlling process parameters, the ultimate compressive strength ($\sigma$) can be adjusted to match the practical application requirement. In previous research, the properties of materials are usually investigated by the experimental methods in which one parameter is changed and the others are fixed, and then the relatively better result is selected. But, not only does this conventional method ignore the mutual effects of different process parameters but also waste time and energy. Consequently, a new method is required to establish the relationship between the process parameters and product properties.

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Artificial neural networks have been widely used in many science and engineering fields due to their remarkable information processing characteristics, such as non-linearity, simplicity, robustness, fault and failure tolerance, self learning and ability to extract useful information from samples [7-9]. Otherwise, it is not necessary to specify mathematical relationships between the input and output variables [10]. In addition, the back propagation (BP) neural network is one of the most commonly used artificial neural networks.

To the best of our knowledge, there has been no report for the prediction of the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foam filter prepared by centrifugal slip casting. In this paper, a BP neural network model was built and used to observe the relationship between process parameters and ultimate compressive properties of $Al_2O_3$-$ZrO_2$ ceramic foam filter based on the experimental data. The accuracy of the model was confirmed by comparing the BP model prediction and the experimental results. According to the registered BP model, the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foam filter with different parameters can be predicted, which contributes to the choice of better process parameters to satisfy the actual application requirement.

## 1 Experimental procedure

$Al_2O_3$ powder with 99.99% purity and an average particle size of 0.2 μm and $ZrO_2$ powder (TZ-3Y) with 99.5% purity and a median diameter of 0.15 μm were used as the starting materials. EPS spheres (hollow and with low density and good compressibility) sieved through a 12-mesh screen were used to array the template. The process for fabricating the alumina matrix ceramic foam is as follows. First, EPS spheres were slowly put into the cylindrical mold to definite height. Then, load was applied at the top of the EPS template to adjust its porosity. Finally, the whole mold was heated to 120℃ for 30 min to improve the linking strength between the spheres and to preserve their deformation. Two kinds of powders were mixed in a special proportion ($Al_2O_3$-15vol.%$ZrO_2$), and then dispersed in distilled water with 1wt.% dispersant and pH 10 by ball milling for 24 h. Aqueous suspensions with different solid contents varying from 30vol.% to 50vol.% were prepared. The prepared slurries were poured into the interstitial spaces of the EPS template, followed by a centrifugal process at different accelerations. After centrifugation, the specimens were removed from the mold and dried for 24 h at room temperature. Then, the dried specimens were sintered at 1,550℃ for 2 h in air. Ultimate compressive strength was measured using a universal testing machine (CMT5105) with a loading rate of 0.5 mm·min$^{-1}$ on the specimens in size of 20 mm × 20 mm.

## 2 BP neural network model

### 2.1 Establishment of BP model

The results from the above experiment are used as the samples for BP neural network model as described below. In principle, it has been proven that a BP neural network with one hidden layer is for most applications because it can approach to any complicated decision-making boundary, while the one with many hidden layers makes the network too complicated, causing lower convergence and larger errors. Therefore, a three-layer BP model with one hidden layer is employed in this study. It is easy to determine the number of neurons in the input layer and output layer in the model. In present study, three inputs including the load applied on the EPS template ($F$), centrifugal acceleration ($v$) and sintering temperature ($T$) are denoted as $a_1$, $a_2$ and $a_3$, and the ultimate compressive strength ($\sigma$), the only output is denoted as $c_1$. However, due to no definite rule, it is difficult to choose the appropriate number of neurons in the hidden layer. Using too many neurons impedes generalization and increases training time. But using too few neurons impairs the neural network and prevents the correctly mapping of inputs and outputs. In this paper, the number of neuron in the hidden layer is determined to be seven by empirical formula [8]. So the network structure is 3-7-1 (as shown in Fig. 1).

