# Analysis and Multi-objective Optimization of Slag Powder Process

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**Abstract**

Slag powder is a process with characters of multivariables, strongly coupling and nonlinearity. The material layer thickness plays an important role in the process. It can reflect the dynamic balance between the feed volume and discharge volume in the vertical mill. Keeping the material layer thickness in a suitable range can not only improve the quality of powder, but also save electrical power. Previous studies on the material layer thickness did not consider the relationship among the material layer thickness, quality and yield. In this paper, the yield and quality factors are taken into account and the variables that affect the material layer thickness, yield and quality are analyzed. Then the models of material layer thickness, yield and quality are established based on generalized regression neural network. The production process demands for highest yield, best production quality and smallest error of material layer thickness at the same time. From this point of view, the slag powder process can be regarded as a multi-objective optimization problem. To improve the diversity of solutions, a CT-NSGAII algorithm is proposed by introducing the clustering-based truncation mechanism into solution selection process. Simulation shows that the proposed method can solve the multi-objective problem and obtain solutions with good diversity.

*Keywords:* Slag powder, Material layer thickness, Modeling, Multiobjective

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optimization algorithm

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## 1. Introduction

In recent years, with the development of construction industry and high-speed rail industry, the demand for steel is increasing rapidly. With the increment of steel production, the waste generated from the steel production is increasing gradually. If the waste is not handled effectively, it will not only cause a lot of waste, but also lead to heave pollution of air and land. The slag can form powder after grinding. When the specific surface area of slag powder is more than 400m$^2$/kg, the strength of the cement is obviously enhanced [1]. So how to ensure the quality and yield of slag powder has been an important issue. Slag powder is a multivariate, strongly coupled and nonlinear process. Normally, the model based on mechanism is very difficult to be set up. During the production process of slag powder, a large amount of data has been recorded, but the data is only kept for maintenance and the information hidden behind the data is not digged out effectively. With the rapid development of artificial intelligence and machine learning, many researches have been developed for slag powder [2, 3, 4, 5, 6, 7, 8, 9, 10]. In the literature[5], a detailed analysis of the particle size has been carried out through the industry vertical mill grinding GGBS (ground granulated blast-furnace slag). On this basis, qualitative analysis has been carried on by using image method and sample preparation method for slag microstructure. Meanwhile the microstructure of slag powders has been quantified by using shape index, roundness coefficient, flat degree, angularity and surface roughness. In the literature [6], the particle size of the slag powder was measured by using support vector regression, fuzzy inference and adaptive fuzzy inference respectively. It was found that the method based on adaptive fuzzy inference is more accurate. The literature [7] compared the coarse iron ores in the ball mill and vertical mill and showed that the vertical mill has a greater advantage in the regrind circuits. In the literature [8], the online monitoring model for cement fineness was established by using several different feedforward neural networks and least square support vector regression. It was found that the elastic backpropagation neural network has the best modeling effect. Hence, the authors designed the cement fineness controller based on this model. In the literature [9], the internal state of the mill and some unknown parameters were estimated by using an extended Kalman filter. After verification, the state is consistent with the actual situation.

From the slag to the final powder, a large amount of electrical power will be consumed. The crushing, grinding and separation process approximately counts for 60%--70% electrical consumption of the whole process. The material layer thickness is an important factor in this process, which reflects the dynamic balance between feeding and discharging in the vertical mill. The thicker the material layer thickness is, the more difficult it is for the vertical mill to completely grind the slag. When the material layer thickness is too thin, the grinding roller and millstone will contact directly, it will lead the vertical mill to vibrate greatly. In some serious cases, it may even cause the vertical mill to shut down, thereby seriously affecting economic benefits. Hence, ensuring the material layer thickness in the suitable range is another important factor besides production yield and quality. In the literature [10], the authors studied the relationship between the feed volume and material layer thickness. The material layer thickness was controlled by a fuzzy controller. However the relationship between the yield and quality was not considered when the material layer thickness was analyzing. In practical industrial engineering, yield, quality and other production indexes are competing in most cases which compose a multi-objective problem [11]. In the literature [12], the author constructed the multi-objective optimal problem of slag powder process and obtained the optimal solutions about yield and specific surface area, but did not consider the material layer thickness as an objective function.

