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RBF Neural Networks and Genetic Algorithms Based Optimization Control of Aluminum Powder Nitrogen Atomization Process

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Abstract— **Aluminum powder nitrogen atomizing process is with nonlinearities, large time delay, strong coupling and severe uncertainty, thus it is difficult to obtain the deterministic model and implement process optimization control by conventional methods. In this paper, the optimization control of aluminum powder nitrogen atomization process is presented to improve the fine powder rate. The process model of nitrogen atomization is established using RBF neural networks and the set values of control variables are optimized dynamically by means of implement of the optimization strategy based on enhanced genetic algorithms. Comparisons of the aluminum powder particle size distribution before and after optimization illustrate that the implement of process optimization control can improve the effect of nitrogen atomization and promote the percentages of ultra-fine aluminum powder greatly.**

I. Introduction

NITROGEN atomization techniques offer many advantages to produce ultra-fine spherical aluminum powder, such as high security, high fine rate, good activity and sphericity of powder, and is widely applied in aluminum powder factories. Aluminum powder nitrogen atomization is a complicated nonlinear process which includes many physical and chemical processes. The mechanism of atomization is still not clear [1]. Presently, the studies of atomization technology are focused on the techniques. The qualitative experiments are implemented by researchers to illustrate the atomization effect can be influenced by some process variables including the level and temperature of melted aluminum in atomization furnace, the temperature and pressure of atomization nitrogen, and the temperature and pressure of recycled nitrogen [2], [3].

Commonly, the set values of the control variables are given according to the experience of the experts. As the aluminum powder production conditions are diversified and the original set values of control variables might not be optimal, the process optimization control should be implemented to optimize the set values of the control variables and achieve the optimal aluminum powder particle size distribution.

For aluminum powder nitrogen atomization process optimization control, modeling is a necessary problem. Aluminum powder nitrogen atomization process is with characteristics of nonlinearities, large time delay, strong coupling and severe uncertainty, thus it is difficult to obtain the deterministic model by mechanism methods.

A radial basis function (RBF) neural network offers many advantages in modeling nonlinear systems, such as global approaching, sample structure, training quickly [4]. In this paper, the nitrogen atomizing process model based on RBF neural networks is presented to estimate the aluminum powder particle size distribution by means of measurements of melted aluminum level and temperature, atomizing nitrogen temperature and pressure, and recycled nitrogen temperature and pressure [5]. Based on enhanced genetic algorithms, the optimization control of aluminum powder nitrogen atomization process is implemented to optimize the set values of process control variables to improve the percentages of ultra-fine aluminum powder. The optimization control algorithms is implemented on the aluminum powder nitrogen atomization production lines of a certain aluminum powder factory and the results illustrate the implement of optimization control can improve the effect of nitrogen atomization and increase the percentages of ultra-fine aluminum powder greatly.

II. Aluminum Powder Nitrogen Atomization Process Model

A. Aluminum Powder Nitrogen Atomization Process

The fundamental principle of aluminum powder nitrogen atomization is that melted aluminum is atomized to small liquid drops utilizing high-speed atomization nitrogen, and solidified to aluminum powder with cooling and protecting of recycled nitrogen. The flowchart of aluminum powder nitrogen atomization production process is shown in Fig.1. Aluminum ingots are heated in ***Melting Furnace*** up to being melted at a certain temperature, and the melted aluminum is delivered to ***Atomization Furnace*** through a guide channel

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and heated again in ***Atomization Furnace*** continuously to keep a higher atomization temperature. Through an atomization nozzle towards ***Atomization Room*** in front of the ***Atomization Furnace***, the melted aluminum is spurted to ***Atomization Room*** and the aluminum powder are atomized by action of high-pressured atomization nitrogen. The atomizing speed of melted aluminum and the size of aluminum powder can be affected by melted aluminum level and atomization nitrogen from circular Venruri distributor. With the protection and cooling of recycled nitrogen, aluminum powder solidified rapidly. The mixtures of aluminum powder and nitrogen are pulled into two ***Bag Filters***, where aluminum powder is separated with nitrogen. The purified aluminum powder are delivered to the inferior store tanks and then classified to six different cuts of powder in classification unit (***Unit B***). The whole atomization process takes place in the ***Atomization Room*** filled with recycled nitrogen. With dust removing and cooling, nitrogen separated from ***Bag Filters*** is used repetitively. Part of the recycled nitrogen is dried, compressed, heated, and sent to circular Venruri distributor as the atomization nitrogen. Fig.2 shows the structure of atomization nozzle.

