Prediction Mechanical Strength of Sand Mold Samples Fabricated by Three-Dimensional Printing

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Three-dimensional printing (3DP) was widely applied in sand mold fabrication. One of the major concerns about sand mold is the mechanical strength which determines such defects as sand cut, sand blister, sand explosion, and expansion of the castings. In this study, the linear regression and the BP neural network were applied to predict the bending strength of 3DP samples. Orthogonal experiments were designed to obtain data for training the prediction models. Three-point bending test was used to characterize the actual bending strength. The results showed that the sample weight, resolution X and layer thickness are significant factors while the activator content, recoater speed and sample location are not significant. The maximum error of linear regression is 11.2%, which is very big. A three-layer BP neural network with 6 input nodes, 14 hidden nodes and 1 output node was proposed to predict the bending strength of 3DP samples, and the maximum error is 4.3%, which is lower than that of linear regression. So it is more valuable in practical applications. [doi:10.2320/matertrans.MT-M2020102]

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1. Introduction

Three-dimensional printing (3DP) technology invented by MIT as a rapid prototyping technique to build object is widely used in sand mold process.¹⁾ During 3DP process, a computer aided design model is used as the input to build up a model layer upon layer, and by jetting resin at specific locations between layers, all layers are bonded together to form a solid. 3DP technology can build complex structural sand components which are difficult to build and produce in conventional way without specific tools or models, which can effectively simplify the production process, shorten the production cycle, and lower the economic cost, especially in the developing stage.²⁻⁴⁾ As a new approach for fabricating complex sand productions, more and more researchers devote to 3DP sand mold technique.^{5,6)} In sand foundry, various physical properties will affect the sand mold and the metal castings, and mechanical strength is the mainly concerned one, which determined a set of defects such as sand cut, sand blister, sand explosion, and expansion of the castings.^{7,8)} Commonly, a set of samples are printed and tested in 3DP process, and the results are averaged to evaluate the mechanical strength. However, all these tests have to wait until sand binder cured. It has been recognized that if mechanical strength can be judged immediately without waiting for curing time, the process parameters can be adjusted to meet the production application and thus the efficiency will be improved.⁹⁾

3DP sand molding generally uses resin as binder. The resin and the curing activator form a bonding bridge among the sand particles through the polymerization reaction to provide strength for the sand mold. There are many factors of affecting the mechanical strength of sand samples, such as resolution X, activator content, layer thickness, recoater

speed, sample weight and sample location.^{10,11)} Resolution X means jetting resin every X length of movement, which is related to the resin content. Activator content also has a certain effect on mechanical strength.¹²⁾ Mitra *et al.*¹³⁾ investigated the effect of binder content on the mechanical strength of 3DP sand mold and the results showed that the mechanical strength was deeply dependent on the binder content and the curing process. Both layer thickness and recoater speed are considerable parameters for 3DP sand molds, and many researches had carried out experiments on them. Vaezi *et al.*¹⁴⁾ considered the influence of the layer thickness on the precision and mechanical strength of the powdering during the powdering process. It is believed that under the same binder saturation condition, with the increasing layer thickness the tensile strength would decrease and flexural strength would increase. Markl *et al.*¹⁵⁾ proposed a random algorithm to generate a random powder bed to numerically simulate the melting process of the powder bed. The algorithm was implemented and validated on the number of relative powder layer densities common during particle bed melting. Khandelwal *et al.*¹⁶⁾ investigated the effect of molding parameters on chemically bonded sand mold properties. Their work paved the way for automatic optimization of the molding parameters of chemical sand molds and cores to achieve the desired quality.

Although many investigations had studied the relationship between printing parameters and mechanical strength, there was rare researches of how to predict the mechanical strength of 3DP samples by influencing factors.¹⁷⁾ Good strength prediction can judge if the strength meets the requirements before using the sand mold, and thus 3DP parameters can be adjusted unless the strength is satisfied.

