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PREDICTION OF SIZE DISTRIBUTION OF IRON ORE GRANULES AND PERMEABILITY OF ITS BED

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Abstract

The granulation process, which is determined by many factors like properties of the mixture and the operating parameters, is of very importance for getting a good permeability of the burden in the sintering strand. The prediction of the size distribution of the granules and the permeability of its bed by the artificial neural network was studied in this paper. It was found by the experiments that the order of significance in the granulation process is water content added into the mixture, the mass fraction of the particles of 0.7-3 mm, and the moisture capacity. The water content added in the mixture and the mass fractions of the particles of 0.7-3 mm have the positive relation to the permeability of granulation, While, the moisture capacity has the negative relation to the permeability of granulation. Both the moisture capacity and the water content added were used as the inputs in the model of artificial neural network, which can give a good prediction on the permeability and mass fraction of the granules of 3-8 mm, as well as the tendency of the samples under instable raw materials conditions. These two models can be used for optimization the granulation.

Keywords: Granulation; Perdition; Permeability; Size distribution; Artificial Neural Network.

1. Introduction

The objective of granulation of the iron ore before sintering is to get the suitable size of the granules and a good permeability of the burden in the sintering strand. The prediction of the size distribution of the granules and the permeability of its bed is very useful to the sintering plant to optimize its production. However, the granulating

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process is a very complex and the properties of the granules are determined by many factors, including the iron ore features referring to the size distribution, surface morphology of the particles, and the contact angle between the water and the iron ore, operating parameters like the water content added into the mixture, and the device parameters which refers to the filling rate of the mixture, inclination angle and the rotating rate of the mixer. Many studies have carried out on the prediction of granule size distribution. As early as 1950's, Rumpf [1], Newitt [2], Kapur [3-4] have studied the mechanism of the granulation of the particles. In 1990's, Litster [5], Venkatara [6], Khosa [7] and other researchers studied the mathematical model of the granulation process based on the mechanistic understanding of the factors affecting the growth of granules. For example, in Venkatara's equation [6], the input is the water content, the mass fraction of the particles <0.147mm, the mass fraction of the limestone added, and the output is the size distribution of the granules. Recently, the optimal water content added into the mixture became a hot topic in the area of iron ore granulation. Matsumura [8] studied the effect of moisture absorption behavior on optimal granulation moisture value of sinter raw material. Lv and Bai [9-11] developed the concept of moisture capacity of iron ore for predicting the optimal water content added into mixture. Most of the previous studies were based on the physical model of the particles and the mechanistic models under the certain assumptions. The models reported can give a good prediction on the granulation in their conditions of the raw materials, however, once the condition of raw materials changes, the agreement between the prediction by the models and the experimental results is poor. The main reason for this problem is that the optimal water content added, which is a key factor determining the granulation, always changes with the raw materials. Therefore, a good model with improved validity in a wide range of raw materials should consider the ability of the moisture absorption of the iron ores.

Artificial Neural Network (ANN), which can solve the prediction problem of the complex and non-linear system very well, was initially suggested in the later 19th century, and well developed in 1940's-1960's in the field of math. The development of computer promoted the application of the ANN in every field [12-13]. The iron ore granulation is a very complex and non-linear process, and the prediction of the size distribution of the granules with high accuracy is of difficulty, especially in the plant in which the properties of the mixture of iron ores always vary. Therefore, the size distribution of the granules and the permeability of its bed were predicted with the ANN in this study.

2. Experimental

2.1. Materials and Scheme

The experiments include granulation of the iron ores and the measurements. In order to simulate the real industrial process, the granulation process was divided into two steps, named the step of mixing, in which the water is firstly added and the materials are mixed well for keeping the chemical composition and the size distribution homogeneously, and the step of granulating, in which the water is complemented to reach a level desired and the particles grow up as moving with the rotating mixer.