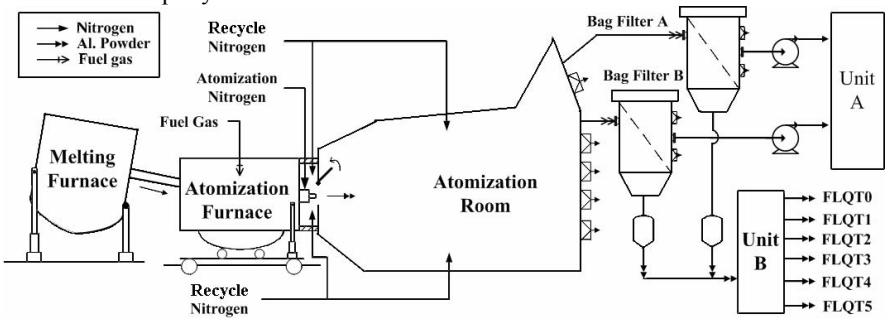

Fig. 1. Flowchart of aluminum powder nitrogen atomization process. Unit A: Nitrogen Recycle Unit; Unit B: Aluminum Classification Unit

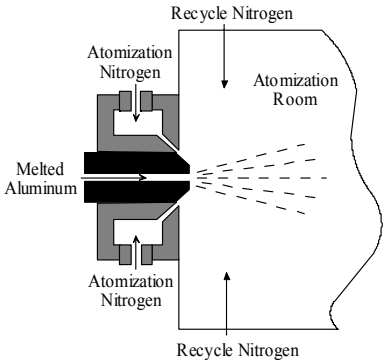

Fig. 2. the structure of nitrogen atomization nozzle

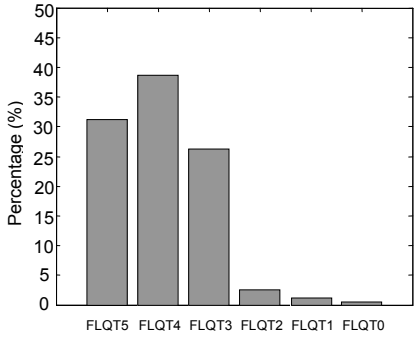

Fig. 3. The percentages of six cuts of aluminum powder

Aluminum powder nitrogen atomization production is followed by a national military criterion *"Ultra-fine Spherical Aluminum Powder Criterion*" (GJB1738-93). According to the size of middle diameter (D_{50}), there are six cuts of aluminum powder named from FLQT0 to FLQT5 (see TABLE I). The percentage of each cut of aluminum powder in gross weight is different at a sampling time of atomization production as shown in Fig.3. In this paper, the aluminum powder particle size distribution refers to the percentage distribution of each cut of aluminum powder.

TABLE I
THE CUTS OF ATOMIZED ALUMINUM POWDER

Cuts (FLQT)	0	1	2	3	4	5
D_{50}(μm)	40±5	29±3	24±3	13±2	6±1.5	2±1

B. Analysis of Factors Influencing Atomization Effect and Description of Nitrogen Atomization Process model

Besides the structure of atomization nozzle, the result of the atomization is also determined by some process variables, such as the level and temperature of melted aluminum in atomization furnace, the temperature and pressure of atomizing nitrogen, and the temperature and pressure of recycled nitrogen. There exists strong coupling and nonlinear relations among them.

1) Level of Melted Aluminum in Atomization Furnace: The gravitation of melted aluminum and the pressure of the atomization nitrogen offer the power to atomize the melted aluminum. The level of melted aluminum in atomization furnace is fluctuated continuously, which implied the optimal control variables should be revised dynamically.

2) Temperature of Melted Aluminum in Atomization Furnace: Generally, the higher temperature of the melted aluminum is, the more fine aluminum powder is atomized owing to the weaken viscosity and increased fluidity of the melted aluminum. However, longer solidification time of the aluminum powder will induce the bigger particle size owing

to the conglutination occurring in the flight process [6].

3) Pressure of Atomizing Nitrogen: A negative pressure area is formed by the high pressure atomization nitrogen at the atomization nozzle. With the higher pressure of atomization nitrogen, the melted aluminum encounters larger concussion and is atomized to finer liquid drop. However, the over-high pressure of the atomization nitrogen will cause the over-velocity of melted aluminum flow and weaken the atomization effect [2].