In this study, the influencing factors of resolution X, activator content, layer thickness, recoater speed, sample weight and sample location were considered, and the linear regression and BP neural network model were proposed to

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predict the mechanical strength of 3DP samples. To begin with, the linear correlation between the mechanical strength and influencing factors was investigated by the experimental data regression. And then a new BP network model was introduced, which can accurately predict the mechanical strength without waiting for the sample strength tested. By comparing these two results, the most accurate and reliable prediction model was obtained. The model provided a simple and effective method for predicting mechanical strength and gave a reliable factor for metal casting.

2. Method and Experiments

2.1 Data preparation

Orthogonal test is a highly efficient, fast and economical experimental design method. The purpose of orthogonal

experimental design is to select some representative points from the comprehensive tests based on the orthogonality. In order to obtain fully and distributed data, the orthogonal experiments with 4 factors and 5 levels were designed to obtain the data for training linear regression and BP neural network. Each test will produce 9 samples (labeled as L1, L2, ..., L9) at different location on the powder bed. The experimental scheme was shown in Table 1, and the orthogonal arrays were contained in Table 2.

Three-point bending test was commonly applied to characterize the mechanical strength of sand mold. And it is usually performed on a rectangular sample, which is positioned over two roller pin supports while the load is applied through a third roller pin typically mounted halfway on the pin supports. The bending stress will be calculated by eq. (1).

Table 1 Levels and notations of factors for training models.

Factors	Notation	Level				
		1	2	3	4	5
Activator Content, w/mass%	A	0.16	0.18	0.22	0.24	0.26
Resolution X, t/mm	B	0.06	0.07	0.08	0.09	0.10
Layer Thickness, d/mm	C	0.2	0.24	0.28	0.34	0.4
Recoater Speed, v/mm·s ⁻¹	D	120	140	160	180	200

Table 2 Orthogonal Arrays of L25 for training models.

No.	Factors			
	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	1	5	5	5
6	2	1	2	3
7	2	2	3	4
8	2	3	4	5
9	2	4	5	1
10	2	5	1	2
11	3	1	3	5
12	3	2	4	1
13	3	3	5	2
14	3	4	1	3
15	3	5	2	4
16	4	1	4	2
17	4	2	5	3
18	4	3	1	4
19	4	4	2	5
20	4	5	3	1
21	5	1	5	4
22	5	2	1	5
23	5	3	2	1
24	5	4	3	2
25	5	5	4	3

Table 3 Results of 3DP sample weight for training models.

No.	Sample Weight, <i>m/g</i>								
	L1	L2	L3	L4	L5	L6	L7	L8	L9
1	126.99	127.03	124.99	125.42	125.88	123.17	126.25	126.70	124.26
2	122.06	122.06	118.61	119.56	119.52	115.54	120.13	120.16	116.82
3	112.83	112.26	109.29	112.51	111.70	108.70	113.34	112.67	109.18
4	103.43	106.31	103.26	103.69	106.70	103.31	101.01	104.46	100.61
5	99.50	99.74	98.31	99.73	99.68	98.29	100.99	101.68	99.71
6	112.33	112.00	109.72	112.18	112.35	109.77	114.59	114.27	110.70
7	104.99	105.24	102.68	104.71	104.51	102.35	104.28	104.18	101.46
8	104.78	104.89	101.76	104.14	104.49	101.81	106.27	107.08	103.01
9	121.58	121.55	116.79	119.76	120.01	117.94	121.43	121.62	119.01
10	120.44	120.23	119.87	119.71	119.87	116.69	120.00	119.72	116.40
11	99.24	99.70	98.04	97.60	98.70	96.97	99.00	99.85	97.42
12	120.98	120.13	118.16	119.99	119.38	116.43	120.71	120.10	117.49
13	113.24	113.04	110.94	112.88	112.62	109.93	114.29	114.01	111.04
14	111.04	110.58	107.87	111.59	111.38	107.97	111.93	111.41	108.05
15	102.75	103.11	101.04	102.44	103.14	100.62	104.69	104.99	101.92
16	112.38	111.31	108.83	112.60	112.28	108.60	112.28	111.76	108.44
17	111.95	112.17	109.17	111.30	112.17	108.45	112.50	112.74	108.95
18	105.46	105.81	103.54	104.45	104.99	102.27	105.27	105.85	102.68
19	100.78	100.64	98.81	99.99	100.65	98.62	100.42	100.85	98.16
20	123.44	123.45	121.41	122.99	122.56	119.71	122.80	123.08	120.64
21	97.96	98.44	97.57	97.97	98.38	96.66	98.75	99.95	97.92
22	98.33	98.86	97.56	98.27	98.93	97.89	100.33	101.16	99.24
23	121.53	120.43	118.58	120.58	119.74	116.81	121.04	120.34	117.36
24	115.93	115.23	111.85	114.19	114.36	110.01	116.16	115.05	111.27
25	107.27	107.19	105.47	106.80	107.23	104.32	108.43	108.16	104.73