According to the previous studies, the factors influencing the granulation include the chemical composition, size distribution, water content added into the mixture, and the moisture capacity of the mixture which represents the maximum water content absorbed by the bed of iron ore particles in a natural status [9, 11]. In the factors of chemical composition, total Fe (TFe) varies in a narrow range with a little sensitivity, while the contents of CaO and SiO_2 in the mixture vary a lot and are easily controlled. The previous studies [14] have approved that the particle bigger than 0.7mm is regarded as the nuclear particle and the particle smaller than 0.2mm is considered to be the cohesive particle during the granulation. The particle of 0.2-0.7mm is the medium, neither as the nuclear nor the cohesive. The more particles of 0.2-0.7, the worse granulation result. In addition, the mass fractions of the particles <0.2mm, 0.2-0.7mm, and >0.7mm are easily controlled. In order to improve the accuracy and the applicability of the prediction model developed, the samples used in the experimental were selected in a relative big range for keeping the diversity. The factors and the levels of the orthogonal experiments are shown in Table 1. According to Table 1, 16 samples were got by adjusting the fraction of several iron ores, and shown in Table 2. It

Table 1. Experimental factors and levels (mass%)

Factors Levels (%)	SiO_2	CaO	0.7-3 mm	0.2-0.7 mm	<0.2 mm
1	4	6	16	13	32
2	5.5	8	17	15	37
3	7	10	18	17	42
4	8.5	12	19	19	47

Table 2. Granulation properties of mixtures (mass%)

Samples	M_c	<0.2mm	0.2-0.7mm	0.7-3mm	SiO_2	CaO	$A1_2O_3$	MgO
1#	9.98	32.00	13.36	16.42	4.65	5.00	1.56	4.85
2#	11.35	37.00	15.00	17.00	4.19	8.00	1.43	7.02
3#	13.27	42.00	17.00	18.00	4.00	10.00	1.46	8.12
4#	15.17	47.00	19.00	18.80	4.00	12.00	1.58	9.16
5#	17.73	47.00	17.00	17.00	5.50	6.00	1.90	4.76
6#	17.73	49.00	19.00	16.00	5.50	8.00	2.14	1.72
7#	14.20	37.00	12.60	18.63	5.50	10.8	1.49	4.26
8#	15.75	32.00	14.60	18.16	5.50	12.6	1.66	3.1
9#	19.8	37.00	19.00	18.40	7.00	6.40	2.51	3.15
10#	19.45	32.00	17.00	19.40	7.00	7.60	2.39	1.92
11#	19.16	47.00	15.00	15.84	7.00	10.00	1.87	3.55
12#	19.45	42.00	13.00	16.80	7.00	12.50	1.74	3.28
13#	19.42	42.00	15.00	18.68	8.50	6.40	2.46	1.02
14#	17.08	45.58	13.40	17.56	8.50	8.40	2.17	1.14
15#	19.97	34.50	18.00	17.50	7.28	9.00	2.61	1.00
16#	21.40	39.500	16.00	16.50	7.82	11.00	2.15	2.02

is necessary to point out that the levels of samples in Table 2 are a little different from that shown in Table 1, because it is impossible to get the most desired samples, which satisfy each level and factor, with the limited iron ores. For each sample, the moisture capacity was measured and the results are listed in Table 2.

In a sintering plant, the time of granulation is about 3-5 minutes, and the filling rate of the mixer is about 15%. Therefore, the granulation time in this experiment was 4 minutes, and the filling rate was 15%. The rotating rate of the mixer was defined according to the Froude dimensionless number which is expressed as:

$$Fr = \frac{D \cdot n^2}{g} \quad \ldots(1)$$

where D, n, and g represent the diameter of the rotating mixer (m), rotating rate of the mixer (rad/min), and the gravity acceleration (m/s^2). In the sintering plant studied, the d and n equal to 4.4 m and 16 rad/min. The d in the experimental mixer is 600mm. According to Eq. 1, the n in the experimental mixer can be calculated as 16 rad/min. The mass of the mixture used in each experiment is about 60-70kg.

Two indexes were adopted for evaluating the granulation in this study. One is the permeability of the burden, and the other is the mass fraction of the particles of 3-8mm. After granulation, the granules were loaded into the laboratory sintering pot for measuring the permeability by reading the negative pressure under different gas flow rate. The permeability index was calculated by the flowing equation.

$$P = \frac{Q}{A}\left(\frac{h}{\Delta p}\right)^{0.6} \quad \ldots(2)$$

where Q, h, A, and Δp represent gas flow rate, depth of burden, surface area of the bottom of the sintering pot, and negative pressure of the burden in mm H2O individually. In this study, Q, h, and A are equal to 0.33m3/min, 100mm, 0.0177m2. The permeability index P increases with increasing Δp. In the sintering plant, the mass fraction of the particles with 3-8mm is an important index for judging the granulation. The permeability of the burden has a positive relation with the mass fraction of the particles of 3-8mm.