4) Temperature of Atomizing Nitrogen: The high temperature atomization nitrogen can not only prevent melted aluminum solidifying at nozzle but also cause increase of the nitrogen speed, which will atomize the melted aluminum to more fine liquid drops [6].

5) Pressure of Recycled Nitrogen: The recycled nitrogen in atomization room maintains feeble positive pressure to prevent the oxygen entering into the atomization devices and affect the negative pressure of the atomization nozzle.

6) Temperature of Recycled Nitrogen: The function of recycled nitrogen is cooling and protecting the aluminum powder. The solidification time is directly influenced by the temperature of recycled nitrogen, shape of aluminum powder and fine powder rate are also related with it.

Analysis of aluminum powder atomization process indicated that the percentage of each cut of aluminum powder was affected by many variables. In this paper, six variables which directly influence the aluminum powder particle size distribution, the level and temperature of melted aluminum, the temperature and pressure of atomizing nitrogen, and the temperature and pressure of recycled nitrogen, are chosen as the inputs of process model, the aluminum powder particle size distribution, that is the percentages of six cuts of aluminum powder are chosen as the prediction outputs. Then the nitrogen atomization process model can be described as

$$\begin{bmatrix} y_0(k) \\ y_1(k) \\ \cdots \\ y_5(k) \end{bmatrix} = f(L(k), T_L(k), T_A(k), P_A(k), T_E(k), P_E(k)) \quad (1)$$

where $y_0(k), y_1(k), \cdots, y_5(k)$ are corresponding to the percentages of the FLQT0, FLQT1, … , FLQT5 aluminum powder; $L(k)$ is the level of melted aluminum; $T_L(k)$ is the temperature of melted aluminum; $T_A(k)$ is the temperature of atomization nitrogen; $P_A(k)$ is the pressure of atomization nitrogen; $T_E(k)$ is the temperature of recycled nitrogen and $P_E(k)$ is the pressure of recycled nitrogen, respectively.

C. Modeling of the Nitrogen Atomization Process Based on RBF Neural Networks

RBF neural networks is a kind of 3-layer forward Networks (see Fig.4). The first layer is a signal input unit; the second is hidden layer, the units of hidden layer are nonlinear; the third is output layer, the units of this layer are linear. The transformation function in hidden layer is varied from different occasions. Theoretically, RBF neural networks have abilities of approaching arbitrary nonlinear functions [5]. The MIMO RBF neural networks showed in Fig. 3 has n input units, a hidden layer including L units, and m linear output units. The mapping of the RBF Networks f_r: $R^n \rightarrow R^m$, is defined by

$$\mathbf{y} = f_r(\mathbf{x}) = \mathbf{W}_0 + \sum_{j=1}^{L} \mathbf{W}_j \phi(\|\mathbf{x} - \mathbf{c}_j\|) \quad (2)$$

Where $\mathbf{x} \in R^n, \mathbf{y} \in R^m$, $\phi(\bullet)$ is the mapping from R^n to R; $\|\bullet\|$ is the Euclid norm; $\mathbf{W}_j$ is the weight vector $\mathbf{W}_j \in R^m, (j = 1, 2, \cdots, L)$; $\mathbf{W}_0$ is bias vector $\mathbf{W}_0 \in R^m$; $\mathbf{c}_j$ is the center vector, and $\mathbf{c}_j \in R^n, (j = 1, 2, \cdots, L)$, respectively. Here $\phi(\bullet)$ is chosen as Gaussian function of the form

$$\phi(v) = \exp(-v^2 / \sigma^2) \quad (3)$$

The width of Gaussian function is σ. Let $\mathbf{c}_0 = \mathbf{x}$, then

$$\phi(\|\mathbf{x} - \mathbf{c}_0\|) = \phi(0) = 1 \quad (4)$$

Let $\mathbf{W}_j = [W_{1j}, W_{2j}, \cdots, W_{mj}], (j = 0, 1, 2, \cdots, L)$, eqn (2) can be rewritten as

$$\mathbf{y} = f_r(\mathbf{x}) = \sum_{j=0}^{L} \mathbf{W}_j \phi(\|\mathbf{x} - \mathbf{c}_j\|) \quad (5)$$