For slag powder process, operational stability of the vertical mill (indexed by the material layer thickness) is the primary concern for production safety and long-term benefits. This paper takes the most concerned control objectives – yield, quality (i.e. specific surface area) and material layer thickness – into consideration, and tries to analyze the control objectives and obtain optimal solutions by solving the multi-objective optimal problems. Because of the multiple variable and strong coupling characters, firstly, we analyze technological process and extract the variables which affect the three objectives. Due to the demand of highest yield, best production quality and most stable material layer thickness, the three-objective optimal problem is constructed. Slag powder is produced in the closed vertical mill where complex physical and chemical change happens, leading to the difficulty of modeling by mechanism. Generalized regression neural network (GRNN) algorithm has the characteristics of fast convergence speed and good nonlinear approximation performance [13]. Hence, GRNN is utilized to construct models of the three objectives using the process data.

In order to get the optimal solution of yield, specific surface area and material layer thickness NSGAII algorithm is firstly used. Because the NSGAII adopts crowding distance mechanism, only when the non-dominance sorting cannot select the required solutions completely, crowding distance sorting is applied. This leads to the result that the convergence is superior to the diversity in NSGAII [14]. To solve this problem, some algorithms are optimized in diversity, such as RL-NSGAII [15], GrEA [16], NSGAII-M2M [14] and so on. Dr Manish Aggarwal proposed PLEMOA algorithm, which aims to aid a decision maker to find his most preferred solutions without exploring the whole set of Pareto optimal solutions. PLEMOA can not only been applied to many subfields of operations research, but also reduce computational complexity [17, 18]. Some scholars also proposed an improved NSGA-II algorithm based on the sub-regional search and archiving strategy, which can reduce computational complexity [19]. In this paper, to improve diversity of solutions, clustering-based truncation is introduced into environmental selection process based on original NSGAII algorithm. Using the CT-NSGAII algorithm and GRNN models, optimal Pareto front of slag powder MOP (multi-objective optimal problem) are obtained. Further more, combining real production demand, optimal solution is determined from the Pareto front to guide the future control process and practical production.

In this paper, the whole slag powder process is introduced firstly. Then some factors affecting the material layer thickness are analyzed. The models of material layer thickness, yield and special surface area are established by using the generalized regression neural network. Finally the optimal yield, special surface area and material layer thickness are determined by the proposed multi-objective optimization algorithms CT-NSGAII.

## 2. Analysis of objectives in the slag powder process

### 2.1. The slag powder process

The slag grinding system is the core of the slag powder control system, which consists of batching station, conveyor belt, vertical mill, hot gas generator, dust collector and product warehouse. The vertical mill is shown in Fig 1.

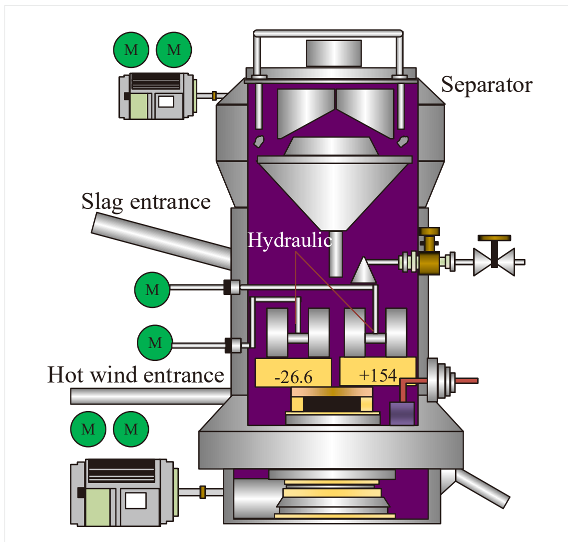



Figure 1: Vertical mill

The entire slag powder process is shown in Fig 2. Firstly raw slag materials are transported into the vertical mill through the conveyor belt after iron removement and drying process. The raw slag is ground under the pressure of the grinding roller and the millstone. The slag powder is blown to the upper part of the vertical mill by the hot gas. Then the slag powder which meets the particle size requirement is screened out by the separator, and the slag powder which does not meet the particle size requirement will be re-entered into the mill through the bucket elevator for re-grinding [12, 20].

### 2.2. Objectives and affecting factors of slag powder process

Except demands for higher yield and better quality, material layer thickness is a very important factor in the slag powder process. Material layer thickness which is too thin or too thick can affect the yield and quality of slag powder in an adverse way.