2.2. Results and discussions

Each sample was added with 3 water levels. Therefore, 48 experiments of granulation were carried out. The size distribution and permeability index were measured or calculated, and the results were shown in Table 3. For the case of 12_1 and 16_1, the gas flow rate is still very small, even smaller than the low-limit of the flowmeter when the negative pressure was very high. It means the water content in these cases is too low to get the good permeability. For each sample, the case with the best permeability index and also highest mass fraction of granules with 3-8mm in size were selected as the optimum water content case (bold font in Table 3). In sample 1, 7, and 11, the optimum water content can be easily determined, because the two parameters, fraction of granules with 3-8mm and the permeability index agreed with each other. For sample 2, 3, 5, 10, 13, and 14, the two parameters do not agree with each other very well, therefore, the measuring error should be considered in those cases. Once two

Table 3. Results of granulation experiment

No.	f (H_2O) Mass %	f (3-8 mm) Mass %	JPU m / min	No.	f (H_2O) Mass %	f (3-8 mm) Mass %	JPU m / min
1_1		63.45	10.86	9_1*	6.24		6.62
1_2	**5.42**	**70.23**	**12.05**	9_2*	6.82		10.02
1_3	6.90	25.16	5.32	9_3*		51.68	
2_1	5.10	29.85		10_1	6.29	42.01	8.64
2_2	**5.73**	**63.48**	**11.72**	10_2	7.46	56.51	11.99
2_3	6.86	53.80	11.85	**10_3**	**8.24**	**69.28**	**11.85**
3_1	6.58	59.90	11.47	11_1	5.21	27.37	6.11
3_2	**6.68**	**61.20**	**11.47**	11_2	6.27	31.96	10.02
3_3		61.33	11.41	**11_3**	**8.00**	**52.18**	**12.88**
4_1*	6.58	42.08	11.24	12_1*		29.04	-
4_2*	7.77	55.72	9.58	12_2*	5.00	33.69	5.99
4_3*	8.61	63.33	10.91	12_3*	7.11	42.24	10.91
5_1	7.04	40.96	10.7	13_1	7.71	42.86	11.35
5_2	**7.99**	**59.16**	**12.56**	13_2		54.6	12.56
5_3	9.32	60.29	12.12	**13_3**	**8.99**	**60.67**	**12.41**
6_1*	5.85	25.92	6.76	14_1	7.24	49.64	10.96
6_2*	6.33	31.35	6.50	**14_2**	**7.88**	**66.11**	**11.6**
6_3*	7.61	43.21	10.02	14_3	8.51	61.08	12.19
7_1	5.42	54.79		15_1*	5.52		6.65
7_2	**6.65**	**66.02**	**12.56**	15_2*	6.84	29.21	10.46
7_3	7.84	55.41	8.14	15_3*	7.8	49.08	12.41
8_1*	5.68	40.24	6.45	16_1*	4.30	25.96	-
8_2*	6.27	47.94	9.81	16_2*	5.78	32.24	7.71
8_3*	6.34	58.23	8.00	16_3*	7.2	49.22	10.6

values for one parameter were very close to each other, another parameter with big difference should become a main factor. If both the values for the two parameters were very similar individually, the case with less water content should be selected. For other samples like 4, 6, 8, 9, 12, 15 and 16 (marked with *), it was very hard to get an optimum water content, because one or two parameters is very bad. For example, in case 4, the JPU does not agree with the mass fraction of granules with 3-8mm in size, even is opposite. According to the mass fraction of granules, case 4_3 has the optimum water content, caes 4_1 is the worst, while according to the JPU, case 4_1 us the optimum one, case 4_2 is the worst.