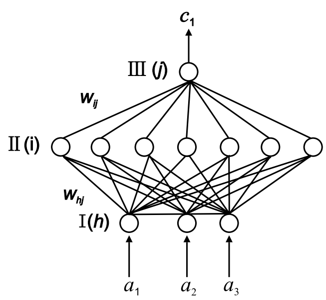


**Fig. 1: 3-7-1 BP neural network structure**

The back propagation (BP) algorithm is as follows:

$$b_i = f\left(\sum_{h=1}^{3} w_{hi} a_h\right) \qquad (i=1, 2, \ldots 7) \qquad (1)$$

$$c_j = f\left(\sum_{i=1}^{7} w_{ij} b_i\right) \qquad (j=1) \qquad (2)$$

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

where, $a_h$ is the neuron in the input layer, $b_i$ is the neuron in the hidden layer, and $c_i$ is the neuron in the output. $w_{hi}$ and $w_{ij}$ are weights between the input layer and the hidden layer, and the hidden layer and the output layer, respectively. $f(x)$ is the activation function. To train a neural network is to adjust the weights so as to model and estimate a complicated non-linear object. The learning error $E_p$ for a sample $p$ is

$$E_p = \frac{1}{2}\sum_{j=1}^{M}(d_{pj} - c_{pj})^2 \qquad (M=1) \qquad (4)$$

where, $d_{pj}$ and $c_{pj}$ are the desired and the calculated output for $j$th output, respectively. $M$ is the number of neurons in output of the network. The average error for the whole system, $E_P$, is obtained by

$$E_P = \frac{1}{2P}\sum_{p=1}^{P}\sum_{j=1}^{M}(d_{pj} - c_{pj})^2 \qquad (M=1) \qquad (5)$$

where, $P$ is the total number of instances. The weights of the network in BP algorithm are expressed as follows [11]:

$$w_{ij}(t+1)=w_{ij}(t)+\eta(t)\delta_j b_i+\alpha\left[w_{ij}(t)-w_{ij}(t-1)\right] \quad (6)$$

$$w_{hi}(t+1)=w_{hi}(t)+\eta(t)\delta_i a_h+\alpha\left[w_{hi}(t)-w_{hi}(t-1)\right] \quad (7)$$

where, $t$ is time, $\alpha$ is the momentum coefficient, $\eta$ is the learning rate, $\delta_j$ and $\delta_i$ are the learning signals as described below:

$$\delta_j=(d_j-c_j)c_j' \quad (8)$$

$$\delta_i=\sum_{j=1}^{2}w_{ij}\delta_j b_i' \quad (9)$$

Where, $d_j$ and $c_j$ are the desired and the calculated output of $j$ neuron, $c_j'$ is the activation function derivative of output layer, $b_j'$ is the activation function derivative of hidden layer. The 48 sets of patterns were obtained by the above experiments. 32 sets of them were used to train the network and the other 16 sets were used to test the network. The maximum, minimum and mean values of training data are shown in Table 1. In order to better train the neural network, the proper initial weights are chosen to avoid the local minimums of the BP network. Neural Network Toolbox 2.0 of Matlab Software Package was used to initiate the weights. When the initial $\eta$ and $\alpha$ are different, the cyclical times to reach the error goal, $E_r$, are also different. In this work, the initial $E_r$, $\eta$ and $\alpha$ are 0.01, 0.95 and 0.1, respectively. According to the running result of Matlab Software, the training goal ($E_r$<0.01) was reached after 273 iterations. Then a convenient training model was obtained and used to evaluate the artificial neural networks processes.