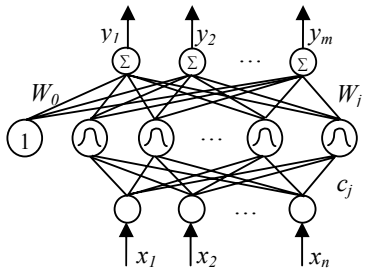

Fig. 4. The structure of MIMO RBF neural networks

Let $\mathbf{x}(k) = [L(k), T_L(k), T_A(k), P_A(k), T_E(k), P_E(k)]$ and $\mathbf{y}(k) = [y_0(k), y_1(k), \cdots, y_5(k)]^T$, from eqns (1) and (5), the aluminum powder nitrogen atomization process model based on RBF neural networks can be obtained

$$\mathbf{y}(k) = f_r(\mathbf{x}(k)) = \sum_{j=0}^{L} \mathbf{W}_j \phi(\|\mathbf{x}(k) - \mathbf{c}_j\|) \quad (6)$$

The training of RBF neural networks can be divided into two steps. Firstly, the center vector $\mathbf{c}_j$ of the excitation function in middle layer should be ascertained by the entire input sampling data; Secondly, after obtaining the parameters of middle layer, working out the weight value $\mathbf{W}_j$ through least square algorithm. Many clustering methods can be used to work out the parameters of excitation function. Among which one of the simplest and most effective methods is K-means. The weight values of Networks output can be obtained through many methods. OLS (Orthogonal Least Squares) is one of the most commonly used methods [7].

III. Optimal Control Algorithms of Aluminum Powder Nitrogen Atomization Process

Aluminum powder particle size distribution is an important quality index in production to judge the atomization effect. With the RBF neural networks process model, the optimization control of aluminum powder nitrogen atomization process can be described as

$$\begin{cases} \min F(\mathbf{x}) = J = \dfrac{1}{2}(\mathbf{y}_d - \mathbf{y})^2 \\ \quad s.t. \quad x_{i\min} \le x_i \le x_{i\max}, \quad i = 1,2,\cdots,6 \\ \qquad \mathbf{y} = f_r(\mathbf{x}) \end{cases} \tag{7}$$

where, $\mathbf{x} \in R^n$; $\mathbf{y}, \mathbf{y}_d \in R^m$; $\mathbf{x} = [L, T_L, T_A, P_A, T_E, P_E]$ is the vector of set value of parameters which will be optimized; $\mathbf{y} = [y_0, y_1, \cdots, y_5]^T$ is the vector of aluminum powder particle size distribution; $\mathbf{y}_d$ is the expectation value of aluminum powder particle size distribution which can be obtained from experience of experts; $x_{i\max}$ and $x_{i\min}$ are upper and lower limits of x_i , respectively; $f_r(\mathbf{x})$ is the process model based on RBF neural networks.

The optimization control of aluminum powder nitrogen atomization process is nonlinear programming with restriction. Although the objective function is sample, there are strong nonlinear hidden relations between restriction and decision variables of restriction condition. It's difficult to solve this kind of optimizing problems with conventional optimizing algorithms. Genetic algorithms (GAs) are guided stochastic search techniques based on the mechanics of genetics. As a global optimizing search algorithm, GAs are widely adopted to solve the complex nonlinear problem which can not be solved by conventional search algorithms [8], [9]. GAs offer several benefits, including the obviation of the need for derivatives in finding the solution (resulting in low probability for GAs getting "trapped" in local minima), the parallel search of the solution space (as opposed to a point-by-point search), and the manipulation of potential solutions (rather than the solutions themselves). In this paper, an enhanced GA is applied to solve the optimization control problem of aluminum powder nitrogen atomization process.

Generally, GA is composed of four parts, which are representation, creation of population, fitness function design and genetic operation. Three genetic operators are selection, crossover and mutation.

A. Representation

In solving optimization problems by GAs, the first task is to represent a solution of a problem as chromosome. For standard GAs, a chromosome is represented by a binary string. But this encoding method is disadvantageous to optimize set values of control variables. In this study, real number encoding is adopted to assemble the control variables which need to be optimized as a chromosome, the new encoding form can be expressed as

$$\text{Chromosome X}=[x_1, x_2, \cdots, x_n] \tag{8}$$

The length of chromosome *n* is the number of the variables need optimized. There are six variables encoded in nitrogen atomization process, the genes $x_1, x_2, \cdots, x_6$ represents level of melted aluminum, temperature of melted aluminum, temperature of atomization nitrogen, pressure of atomization nitrogen, temperature of recycled nitrogen, and pressure of recycled nitrogen, respectively.

B. Creation of Population

Initialization is done by randomly generating chromosomes representing the GAs' population. For real encoding is adopted for our problem and each chromosome contains six genes which correspond to the variables in the vector solution, the generated random real numbers have a range obtained from the experts' experience.