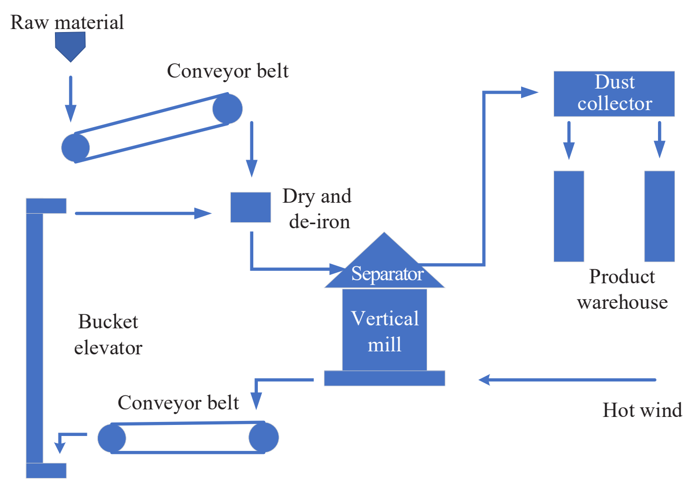



Figure 2: Slag powder process

From the practical experience, main factors that affect the material layer thickness include the feed volume, grinding roller pressure, separator speed and temperature d-ifference between mill inlet and outlet. These factors can not only affect the material layer thickness, but also have a large influence on the yield and specific surface area. The effects of these variables on the material layer thickness will be explained separately below.

1) Feed volume. The hardness, humidity and feed volume of raw slag can have a large effect on the material layer thickness in the vertical mill. Suppose that the hardness of the material, the moisture content of the material, the separator speed and other factors are fixed. The larger the feed volume, the thicker the material layer thickness will be.

2) Grinding roller pressure. When the feed volume and other variables are fixed, the grinding roller pressure has a large impact on the material layer thickness. The greater the grinding roller pressure is, the thinner the material layer thickness will be. When the material layer thickness is too thin, the grinding roller will directly contact the millstone. This will make the vertical mill vibrate fiercely, even stop running.

3) Separator speed. Separator is used to screen out the slag powder that meets the requirement. Separator speed is an important factor that determines the specific

surface area of slag powder. The faster the separator speed is, the better the quality of slag powder will be. Also when other variables are fixed, the faster the separator speed is, the more circulating material there will be. This will lead to the increment of material layer thickness.

4) Temperature difference between mill inlet and outlet. When the temperature difference is large, it means the moisture content of the material in the vertical mill is high. This will lead to the slag being ground insufficiently and increase material layer thickness. When the temperature difference is small, it means the moisture content of the material is low and the slag is dry. This will make the vertical mill vibrate.

## 3. The description of the slag powder process optimal problem

In actual production, the company always wants to obtain more powder with better quality. In other words, the company hopes that both specific surface area and the yield are large. This could ensure better profit of a company. As mentioned above, material layer thickness will indirectly affect the yield and specific surface area. And material layer thickness demands to be as close to 13.73mm as possible in actual production. To maintain the stable operation, based on engineer experience, the maximum value of material layer thick is 25.11mm, and the minimum is 2.33mm. Therefore, considering yield, specific surface area and material layer thickness comprehensively, the optimal value of material layer thickness can be obtained by multi-objective optimization algorithm. Through above analysis, feed volume, grinding roller pressure, separator speed and temperature difference between mill inlet and outlet can affect yield, specific surface area and material layer thickness. However, mechanism model is normally hard to be obtained, the models based on data will be given instead.

$$Y_i = f_i(X_1, X_2, X_3, X_4) \quad i = 1, 2, 3 \tag{1}$$

Where $Y_1$ is the yield, $Y_2$ is the specific surface area and $Y_3$ is the material layer thickness. $X_1$ is the feed volume, $X_2$ is the grinding roller pressure, $X_3$ is the separator speed, $X_4$ is temperature difference between mill inlet and outlet. By experience of engineers, the initial ranges of the feed volume, grinding roller pressure, separator speed and temperature difference between mill inlet and outlet can be given in Table 1. After normalization, these variables are mapped into the range of [0, 1]. Meanwhile