**Table 1: Max, min and mean values of training data**

| No. | $F$ (N) | $v$ (g) | $T$ (℃) | $\sigma$ (MPa) |
|---|---|---|---|---|
| Min. | 7.3 | 2,860 | 1,550 | 4.51 |
| Max. | 19.8 | 1,610 | 1,450 | 0.32 |
| Mean | 17.2 | 2,191 | 1,550 | 2.55 |

## 2.2 Predicted results of BP network

The comparison between experimental data and the predicted results from the BP model are shown in Table 2. The relative error of $\sigma$ is within 3%, and its maximum absolute error is 0.026 MPa which meets the error bars (±0.1 MPa) in the experiment. According to Table 2, the predicted results agree with the measured results within reasonable error. The BP neural network model established in this paper can effectively consider the influential factors of the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foams prepared by centrifugal slip casting, such as applied load on the EPS template, centrifugal acceleration and sintering temperature. Therefore, it is feasible and effective to predict the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foams. If other mechanical properties are chosen as predicted targets, new BP models can be used to study other mechanical behavior of $Al_2O_3$-$ZrO_2$ ceramic foams.

## 2.3 Discussion

Based on the prediction of the above BP model, the effect of process parameters including the load applied on the EPS template ($F$), centrifugal acceleration ($v$), and sintering temperature ($T$) on the ultimate compressive strength ($\sigma$) are shown in Figs. 2–4, respectively. It can be seen from Fig.2 that the ultimate compressive strength decreases with the increase of the EPS template. This is mainly due to the deformable nature of the EPS spheres. These spheres are compressed

**Table 2: Predicted results of gradient descent BP model**

| No. | Process parameters | | | $\sigma$ (MPa) | | |
|---|---|---|---|---|---|---|
| | $F$ (N) | $v$ (g) | $T$ (℃) | EXP | PRE | Error (%) |
| 1 | 7.3 | 1,610 | 1,550 | 3.82 | 3.846 | 0.68 |
| 2 | 7.3 | 2,191 | 1,500 | 1.85 | 1.865 | 0.81 |
| 3 | 7.3 | 2,860 | 1,600 | 4.17 | 4.152 | 0.43 |
| 4 | 12.3 | 1,118 | 1,450 | 0.53 | 0.538 | 1.51 |
| 5 | 12.3 | 2,191 | 1,550 | 3.38 | 3.372 | 0.24 |
| 6 | 12.3 | 2,860 | 1,600 | 3.56 | 3.546 | 0.39 |
| 7 | 17.2 | 1,118 | 1,550 | 1.48 | 1.493 | 0.88 |
| 8 | 17.2 | 1,610 | 1,550 | 1.86 | 1.841 | 1.02 |
| 9 | 17.2 | 2,191 | 1,550 | 2.55 | 2.573 | 0.90 |
| 10 | 17.2 | 2,860 | 1,450 | 0.64 | 0.632 | 1.25 |
| 11 | 17.2 | 2,860 | 1,500 | 1.35 | 1.357 | 0.15 |
| 12 | 17.2 | 2,860 | 1,550 | 2.86 | 2.835 | 0.87 |
| 13 | 17.2 | 2,860 | 1,600 | 2.62 | 2.604 | 0.61 |
| 14 | 19.8 | 1,118 | 1,500 | 0.72 | 0.708 | 1.67 |
| 15 | 19.8 | 1,610 | 1,450 | 0.43 | 0.441 | 2.56 |
| 16 | 19.8 | 2,860 | 1,600 | 1.94 | 1.935 | 0.26 |

Note: EXP=Experimental; PRE=Predicted

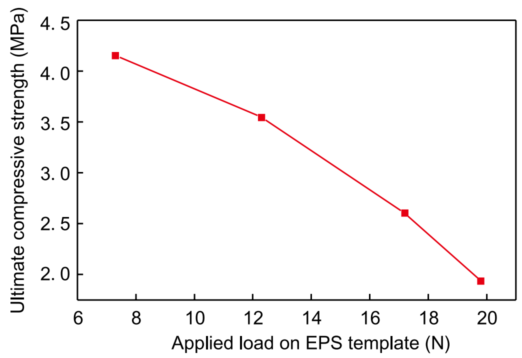


**Fig. 2: Effect of load applied on EPS template (*F*) on ultimate compressive strength ($\sigma$) ($v$ is 2,860 g and *T* is 1,600℃)**