$$\sigma_b = F_b \frac{3l}{2bd^2} \quad (1)$$

where, F_b is the force at the middle section of the rectangular sample, l is the length between the support points, b and d is the width and thickness of the test sample, respectively. The entire experiment was carried out at unchanged materials and environments. By means of 3DP method, the results of sample weight and bending strength for training models were shown in Table 3 and Table 4, respectively. To verify the effect of two models, some other samples that processed with different parameters were tested by experiments, and the results were shown in Table 5, Table 6 and Table 7.

2.2 Prediction method

In this study, both linear regression method and BP neural network model were employed to predict the bending strength by MATLAB (R2016a). Linear regression uses regression analysis in mathematical statistics to determine the quantitative relationship between two or more factors.^{18,19)} By the linear regression method, the relationship between the bending strength and influencing factors of 3DP samples were determined.

As one of the most widely used neural network, BP neural network is trained by bias backpropagation based on the gradient descent method.²⁰⁾ Many studies had proved that a three-layer BP network with one hidden layer can acquire

Table 4 Results of 3DP sample bending strength for training models.

No.	Bending Strength, σ_b /MPa									
	L1	L2	L3	L4	L5	L6	L7	L 8	L 9	Aver.
1	5.0	5.0	4.8	5.1	4.7	4.6	4.5	4.4	4.8	4.77
2	4.8	4.2	4.0	4.8	4.1	3.8	5.9	4.4	4.2	4.47
3	3.5	3.4	3.0	3.2	2.8	2.7	3.8	3.6	3.0	3.22
4	1.9	2.5	1.8	1.8	2.6	1.8	1.5	2.1	1.5	1.94
5	0.8	0.7	0.8	0.7	0.6	0.4	0.8	0.8	0.7	0.70
6	3.7	3.6	3.2	4.2	3.7	3.0	4.3	3.6	3.4	3.63
7	2.1	2.8	2.2	2.5	2.1	2.0	2.6	2.5	1.9	2.30
8	2.0	1.9	1.4	1.7	1.5	1.2	2.1	2.0	1.6	1.71
9	5.8	5.4	5.7	4.4	4.7	5.0	5.8	4.7	5.1	5.18
10	7.0	7.7	5.2	7.2	6.4	5.4	7.0	5.4	5.3	6.29
11	1.7	2.0	1.5	1.5	1.6	1.3	1.8	2.0	1.6	1.67
12	6.5	6.8	4.7	6.9	6.7	5.6	6.9	6.8	5.9	6.31
13	3.3	3.8	3.1	3.7	3.4	3.0	4.1	4.0	3.6	3.56
14	5.1	4.6	4.7	5.2	4.8	4.5	6.0	5.3	4.8	5.00
15	2.8	2.8	2.6	2.7	2.6	2.3	3.0	3.3	2.6	2.74
16	4.7	4.3	4.0	4.5	4.2	3.3	4.5	4.6	3.9	4.22
17	3.7	3.6	3.2	3.5	3.6	3.0	3.8	3.2	3.0	3.40
18	4.2	4.4	3.6	4.3	3.7	3.0	3.8	4.2	3.7	3.88
19	2.2	2.3	2.0	2.3	2.0	2.2	2.3	2.2	1.9	2.16
20	5.2	6.6	4.9	5.0	5.9	5.5	6.5	6.6	4.9	5.68
21	1.1	1.0	0.9	0.8	0.8	0.7	1.1	1.0	0.8	0.91
22	2.0	1.9	1.8	1.9	1.8	1.7	2.3	2.2	1.7	1.92
23	9.0	11.1	9.0	10.0	10.0	9.0	10.0	10.0	9.0	9.68
24	5.6	5.8	5.2	5.9	6.0	4.1	6.7	5.8	5.0	5.57
25	5.0	3.2	3.0	3.3	3.3	2.7	3.8	3.6	3.1	3.44