C. Fitness Function Design

Each chromosome is evaluated based on a fitness function. The fitness function is developed in a way that accurately determines how close the randomly generated solutions are to the optimal solution. Generally, fitness function can be obtained by mapping objective function directly. Our problem is a nonlinear programming with restriction, and objective function need to be rebuilt to the non-negative max format to map the fitness function.

For the aluminum powder nitrogen atomization process, the anticipant aluminum powder particle size distribution is to obtain the maximum percentages of fine aluminum powder (FLQT3-FLQT5) and the minimum percentages of rough aluminum powder (FLQT0-FLQT2). So the objective function can be transformed as

$$\begin{cases} \max F(\mathbf{x}) = J = \sum_{n=3}^{5} y_n \\ \quad s.t. \quad x_{i\min} \le x_i \le x_{i\max}, \quad i = 1, 2, \cdots, 6 \\ \qquad y_n = f_{rn}(\mathbf{x}), \quad n = 0, 1, \cdots, 5 \end{cases} \tag{9}$$

The objective function can be written as

$$\begin{cases} \max F(\mathbf{x}) = J = \sum_{n=3}^{5} f_{rn}(\mathbf{x}) \\ \quad s.t. \quad x_{i\min} \le x_i \le x_{i\max}, \quad i = 1, 2, \cdots, 6 \end{cases} \tag{10}$$

Introducing the punishment function d_i with inequality restriction

$$d_i(x_i) = \begin{cases} 1 & if \quad x_{i\min} \le x_i \le x_{i\max} \\ 0 & otherwise \end{cases} \tag{11}$$

Introducing of the punishment function d_i, the restriction can be included in the fitness function, and the optimization problem is transformed into the nonlinear programming problem without inequality restriction.

$$\max F(\mathbf{x}) = J = \sum_{n=3}^{5} f_{rn}(\mathbf{x}) \prod_{i=1}^{6} d_i \tag{12}$$

For an arbitrary individual (chromosome) which

dissatisfied with inequality restriction, the output of punishment function is d_i=0 and the corresponding target function value (fitness) is zero too. As a result, this individual will lose its chance of reproduction in genetic operation, which guaranteed the validity of optimal solution.

D. Genetic Operators

1) Selection: Selection operator is a basic operator of genetic algorithms. It is operated on the basis of the survival of the fittest individuals. In each generation, the chromosome of the current population is selected and reproduced in the next generation according to the selection probability P_{si}, which is defined as

$$P_{si} = \frac{F(\mathbf{x}_i)}{\sum_{i=1}^{P_l} F(\mathbf{x}_i)} \tag{13}$$

where P_l is the population size. It is shown that the higher fitness value, the higher selection probability.

2) Crossover: Crossover performs to exchange the information of any two chromosomes via probabilistic decision and provides a mechanism to mix and match the desirable qualities through a random process. Uniform crossover operator is adopted in our problem, and the genes of offspring individuals are determined by two parent individuals and a randomly generated mask word. TABLE II shows the procedures of the uniform crossover, the offspring individual X' is built of the genes of the parent individual X and Y which corresponding to the "1" and "0" bits in the mask word, respectively. In the same way, the offspring individual Y' is built of the genes of the parent individual X and Y which corresponding to the "0" and "1" bits in the mask word, respectively.

TABLE II
THE UNIFORM CROSSOVER OPERATION OF PARENT INDIVIDUALS X AND Y

Parent individual X	X_1	x_2	x_3	x_4	x_5	x_6
Parent individual Y	y_1	y_2	y_3	y_4	y_5	y_6
Mask	1	0	1	1	0	1
Offspring individual X'	x_1	y_2	x_3	x_4	y_5	x_6
Offspring individual Y'	y_1	x_2	y_3	y_4	x_5	y_6

3) Mutation: For real number representation, the disturbance mutation is widely applied. A stochastic disturbance is adding on the gene with the point determined uniformly at random according to the mutation probability P_m.

To ensure the validity of the gene after adding disturbance, the random disturbance is given by the following eqn

$$\Delta x_i = random(x_{i\min}, x_{i\max}) - x_i \tag{14}$$

After adding disturbance, the gene's value changed to

$$x_i' = x_i + \Delta x_i = random(x_{i\min}, x_{i\max}) \tag{15}$$

In this way, the individual will be valid after mutation.