Table 1: Initial range

| variable \ range | $X_{i\min}$ | $X_{i\max}$ |
|---|---|---|
| $X_1$ | 83 | 109 |
| $X_2$ | 115 | 128 |
| $X_3$ | 1010 | 1160 |
| $X_4$ | 114 | 171 |

these variables are also decision variables for multi-objective optimization. The multi-objective problem can be described as follows:

$$
\begin{aligned}
&max \quad f_1\left(X_1, X_2, X_3, X_4\right) \\
&max \quad f_2\left(X_1, X_2, X_3, X_4\right) \\
&min \quad \left|f_3\left(X_1, X_2, X_3, X_4\right) - 13.73\right| \\
&s.t. \quad X_{i\min} < X_i < X_{i\max} \quad i = 1,2,3,4 \\
&\qquad\ 2.33 \leq f_3 \leq 25.11
\end{aligned}
\tag{2}
$$

The optimal solution set of yield, special surface area and material layer thickness is obtained by solving the multi-objective problem. Combing practical production situation and production demand, optimal yield, quality, material layer thickness and corresponding production variables is determined from the obtained Pareto solutions. The entire solution scheme can be seen in Fig 3.

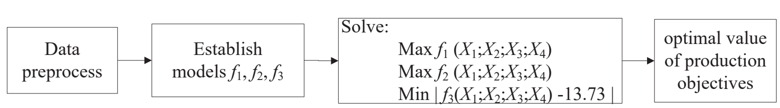



Figure 3: Entire solution scheme

## 4. Modeling with GRNN

### 4.1. Data preprocessing method

The field data is adopted at every sample time. Some abnormal values inevitably appear. In this paper, we collected a total of 546 samples. The sample sets can be expressed as $(x_i; y_i)_{i=1}^N$, where $N$ is the number of sample size, $x_i \in R^m$, $y_i \in R^n$. Denote $z_i = (x_i; y_i) \in R^{m+n}$. To reduce the gross error, data is preprocessed by the box-plot method [21]. The method is described as follows:

Step1: Sort sample data from small to large.

Step2: Calculate the upper and lower boundaries, the median, the lower quartile $Q1$, the upper quartile $Q3$, define $IQR$=$Q3$-$Q1$.

Step3: When the sample data $z_{ij}$ is less than ($Q1_j$ - 1.5$IQR_j$) or $z_{ij}$ is greater than ($Q3_j$ + 1.5$IQR_j$), $j$=1,2,...,$m$+$n$. It indicates that $z_i$ is an outlier sample. Then delete $z_i$. Otherwise, $z_i$ is reserved.

After data preprocessing, 448 sets of sample remain.

### 4.2. The generalized regression neural network algorithm

The GRNN neural network has strong nonlinear mapping capability, high fault tolerance and robustness. The network eventually converges to the optimized regression surface with more sample accumulation, which is suitable for solving nonlinear problems [13]. And GRNN is suitable for small sample data. To establish the data-based models, GRNN algorithm is adopted. For a given sample set $(x_i; y_i)_{i=1}^N$, three data-based models in regard with yields, specific surface area and materia layer thickness are expected to be established. The feed volume, grinding roller pressure, separator speed and temperature difference between the mill inlet and outlet are taken as input, yield, specific surface area and material layer thickness are taken as the output. The GRNN model is shown in Fig 4.

Suppose the input variable of the network is $X = [x_1, x_2, \cdots, x_m]^T$, and the output variable of the network is $y \in R$. In this experiment, the number of input layer neurons is equal to the dimension of the input vector in the training sample $m$, the number of pattern layer neurons is equal to the number of training samples $k$, and the number of output layer neurons is equal to the dimension of output vectors in the training sample.

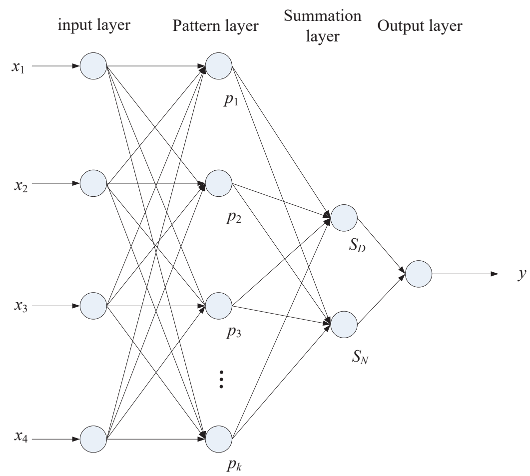



Figure 4: GRNN neural network

The data processing flow is as follows:

Input layer: Input test samples, the number of node is equal to dimension of the sample.