Table 5 Factors of experiments for verifying models.

Factors	Test No.				
	a	b	c	d	e
Activator Content, w /mass%	0.16	0.16	0.19	0.19	0.25
Resolution X , t /mm	0.08	0.09	0.07	0.08	0.07
Layer Thickness, d /mm	0.28	0.32	0.28	0.24	0.36
Recoater Speed, v /mm·s ⁻¹	150	180	180	210	150

Table 6 Results of 3DP sample weight for verifying models.

Test No.	Sample Weight, m /g							
	L1	L2	L3	L4	L5	L6	L7	L8
a	118.79	118.58	117.79	117.82	119.80	118.83	119.86	120.88
b	109.67	110.6	108.18	111.87	111.09	110.19	112.13	112.89
c	113.73	112.26	109.70	116.93	116.99	112.49	119.24	117.30
d	116.98	115.03	113.11	119.11	118.11	114.52	121.05	119.91
e	101.01	101.34	98.39	102.52	102.10	99.91	104.43	104.07

any non-linear reflecting from n to m dimensions.²¹⁾ Any continuous function in a closed interval can be approximated by the BP network with only one hidden layer. Therefore, the BP network model used in this study has a three-layer

network structure, composed of an input layer, a hidden layer, and an output layer. Each layer is consisted of multiple nodes that can be calculated parallelly. The hidden layer and the input layer are connected by an activation function. At the

Table 7 Results of 3DP sample bending strength for verifying models.

Test No.	Bending Strength, σ_b /MPa									
	L1	L2	L3	L4	L5	L6	L7	L8	L9	Aver.
a	4.6	4.4	3.8	4.6	4.0	3.6	5.0	4.9	3.5	4.26
b	2.6	2.4	1.9	3.5	3.0	2.2	3.1	2.7	2.2	2.62
c	3.7	4.2	3.3	4.1	4.5	3.5	4.4	4.4	3.9	4.01
d	5.0	5.4	4.0	4.9	5.0	4.3	5.6	4.7	4.0	4.77
e	3.4	2.9	2.4	3.6	3.1	2.6	3.4	3.5	2.4	3.04

Fig. 1 Change of sample weight and mechanical properties with location: (a) sample weight, (b) bending strength.

same time, the output layer and the hidden layer are also connected by an indeterminate activation function.

Besides the activator content, layer thickness, resolution X and recoater speed, the experiments showed that the sample weight and location are very important when evaluating the bending strength, as shown in Fig. 1. There are fluctuations in one printing process, and the bending strength will differ at different locations of the same plane. The sample mechanical strength at warm color area is higher than that at cool color area, and compared with Fig. 1(a) and Fig. 1(b), there is an approximate correspondence between sample weight and bending strength. Therefore, the weight and location of the samples are also taken as factors reflecting the bending strength.