The stepwise regression method was used to analysis the factors which influences the granulation according to the experimental results. The results are shown in Table 4. The interaction coefficient represents the influence degree. The big interaction coefficient means that the factor is very

Table 4. Stepwise linear regression analysis

Factors	**Water content added**	**0.7-3 mm**	**Moisture capacity**	**0.2-0.7 mm**
Interaction coefficient a	5.87	3.32	-1.65	-1.38
Significance level **α**	0.005	0.024	0.05	0.46

important for the process. The significance level means the credibility of the results. The significance level which is smaller than 0.05 means the result is credit. It can be found that the significance level of the particle of 0.2-0.7mm is 0.46, much higher than 0.05, meaning the results for this factor is not very sure. The order of influencing degree of the granulation process from big to small is water content added, the mass fraction of the particles of 0.7-3mm, and the moisture capacity. The interaction coefficients of water content added in the mixture and the mass fraction of the particles of 0.7-3mm are both positive. They mean that these two factors have the positive relation with the permeability of granulation, the more content added into the mixture and the more faction of the particles of 0.7-3mm are both good for the granulation in the range of the experiments. In the opposite, the interaction coefficients of moisture capacity is negative, meaning the big moisture capacity is bad for granulation. These conclusions are thought to be reasonable. The previous studies [15-16] have proved that the size of the granule increases with increasing the water content added into the mixture. According to Table 4, the water content added into the mixture is the first important factor which can control the granulation process. In the industrial practice, the water content added into the mixture is also a factor can controlled easily once the iron ores used is limited.

3. Prediction of granules properties

3.1. BP Neural Network Model

3.1.1. Input and output parameters

As mentioned before, the operating parameters and the properties of the mixture have a great effect on the granulation. Actually, the operating parameters are always fixed, and the properties of the mixture become the most important factors. The properties of the mixture include the chemical composition, size distribution, moisture capacity, and the morphology of the particles. The chemical composition includes TFe (total Fe), FeO, SiO_2, Al_2O_3, MgO, CaO, MnO, TiO_2, K_2O, Na_2O, S, P and etc. Fe is the element with the most content in all the samples, and the difference of TFe in the various samples is very little, therefore, it is meaningless that the TFe is regarded as the input parameter in the model. FeO has a great effect on the surface property of the sample, for example, the contact angle between the water and the particle; however, such factors can be represented by the moisture capacity in the model. The CaO, Al_2O_3, and MgO are good for granulation, while the SiO_2 is bad for granulation. These four parameters which vary a lot in the samples studied should be included in the model. The other chemical compositions like MnO, TiO_2, K_2O, Na_2O, S, and P only take a small fraction of the sample, and should not be used as the input parameters for avoiding or reducing the complexity of the model.

The effect of the size distribution of the particles on the granulation has been reported before. The mass fractions of the particles of <0.3mm, 0.2-0.7mm, and the 0.7-3mm are used as the input parameters of the neural network model.

Morphology, porosity, surface area, and the mineralogy of the particles all have the effect on the granulation. However, some of them are not qualified easily. In order to simplify the complexity of model, the total effect of these factors is represented by the moisture capacity. The water content added into the mixture influences the granulation greatly. The experiments in this study have also proved that it is the first important factor influencing the granulation. Definitely, the water content should be as an input parameter. Moisture capacity [17-18] and the water content added into the mixture are the two most important parameters in the input to improve the prediction of the model, because the moisture capacity is the optimal value of the water content, and the difference between the real value and the optimal value represents the degree approaching the best result. By this way, the model was hoped to improve the prediction once the conditions of the raw materials change greatly.

In order to improve the accuracy of the model, two individual models will be developed for predict the permeability of the burden and the mass fraction of the particles of 3-8mm. In the two individual models, the permeability of the burden or the mass fractions of the particles of 3-8 mm are regarded as the output parameters.

3.1.2. Structure of the model

A three layers feedback model was adopted in this study, which is schematically shown in Fig. 1. There are nine neurons in the input layer, and two neurons in the output layer. The number of hidden node is very important to the convergence of the model. It is related to the neurons in the input and output layers. There is no a definite analytic expression for determining the number of the node in the hidden layer up to now. However,

