AN IMPROVED MULTI-OBJECTIVE EVOLUTIONARY OPTIMIZATION ALGORITHM FOR SUGAR CANE CRYSTALLIZATION

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Abstract- The nature of optimization for intermittent sugar cane crystallization process is to obtain ideal crystals. One typical difficulty in crystallization optimization refers to the simultaneous effects of both seeding characters and process variables on the final crystal size distribution (CSD) parameters, including mean size (MA) and coefficient of variation (CV). And the application of traditional multi-objective evolutionary algorithm in crystallization process could not optimize all of them. Therefore, this paper puts forward a different multi-objective framework, and correspondingly, an improved optimization algorithm is applied to intermittent sugar cane crystallization. This method combines the elitist non-dominated sorting genetic algorithm (NSGA-II) with technique for order preference which is similar to an ideal solution (TOPSIS), and it provides a quantitative way to analyze the effect of both seed characteristics and process variables on the trade-off between MA and CV. Furthermore, the proposed algorithm has been adapted here to be compared with the NSGA-II, and the comparing results demonstrate better Pareto-optimal solutions of the novel approach.

Index terms*: Multi-objective optimization, Intermittent sugar cane crystallization, NSGA-II, TOPSIS.*

I. INTRODUCTION

The purpose of an optimized crystallization process is to obtain a ideal crystal size distribution (CSD), which is a significant index in the quality of crystalline production. The optimized crystallization process is carried out by setting the CSD parameter in advance as the final product quality index. And the CSD parameter expressed by the final mean size (MA) of crystals, the respective final size distribution, and the coefficient of variation (CV).

The optimization of intermittent sugar cane crystallization has been traditionally conducted with the respect to the temperature trajectory. By optimizing the temperature trajectory, a wide variety of techniques have been applied to achieve the optimum property of product crystals. For example, in 1994, Miller and Rawlings [1], utilizing the model identification method for assessing the parameter uncertainty, increased the MA of crystals compared to natural cooling crystallization process through the implementation of optimal temperature policies. And a dynamic programming formulation considered the both moment and thermodynamic equations, proposed by Yang and et al [2], was applied for the optimization of a batch crystallization process, which presented important improvement of the MA of crystals with the optimal temperature profiles. Apart from the examples presented above, other techniques using optimal temperature trajectory for achieving desired product quality are partly shown in [3-8].

Another traditional optimization approach for intermittent sugar cane crystallization process is sought with the respect to supersaturation profile. High supersaturation values yield high growth rates but also high nucleation rates which lead to an undesirable crystals, but it is the most primary and direct factor that influences the CSD. So many works have been involved to investigate the optimal supersaturation with an objective to achieve desired CSD, partly described in [9-11]. However, Supersaturation has to be detected with advanced measuring instruments that bring about tremendous initial investment to a corporation or to be measured with soft-sensor techniques, and its general replacement for optimizing is the solution concentration or conductivity. In sugar industry, the solution concentration is particularly substituted by the syrup brix. But there are other possibilities also to influence the product CSD. In particular, the initial amount and size of seed crystals and the responding properties have significant effects on the final product CSD and the effect of seeding characteristics of crystals on

the final CSD has been experimentally investigated with an objective to achieve desired CSD [12-14].

All those techniques described above hold a significant proportion of research and application in the field of optimization for crystallization processes. Nevertheless, they consider only one single objective, and the majority of real world problems often involves multiple objectives with conflicting natures each other, where crystallization processes take a typical position.

A kind of widespread typical method of handling multiple objectives is to combine them into one objective by a weighted sum approach [15]. Another method of dealing with those problem is to choose one objective as a single objective function and others are used as the constraints of this function [16, 17].

Those traditional approaches dealing with the multiple objectives still belong to the category of single-objective optimization. In order to eliminate their disadvantages essentially, a kind of multi-objective optimization approach based on Multi-objective evolutionary algorithms (MOEAs) is developed [18-20]. Among the many MOEAs, a widely adopted method is the elitist non-dominated sorting genetic algorithm (NSGA-II) [21]. In this paper, an improved multi-objective optimization approach called the twin non-dominated sorting genetic algorithm (TNSGA-II), is applied to intermittent sugar cane crystallization process. The TNSGA-II program includes two NSGA-II procedures and one technique for order preference by similarity to an ideal solution (TOPSIS) procedure. The optimization of crystallization can come true, including the optimization of seed characteristics and process variables.