So, the nod number of input layer should set as 6. After determining input nodes, it requires the determination of the nod number of the hidden layer. The nod number n of the hidden layer can be obtained by the eq. (2).

$$n = a + \sqrt{p + q} \quad (2)$$

where, n is the nod number of the hidden layer which is a rounded integer, p is the nod number of input layer, $p = 6$, q is the nod number of output layer, $q = 1$, and a is the positive integer from 1 to 10.

According to the eq. (2), the nod number of hidden layer is 4–13. Because the range of the empirical formula is not precious, and in order to obtain the optimal nod number of hidden layer, it was expanded as 3–15.

Summarily, the topology of proposed BP neural network was shown in Fig. 2. As illustrated, it is a three-layer neural network. The nodes of input layer are the activator content, layer thickness, resolution X, recoater speed, sample weight, and sample location. The nod of output layer is the bending strength of 3DP sand samples.

Fig. 2 BP network topology for predicting the 3DP sample strength.

3. Results and Discussion

3.1 Linear regression analysis

According to the experimental results listed in Table 3 and Table 4, the regressions between the bending strength and 3DP parameters were shown in Fig. 3. It can be concluded that the sample weight reflects the bending strength, as shown in Fig. 3(a). According to linear regression theory,²²⁾ The P value represents the probability that the test statistic appears in a certain range, and by comparing with the given level, the significance of the factors can be judged. When P value is less than 0.005, the influencing factor will be significant, and if the R^2 value is more closed to 1, the linearity between output and input will be better. Figure 3 also showed that the sample weight, resolution X and layer thickness are

Fig. 3 Linear regression between bending strength and influencing parameters: (a) strength vs. sample weight, (b) strength vs. activator content, (c) strength vs. resolution X, (d) strength vs. layer thickness, (e) strength vs. recoater speed, (f) strength vs. sample location.

Table 8 Comparison of linear regression prediction and experimental results.

Test No.	Bending Strength, σ_b /MPa		Absolute Error, Δ /MPa	Relative Error, δ /%
	Prediction	Experiment		
a	4.33	4.26	0.07	1.6
b	2.82	2.62	0.20	7.6
c	4.35	4.01	0.34	8.5
d	4.72	4.77	0.05	1.0
e	2.70	3.04	0.34	11.2

significant factors affecting the bending strength while the activator content, recoater speed and sample location are not significant. There is a positive relationship between the bending strength and the sample weight. As the sample weight increases, the bending strength will also increase gradually. Meanwhile, as the resolution X and layer thickness increase, the bending strength of 3DP sample decreases. To quantify the accuracy of the linear regression, the bending strength were predicted according to the data in Table 5, Table 6 and Table 7, and the deviation between the prediction and experimental results were shown in Table 8. The predicted results obtained by the linear regression

equation are close to the experimental results, and the maximum relative error is 11.2%. So, the linear regression can predict the bending strength of sand molds but the accuracy is not well. In addition, the relationship between the bending strength and three non-significant factors is uncertain. Consequently, the linear regression method can predict the tendency of bending strength, but it does not reflect non-linear relationships.

3.2 BP neural network prediction analysis

Because of the limitation of linear regression, BP neural network was used to make further improvement. It is

necessary to determine whether the running results can converge swiftly and the model can achieve the prediction accuracy.

After determining the network structure and the layer parameters, the transfer function of the hidden layer should be confirmed that *tansig* or *logsig* is usually employed. Mean squared error (MSE) was used to assess whether the nod number of hidden layer and transfer function are appropriate. Figure 4 showed the results between the selected transfer function and neuron number. As the number of hidden neurons increases, the MSE values of two transfer functions decrease, but the value of *logsig* is always greater than that of *tansig*. So, the *tansig* function is selected as the optimal one. The MSE value will reach the minimum when the number of hidden neurons reached 14. As a result, the transfer function of this network is *tansig* and the number of neurons is 14.