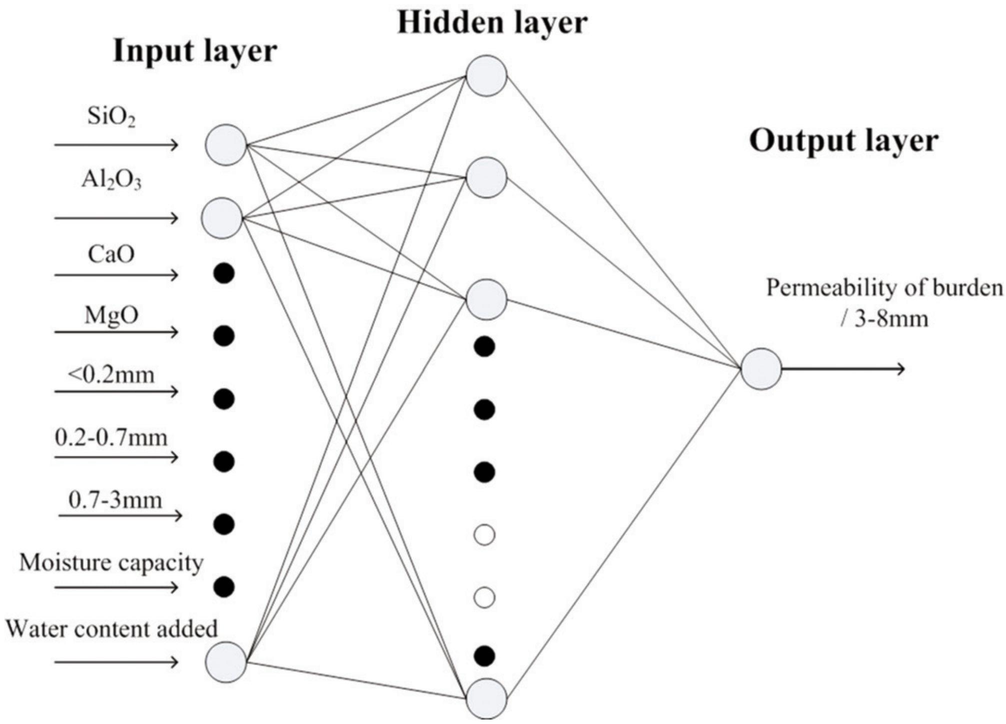

Fig.1 Structure of the three layers BP neural network

there are some empirical equations reported for the model design [13, 19]. According those experienced equations, many values (9-20) were tried by the model training. It was found that the model can converge quickly when the number of the node in the hidden layer equals to 18.

3.1.3. Activation and training function

The activation function used in the hidden and output layers is expressed by:

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

Eq. 3 is also called S function (sigmoid function). The output of Eq. 3 varies from 0 to 1. The traingdx equation, which updates weight and bias values according to gradient descent momentum and an adaptive learning rate, was adopted as the training equation in this study because it has a good performance on convergence.

3.2. Model Training

The 48 samples in Table 3 were used to develop the neural network model. In order to improve the accuracy of the model, two bad samples (sample 12-1 and 16-1) were removed out. In the 46 samples left, 38 samples were used to train the model and the other 8 samples were used to validate the accuracy of the model developed.

3.2.1. Pretreatment of the samples

The dimension and the order of the magnitude of each variable in the input layer vary a lot. The accuracy and the robustness of the model become worse when the original data used. Therefore, The samples used in the modeling were pretreated with the method of normalization first, which is expressed by:

$$y_{ij} = \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}} \times (0.8 - 0.2) + 0.2 \quad \ldots(4)$$

where xij is the element to normalize in row i and column j, and yij is the correspond value normalized, xjmin and xjmax are the maximum and minimum sample in column J. In Eq. 4, the output varies from 0.2 to 0.8 for avoiding the saturation zone which locates in [0, 0.2] and [0.8,1], because the ability on resolution of the activation function becomes worse in the saturation zone. The samples after pretreatment need rever-pretreatment for the output of the model. As a summary, all the parameters used in the model are listed in Table 5.

3.2.2 Training times and error

For the model whose output parameter is the mass fraction of the granules of 3-8mm, the training error approached to 0.0017 when the model was trained 5400 times. The training error continued to decrease with

Table 5. Parameters of BP net

Parameter	**Neurons input**	**Neurons ouput**	**Hidden layer**	**Node in the hidden layer**	**Activation function**
Value	9	1	1	18	logsig, logsig
Parameter	**Learning rate**	**Training no.**	**accuracy**	**Training function**	
Value	0.02	6000	0.001	traingdx	

increasing the training times to 6000. However, the results were over-fitted. For the model whose output parameter is the permeability of the burden, the training error approached to 0.0025 when the model was trained 1000 times. The results predicted were satisfied.