Pattern layer: Calculate the value of the Gauss function about each sample in the training sample and the the label sample. The number of nodes is equal to the number of training samples. Gauss function value ($p_i$) between the *i*th test sample and the *j*th training sample could be calculated as Eq.(3).

$$p_i = \exp\left[-\frac{\left(Xte_j - Xtr_i\right)^T\left(Xte_j - Xtr_i\right)}{2\sigma^2}\right] \quad i = 1,2,\cdots,k; j = 1,2,\cdots,n \qquad (3)$$

where $\sigma$ is the smooth factor, $Xte_j$ is the input vector which is a test sample. $Xtr_i$ is a train sample, corresponding to the *i*th neuron. $Xte$ connects input layer serially. $k$ is the number of train sample. $n$ is the number of test sample.

Summation layer: Two types of neurons are used for summation in the summation layer, one is $S_D = \sum_{i=1}^{k} p_i$, another is $S_N = \sum_{i=1}^{k} y_i p_i$, where $y_i$ is $i$-th sample output.

Output layer: Finally, the output of the GRNN is: $\hat{y} = \frac{S_N}{S_D}$.

Using the above method, the models of yield, specific surface area and material layer thickness are established respectively. The model of yield is $f_1 = \frac{S_{N1}}{S_{D1}}$, the model of specific surface area is $f_2 = \frac{S_{N2}}{S_{D2}}$, and the model of material layer thickness is $f_3 = \frac{S_{N3}}{S_{D3}}$.

### 4.3. Simulation results of GRNN

A total of 448 sets of data were collected in this experiment. The first 300 sets of data are used for the training of GRNN, and the remaining 148 sets of data are tested. The feed volume ($X_1$), grinding roll pressure ($X_2$), separator speed ($X_3$) and temperature difference between mill inlet and outlet ($X_4$) are taken as input, and yield, specific surface area and material layer thickness are taken as the output respectively. Shown as in Table 2, the number of neurons in the input layer is $N_i = 4$, the number of neurons in the pattern layer is $N_p = 300$, the number of neurons in the summation layer is $N_s = 2$, and the number of neurons in the output layer is $N_o = 1$. Given smooth factors $\sigma_1 = 0.1$, $\sigma_2 = 0.2$ and $\sigma_3 = 0.1$, modelling results of yield $f_1$, specific surface area $f_2$ and material layer thickness $f_3$ are shown in Fig 5-7:

Table 2: Parameters of GRNN

| Model | $N_i$ | $N_p$ | $N_s$ | $N_o$ | $\sigma$ |
|---|---|---|---|---|---|
| Yield | 4 | 300 | 2 | 1 | 0.1 |
| Specific surface area | 4 | 300 | 2 | 1 | 0.2 |
| Material layer thickness | 4 | 300 | 2 | 1 | 0.1 |

Mean square error (MSE), mean absolute error (MAE) and average relative error (MRE) are used to evaluate three models. The result is shown in Table 3.

## 5. Optimizing with multi-objective algorithm

### 5.1. Brief introduction of NSGAII

The above established models are nonlinear, and the variables are continuous. NSGAII algorithms [22] show good performance in handling with optimization problems based on nonlinear models.

NSGAII adopts elite strategy, which not only guarantees the uniform distribution of non-inferior optimal solutions, but also improves the calculation speed. The NSGAII