E. Optimization Strategy

Among the six input variables of aluminum powder atomization process model, the level of melted aluminum is a measurement variable and the others are control variables. The level of melted aluminum is fluctuating continuously, and different level is corresponding to different optimal set values of control variables.

The optimization strategy is to select a group of points in the range of the level, and optimization search will be implemented at the level points selected. Corresponding to each control variable, a curve of optimal set values is obtained by using linear interpolation. The set values of control loops are updated dynamically by the curve of optimal set values, and the production process runs under an optimal work condition.

As one of the input variables of process model, the level of melted aluminum in atomization furnace is a gene on the chromosome. As the inequality restriction, the upper limit and lower limit of the level is set as the same one in order to hold the gene invariable during the optimization process. The optimal solution is the optimal set values of the control variables at this level condition.

IV. IMPLEMENT AND EFFECT OF OPTIMAL CONTROL

The optimization control algorithm is implemented on the aluminum powder nitrogen atomization production lines of an aluminum powder factory. The process control system is composed of optimization layer and control layer (see Fig.5). The aluminum powder nitrogen atomization process model based on RBF neural networks and optimization algorithms are included in optimization layer. The process model simulates the characteristics of the production process and offers the restriction conditions for the process optimization algorithms. A curve of optimal set values of control variables can be given by the optimization algorithms. The set values of control loops in the control layer are updated dynamically by the curve of optimal set values, and the production process runs under an optimal work condition.

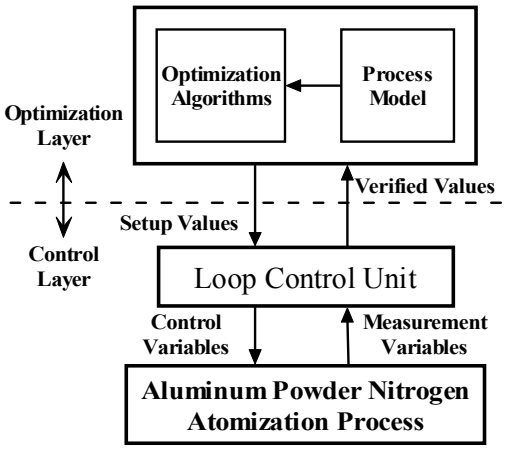

Fig. 5. The structure of aluminum powder nitrogen atomization process optimization control system

The weights and center vectors of the neural networks model are trained offline, so the validity of the model should

be guaranteed by means of verifying periodically, and the curve of optimal set values are revised through re-implementing the optimization search procedure.

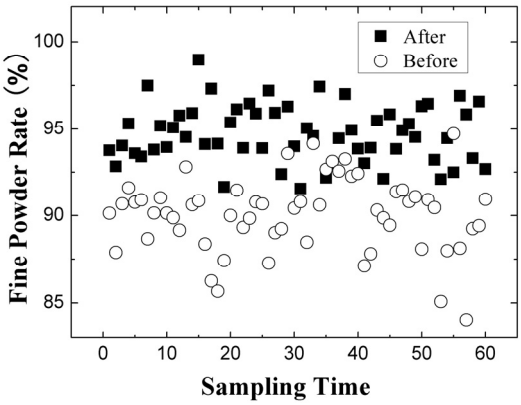

Fig. 6. The comparison of fine powder rate before and after optimization

The aluminum powder nitrogen atomization process optimization control system has been put into use two years over, and the effect of implementing is satisfying. Fig.6 shows the fine powder rate increases obviously and the distribution is concentrative after optimization. The analysis of aluminum powder particle size distribution illustrates that the percentages of the ultra-fine aluminum powder is improved about 8% (see TABLE III).

TABLE III
THE ALUMINUM POWDER PARTICLE SIZE DISTRIBUTION BEFORE AND AFTER OPTIMIZATION

Cuts (FLQT)	0	1	2	3	4	5
Before	1.356	2.622	8.921	35.490	29.923	21.688
After	0.584	0.930	3.480	23.026	38.925	33.055

V. CONCLUSIONS

In this paper, the optimization control of aluminum powder nitrogen atomization process is presented to improve the fine powder rate. The process model of nitrogen atomization is established using RBF neural networks and the set values of control variables are optimized dynamically by means of implementing of the optimization strategy based on enhanced genetic algorithms. From comparisons between the aluminum powder particle size distribution and the fine powder rates, the effect of nitrogen atomization is improved obviously and the percentage of super-tiny aluminum powder is promoted about 8% and the stability of the production process is promoted with the implementation of the optimization control.

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