3.3. Model Prediction

The prediction of the model should be evaluated from two aspects. One is the hit rate of the prediction, and the other is the tendency of the prediction. The hit rate is defined as that the number of the prediction which lies in range of permissible error (*h*) to the total number of prediction (H). The equation for calculation of hit rate is expressed by:

$$p = \frac{h}{H} \times 100\% \qquad ...(5)$$

where p is the hit rate. The prediction and the real value are represented by x and y, and the permissible error is δ. The equation used to judge whether the prediction hit the goal is expressed by:

$$y - \delta \leq x \leq y + \delta ....(\delta > 0) \qquad ...(6)$$

For a same model, the p increase with increasing the δ. The δ should be fixed at a reasonable value according to the demand of industrial and the experience.

The prediction of the mass fraction of the granules of 3-8 mm is shown in Fig. 2, from which it is indicated the tendency of the predictions agrees well with the samples. The absolute error of the prediction varies from 5 to 8. The relationship between the hit rate and the permissible error is listed in Table 6. The hit rate is about 87.5% when the δ equals to 8.

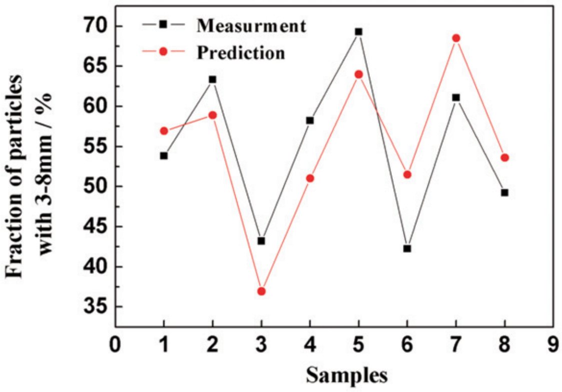

Fig.2 Prediction of fraction of granule of 3-8mm verse the samples

The prediction of the permeability of the burden is shown in Fig.3, and the relationship between the hit rate and the permissible error. Comparing the Fig.3 with Fig.2, it was found that the absolute error of the Fig.3 is a little greater than that of Fig.2. The hit rate in Table 7 is also lower than that of Table 6. However, the tendency of the prediction basically agrees with the samples,

Table 6. Hit rate of permeability of the burden

Absolute error / %	5	6	7	8
Hit rate / %	37.5	50	62.5	87.5

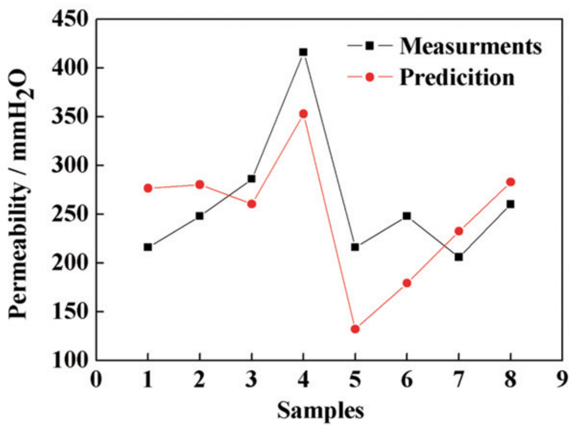

Fig.3 Prediction of the permeability of the burden verse the samples

Table 7. Hit rate of permeability of the burden

Absolute error / mm H_2O	40	50	60	70
Hit rate / %	50	50	62.5	87.5

although the related error is a little high. The accuracy of the model should be improved by using more samples to train. In general, both of the predications of the two models are basically accepted. They can give some guidance on optimization the granulation process for getting a optimal permeability of the burden.

4. Conclusions

The dependency of the size of granules and the permeability of its bed on the raw materials and process parameters were studied by the experiments, and then the prediction of the granulation by the artificial neural network was carried out in this paper. The conclusions are summarized as followings:

(1) The order of influencing degree of the granulation process from big to small is water content added into the mixture, the mass fraction of the particles of 0.7-3 mm, and the moisture capacity.

(2) The water content added in the mixture and the mass fractions of the particles of 0.7-3mm have the positive relation with the permeability of granulation. The more water content added into the mixture and the more faction of the particles of 0.7-3mm in the mixture are both good for the granulation in the range of the experiments. In the opposite, the moisture capacity is bad for granulation.

(3) The moisture capacity was used as one of the inputs in the model of artificial neural network, which can give a good prediction on the permeability and mass fraction of the granules of 3-8 mm, as well as the tendency of the samples. These two models can be used for optimization the granulation.

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