II. INTERMITTENT CRYSTALLIZATION MODEL

a. Population balance

A model-based optimization strategy describing intermittent sugar cane crystallization dynamics typically involves the solution of population balance equations, where nucleation, growth and agglomeration mechanisms are accounted for [22]. In this section, the solution procedures of the model equations can be outline and the multi-objective optimization problem appeared in the intermittent sugar crystallization process can also be formulated.

The population balance represented by Eq. (1) and the subsequent transformations leading to moment equations (6) are based on the theory published by Hulburt and Katz [23] and Randolph

and Larson [24]. The population balance equation in volume coordinate system is given by the following partial differential equation:

$$\frac{\partial n(v)}{dt}+\frac{\partial G_v n(v)}{dv}=B(v)-D(v) \tag{1}$$

where $n(v)$ is the number-volume distribution function, G_v is the overall volume growth rate, $B(v)$ is the birth rate function, $D(v)$ is the death rate function. The expressions are as:

$$G_v=3k_v^{1/3}\left(\frac{v}{m_0}\right)^{2/3}G \tag{2}$$

$$B(v)=\frac{1}{2}b'\int_0^v n(u)n(v-u)du \tag{3}$$

$$D(v)=b'\int_0^\infty n(v-u)du \tag{4}$$

Where k_v is the volume shape factor of the sugar crystallizer, v is the crystal volume, G is the linear growth rate, β' is the agglomeration kernel at any time for the crystallizer volume. Define the j -th moment of a crystal number-volume distribution function by

$$u_j(v)=\int_0^\infty v^j n(v)dv \tag{5}$$

And a procedure developed by Hulburt and Katz for conveniently modeling purposes is then carried out to substitute the Eq. (1) with a set of ordinary differential equations representing the distribution moments in a coordinate system. The equations is shown as follow:

$$\frac{dm_j(v)}{dt}=G_v\left[jm_{j-1}-n(v)v^j\Big|_0^\infty\right]+b'\left[\frac{1}{2}\left(\sum_{k=0}^{j}\binom{j}{k}m_k m_{j-1}\right)-m_0m_j\right] \tag{6}$$
$$j=0,1,2,\cdots$$

In order to model the population balance for the intermittent sugar crystallization process, the four moments from Eq. (6) are derived as

$$\frac{dm_0}{dt}=B_0-\frac{1}{2}b'm_0^2 \tag{7}$$

$$\frac{dm_1}{dt}=G_v m_0 \tag{8}$$

$$\frac{dm_2}{dt}=2G_v m_1+b'm_1^2 \tag{9}$$

$$\frac{dm_3}{dt} = 3G_v m_2 + 3b' m_1 m_2 \tag{10}$$

Among them， B_0 is the nucleation rate. According to the derivative of the first moment, the crystallization rate is determined as:

$$\frac{dM_c}{dt} = \rho_c \frac{du_1}{dt} \tag{11}$$

And according to Eq. (2) and Eq. (8), Eq. (11) is further deduced as

$$\frac{dM_c}{dt} = 3(k_v r_c m_0)^{1/3} (M_c)^{2/3} G \tag{12}$$

In the process of solving the population balance, the linear growth rate G , the nucleation rate B_0 and the agglomeration kernel β' are the kinetic parameters that reflect the crystallization mechanism. And the three kinetic parameters are given by the following empirical correlations.

$$G = K_g \exp\left[-\frac{57000}{R(T_m + 273)}\right](S-1) \times \exp\left[-13.863(1-Pur)\right]\left(1+2\frac{v}{V_m}\right) \tag{13}$$

$$B_0 = K_n \times 2.894 \times 10^{12} G^{0.51} \left(\frac{m_1}{k_v V_m}\right)^{0.53} V_m \tag{14}$$

$$b' = K_{ag} G \left(\frac{m_1}{k_v V_m^2}\right) \tag{15}$$

where R is the gas constant, T_m is the massecuite temperature, S is the syrup supersaturation in the sugar crystallizer, Pur is the syrup purity in the crystallizer, V_m is the massecuite volume, and K_g , K_n , K_{ag} are respectively the kinetic constants of crystal growth, nucleation and agglomeration.