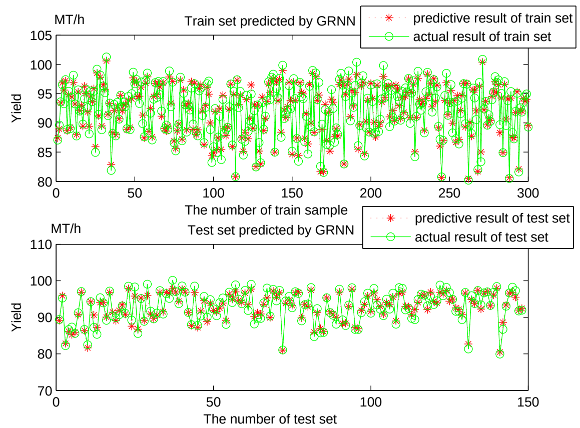



Figure 5: Simulation of yield

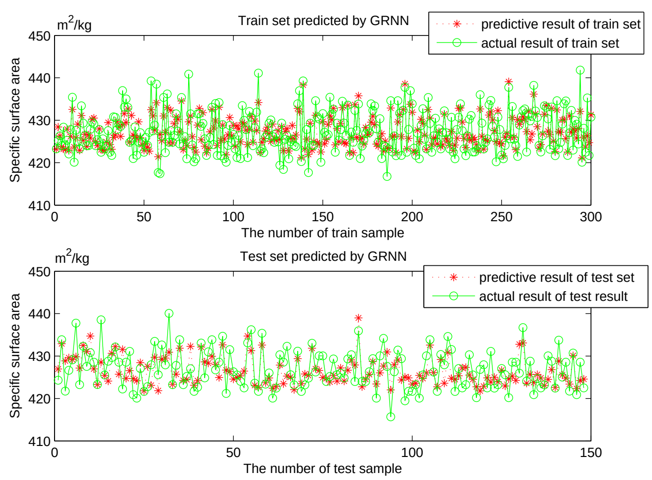



Figure 6: Simulation of specific surface area

algorithm is widely applied to many occasions and it is one of the best algorithms to this day [22]. The NSGAII algorithm flow is as follows:

Step1: The initial population $P_0$ is randomly generated and then sorted by non-dominated rule. Set population size $N = 200$. $P_0$ is composed of 100 individuals. Each individual represents a four-dimensional vector. After the stratification, new population $P_0^{'}$ is obtained by selection, cross and mutation operations. Then $P_0$ and $P_0^{'}$ are merged

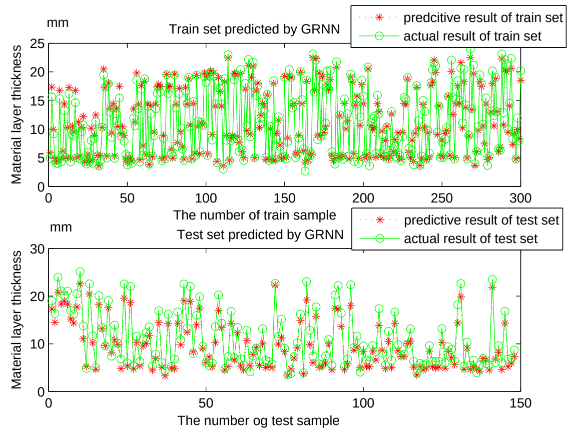



Figure 7: Simulation of material layer thickness

into a new population $Q_0$, $Q_0 = P_0 \bigcup P_0^{'}$.

Step2: Fast non-dominated sorting for $Q_0$. Two parameters ( $D_q$, $N_q$ ) are set for every individual in the population $Q_0$. $D_q$ is the set of all individuals that $q$ dominates. $N_q$ is the number of individuals who dominate $q$. $D_q = \{j|q \succ j; \quad q, j \in Q_0\}$, $N_q = |\{k|k \succ q; \quad q, k \in Q_0\}|$. The algorithm searches the population $Q_0$ to get all the non-dominated solutions and puts them into the set $F_1$. $F_1$ is the first level of individuals. Then, for every individual in $F_1$, the corresponding set $D_q$ is searched. The parameter $N_l$ of each individual in $D_q$ is reduced by 1. $N_l$ is the number of individuals who dominate individual $l$. If $N_l$-1 is 0, the individual $l$ is non-dominated in the set $D_q$. The individual $l$ is put into the set $F_2$ and the $F_2$ is the second level. So the set of different levels can be obtained according to above algorithm.

Step3: Calculate the crowding distance and sort all the individuals in the non-dominated solution set.

Step4: Choose the best $N$ individuals in $Q_0$ to form a new population $P_1$. Then sort $P_1$ by non-dominated order and calculate the crowding distance to get $P_2$. When maximum number of iterations is reached or other termination conditions are met, the algorithm stops.