Training function is a very important part of neural network, and commonly used training functions of BP neural network are *traindg*, *trandga*, *traincgb*, *trainlm*, *traingdm* and *tranrp*.²³⁾ The MSE values calculated by different training functions are shown in Fig. 5. As shown in Fig. 5(a), (b), and (e), there are no convergences even after 2000 time

Fig. 4 The effect of different transfer functions on the MSE.

for the functions of *traindg*, *trandga* and *traingdm*. However, the convergences can be achieved for the functions of *traincgb*, *trainlm* and *tranrp*. In the BP neural network of predicting the bending strength, there is a need of fast convergence for training function. As shown in Fig. 5(c), (d), (f), The convergence can be achieved at 70 epochs for

Fig. 5 Effect of training function on the MSE value: (a) *traindg*, (b) *traingda*, (c) *traincgb*, (d) *trainlm*, (e) *traingdm*, (f) *tranrp*.

Table 9 Structure parameters of BP network for predicting bending strength.

No.	structural parameters	range	appropriate value
1	input variable	≥ 1	6
2	number of hidden layers	≥ 0	1
3	initial weight	-1 to 1	-1 to 1
4	number of hidden neurons	3-15	14
5	training function	<i>Traingd, Traingda, Traincgb, Trainlm, Traingdm, Trainrp</i>	<i>Trainlm</i>
6	implicit layer transfer function	<i>Logsig, Tansig</i>	<i>Tansig</i>
7	output layer transfer function	<i>purelin</i>	<i>purelin</i>
8	momentum factor	0.95	0.95
9	maximum number of training steps	2000	2000
10	allowable error range	0.01	0.01

Table 10 Comparison of BP network predicted and experimental results.

Test No.	Bending Strength, σ_b /MPa		Absolute Error, Δ /MPa	Relative Error, δ /%
	Prediction	Experiment		
a	4.34	4.26	0.08	1.9
b	2.61	2.62	0.01	0.4
c	4.05	4.01	0.04	1.0
d	4.96	4.77	0.19	4.0
e	2.91	3.04	0.13	4.3

traincgb, 5 epochs for *trainlm* and 40 epochs for *traingrp*. Therefore, the convergence rate of function *trainlm* is better than those of the other functions, and the best training function is *trainlm*.

To get high predicting accuracy, other parameters of the proposed neural network model are also adjusted to the most appropriate values, as shown in Table 9. Different input factors often have different dimensions and units, which will affect the results of data analysis. In order to eliminate the dimensional impact of input factors, data normalization is required to solve the comparability between different factors. The input data was normalized to the range between -1 and 1. The momentum factor was set as 0.95, and the maximum training steps is 2000, and the allowable error is 0.01.

The experimental results were used as the training data, meanwhile, the data shown in Table 6 and Table 7 were used to verify the accuracy of predicting the bending strength of 3DP samples. The prediction results are shown in Table 10. Compared with the results of linear regression, the absolute error of the prediction is very small. The maximum absolute error is 0.19 MPa while it is 0.34 MPa for linear regression, and the maximum relative error is 4.3% while it is 11.2% for linear regression, which means the BP neural network has a high prediction accuracy and reliability.

4. Conclusion

- (1) The orthogonal experiments and three-point bending test were used to characterize bending strength of 3DP samples with different process parameters. The bending strength was predicted by six factors of activator

content, resolution X, layer thickness, recoater speed, sample weight and sample location.

- (2) The results of linear regression showed that the sample weight, resolution X and layer thickness are the most significant factors while the activator content, recoater speed and sample location are non-significant. Compare the prediction results, the maximum error of linear regression was 11.2%, which means that three non-significant influencing factors also have impact on the prediction results.
- (3) Based on six influencing factors, a three-layer BP neural networks with 6 input nodes, 14 hidden nodes and 1 output node was established to predict the bending strength of 3DP samples. Compared the actual experimental strength, the maximum absolute and relative errors are 0.19 MPa and 4.3%, which are lower than those of linear regression.

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