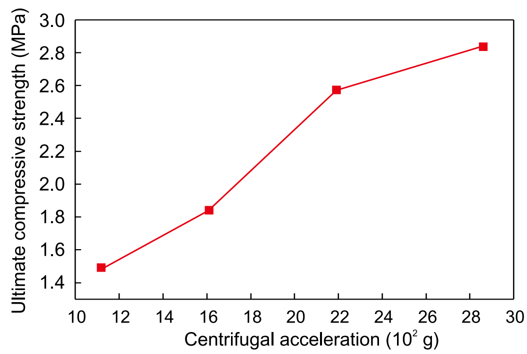


**Fig. 3: Effect of centrifugal acceleration ($v$) on ultimate compressive strength ($\sigma$) (*F* is 17.2 N and *T* is 1,550℃)**

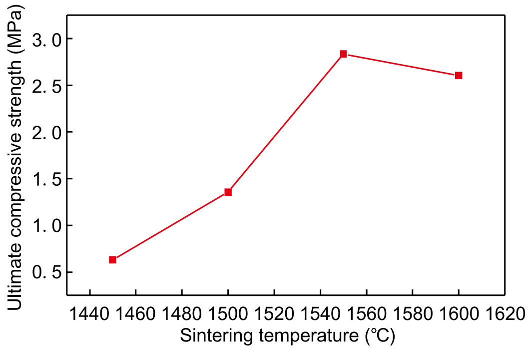


**Fig. 4: Effect of sintering temperature (*T*) on ultimate compressive strength ($\sigma$) (*F* is 17.2 N and $v$ is 2,860 g)**

into denser packing at a higher load, resulting in a higher porosity in the final foam product. Higher porosity induces the reduction of effect area to support the load, and therefore, leading to the reduction of ultimate compressive strength. As can be seen in Fig.3, with the increase of centrifugal acceleration, the ultimate compressive strength increases. The reason is that at a higher centrifugal acceleration, the $Al_2O_3$ and $ZrO_2$ particle packing is denser, and the sintered products have higher density, resulting in the increase of the ultimate compressive strength. With increasing sintering temperature ($T$), the ultimate compressive strength first increases and then decreases (Fig.4), and the ultimate compressive strength value peaks at 1,550℃. This is mainly because that with the increase of sintering temperature, the irregular particles of cell struts in $Al_2O_3$-$ZrO_2$ foam filters grow up and turn into large grains. These large grains are closely bonded together and have more contact area, inducing a decrease in the porosity and an increase in the ultimate compressive strength. When the samples sintered at 1,600℃, fewer grains preferentially grow into very large size compared with other grains, which is caused by overfiring. This overfiring usually causes a little decrease in strength.

According to the aforementioned BP model, the optimal ultimate compressive strength can be predicted to meet practical requirement. So the model is critical for the quality control of the $Al_2O_3$-$ZrO_2$ ceramic foam filter and can be widely used in centrifugal slip casting process.

## 3 Conclusion

The non-linear relationship between process parameters including applied force on the EPS template ($F$), centrifugal acceleration ($v$), sintering temperature ($T$) and ultimate compressive strength ($\sigma$) is built by BP artificial neural network model based on the experimental results of centrifugal slip casting. The results showed that the BP neural network model can very well predict the ultimate compressive strength of $Al_2O_3$-$ZrO_2$ ceramic foam filter. The prediction results show that the ultimate compressive strength decreases with the increase of applied force, and increases with the increase of centrifugal acceleration. With increasing sintering temperature, the ultimate compressive strength first increases and then decreases a little in the given range. Hence, BP neural network model is a very useful tool to optimize process parameters, control the ultimate compressive properties of sintered products and satisfy the practical demand. Compared with regression analysis, BP model is more effective, and can be widely used in centrifugal slip casting study.

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