Table 3: Index results of models

| Index \ Model | $f_1$ | $f_2$ | $f_3$ |
| --- | --- | --- | --- |
| MSE(train) | 0.6575 | 9.0121 | 0.7127 |
| MSE(test) | 1.0799 | 12.0305 | 2.9075 |
| MAE(train) | 0.6191 | 2.3065 | 0.6437 |
| MAE(test) | 0.8125 | 2.7353 | 1.4216 |
| MRE(train) | 0.67% | 0.54% | 6.79% |
| MRE(test) | 0.88% | 0.64% | 13.34% |

### *5.2. Improved NSGAII using clustering-based truncation*

In NSGAII, environmental selection used fast non-dominated sorting and crowding distance to select elite solutions. However, in order to obtain non-dominated solutions with good diversity, inspired by [23, 24], clustering-based truncation is introduced into environmental selection to select the solutions in the last front. The CT-NSGAII algorithm has made following modifications mainly in environmental selection compared with original NSGAII.

First, offspring population $O$ is evaluated combined with the parent population $P$. Then sorted to different layers according to the non-dominated relationships ($F_1$,$F_2$, $\ldots$,$F_l$). Where $l$-th layer is the last accepted layer that cannot be fully accommodated. In this case, only these solutions with good performance will be selected to next generation according to the second selection criterion. Second, the truncation procedure is performed as follows.

1) A set of uniformly distributed reference vectors $W$ is generated [25]. The number of reference vector $W$ is defined as follow:

$$W = \left\{ \begin{matrix} M+p-1 \\ p \end{matrix} \right\} \tag{4}$$

Where $M$ is the number of objective, $p$ is the divisions of each objective.

2) For each solution in the last layer $\mathrm{F}_l$, the objectives are translated as:

$$f_i = (f_i - z_{min}) \Big/ \sum_{j=1}^{m} (f_i - z_{min}) \quad \forall i \in \{1, 2, \cdots, m\} \tag{5}$$

where $f_i$ is the objective function value, $z_{min}$ is the minimum value in each objective.

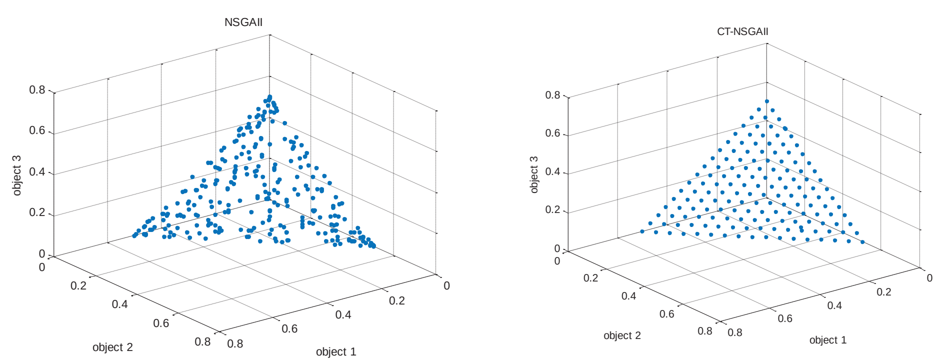
3) The vertical distance metric between each solution and reference vector is calculated as follows:

$$dis = d\,(i, w) \tag{6}$$

where $i$ represents the $i$-th solution, $w$ is reference vector.

The smaller value of $dis$, the better quality of solution $i$ will be. Therefore, after computing the distance metric $dis$ for each solution in $\mathrm{F}_l$, the set $\mathrm{F}_l$ is sorted in descending order with respect to $dis$. Finally, first $k$ elements of the sorting set are included into $P$.

The simulation results of NSGAII and CT-NSGAII in DTLZ1 problem are shown in the Fig 8. It shows that the proposed CT-NSGAII algorithm can obtain Pareto solutions with better diversity for the 3-objetives DTLZ1 problem.




($a$) ($b$)

Figure 8: NSGAII and CT-NSGAII results in DTLZ1 problem

### 5.3. *Simulation results of multi-objective algorithm*

Set the population size $N = 200$ and the maximum number of iteration steps $t = 400$ in NSGAII algorithms. Each individual represents a four-dimensional vector. Simulation result of two multi-objective optimization algorithms is shown in Fig 9:

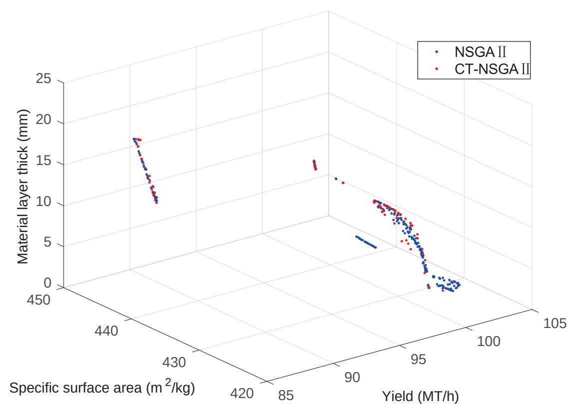



Figure 9: Simulation results of NSGAII and CT-NSGAII algorithms

HV index: Hypervolume [26] evaluation index is a comprehensive performance evaluation index. The HV is used to represent the coverage of Pareto solution set in a certain area. Suppose $P = \{a, b, c\}$ is a set of Pareto solutions and the reference point $R$ is an individual with the worst objective function value. Reference point $R$ will form a hypercube $V_i$ with every point $i$ in $P$. The equation is as follows:

$$HV = volume\left(\sum_{i=1}^{|P|} V_i\right) \tag{7}$$

$|P|$ represents the number of Pareto solution sets. The greater the value of HV, the better the convergence and diversity of the algorithm is.

Obtained pareto fronts, HV was used to evaluate the performance of NSGAII and CT-NSGAII. Reference point is $(0, 0, 0.5)$. The HV index of NSGAII is 0.8802. The HV index of CT-NSGAII is 0.8901. It can be seen that CT-NSGAII is better than NSGAII in convergence and diversity.

### 5.4. Selection of optimal solution from Pareto front

According to the results in the Fig 10, the pareto front can be roughly divided into $\alpha$, $\beta$ and $\gamma$ regions. In the $\alpha$ region, the specific surface area is better but the yield is relative low; in the $\beta$ region, material layer thickness is almost the best, at the same time, yield and specific surface area are both in the neutral position; in the $\gamma$ region, the yield is higher but the specific surface area is relative low. Based on above analysis, $\beta$ region is selected as the optimal index. The optimal value of three objectives is $(98.39, 439.2, 13.4)$.

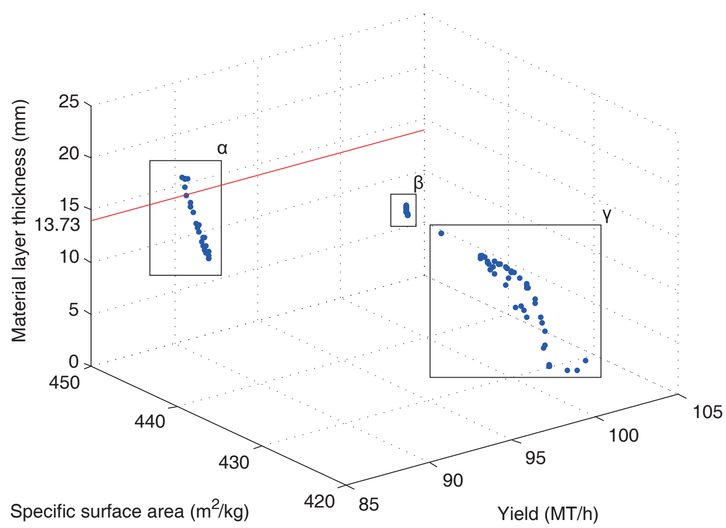



Figure 10: Result-analysis of multi-objective algorithm

## 6. Conclusion

Firstly, the slag powder process is introduced and the factors affecting the yield, specific surface area and material layer thickness are determined. The models of yield, specific surface area and material layer thickness are established by GRNN. Introducing the clustering-based truncation into environmental selection, a norval CT-NSGII algorithm is proposed to improve diversity of optimal solutions. For the optimal objectives of highest yield, best quality, and smallest material layer thickness, experiment shows that the proposed CT-NSGAII algorithm obtains better convergence and diversity compared with original NSGAII. Combing production demand with obtained Pareto solutions, optimal solution for slag powder production process is determined. This solution can be used as a setpoint for subsequent control problem and can provide a reference for predictive monitoring.

**Acknowledgments**

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