b. CSD model

Obtaining the CSD parameter (namely the MA and the CV) is the key to solve the population balance. A mathematical model of the CSD needs to be established for obtaining the two parameters. Mathematically, the j -th moment of the mass-size distribution is defined as

$$h_j(L) = \int_0^\infty L^j m(L) dL, \quad j = 0,1,2,3,\cdots \tag{16}$$

Where L is the crystal size and $m(L)$ is the mass-size distribution functions. Then the MA is determined by

$$MA = \bar{L} = \int_0^\infty Lm(L)dL \Big/ \int_0^\infty m(L)dL \tag{17}$$

Namely:

$$MA = \eta_1 / \eta_0 \tag{18}$$

And CV is determined by

$$CV = \frac{\sigma}{\bar{L}} \tag{19}$$

Where σ is given by the following equation

$$\sigma^2 = \frac{1}{\eta_0} \int_0^\infty \left(L - \bar{L}\right)^2 m(L)dL \tag{20}$$

According to Eq. (17), Eq. (18) and Eq. (20), the Eq. (19) is derived as

$$CV = \left(\eta_0 \eta_2 / \eta_1^2 - 1\right)^{1/2} \tag{21}$$

Eq. (18) and Eq. (21) imply that it is relevant to find out the definitions and relationships between the $m(L)$, $n(v)$ and the number-size distribution function ($n(L)$).And the equations are as follow:

$$v = k_v L^3 \tag{22}$$

$$n(L) = n(v)dv \tag{23}$$

$$m(L) = \rho_c k_v n(L) / M_C \tag{24}$$

Substituting Eqs. (22)-(24) into Eq. (16), a relation between $u_j(v)$ and $\eta_j(L)$ is obtained as

$$h_j = \frac{1}{M_c}\left(\frac{r_c}{k_v^{k-1}} m_k\right) \qquad k = \frac{j}{3} + 1, j = 0, 3, 6, \cdots \tag{25}$$

Based on the theory of Randolph and Larson [34], the j th moment of a normal distribution can be defined as a function of the $\bar{L}$ and the s :

$$h_j(L) = \sum_r \left[\left(2^{1/2} s\right)^{j-r} \left(\bar{L}\right)^r \frac{j! \times 1 \times 3 \times \ldots \times (j-r-1)}{(j-r)! 2^{(j-r)/2}} \right] \tag{26}$$

Where $r = 0, 2, 4, \cdots, j$ for j even and $r = 1, 3, 5, \cdots, j$ for j odd. To solve MA and CV, the third and the sixth mass-size distribution moments of Eq. (26) are derived as

$$h_3/\bar{L} = 1+3\left(\frac{s}{\bar{L}}\right)^2 \tag{27}$$

$$h_6/\bar{L} = 1+15\left(\frac{s}{\bar{L}}\right)^2 + 45\left(\frac{s}{\bar{L}}\right)^4 + 15\left(\frac{s}{\bar{L}}\right)^6 \tag{28}$$

Let

$$X = \left(\frac{s}{\bar{L}}\right)^2 \tag{29}$$

Solving together Eqs. (19), (27), (28) and (29) leads to

$$15h_3^2X^3 + \left(45h_3^2 - 9h_6\right)X^2 + \left(15h_3^2 - 6h_6\right)X + h_3^2 - h_6 = 0 \tag{30}$$

$$\mathrm{CV} = \sqrt{X} \tag{31}$$

$$\mathrm{MA} = \left(\frac{h_3}{1+3X}\right)^{1/3} \tag{32}$$

III. MULTI-OBJECTIVE OPTIMIZATION ALGORITHM

From the implementation procedure of modeling CSD, it is obviously known that the final product quality does not only have tight relationship with process variables (mainly including massecuite temperature, syrup supersaturation, syrup purity, crystal volume and massecuite volume), but also the seeding characters, expressed by the initial first two moments of the crystal number-volume distribution and the mass. In order to solve the multi-objective optimization problem in sugar crystallization process, three formulations that are related to the quality of product CSD have been studied by Debasis Sarkar, Sohrab Rohani and Arthur Jutan [25].

The MA and CV of product CSD and the seeding characters are not all simultaneously included in the three formulations. So in the case of a seeded intermittent sugar cane crystallization process, the three formulations are not suitable here when considering the process variables and all seeding characters and the two objectives of MA and CV are not directly represented. By the way, the number and size of seeding characters can be transformed into the first two initial moments of the crystal number-volume distribution. Therefore, in this paper, a different multi-objective optimization algorithm is put forward for the seeded intermittent sugar cane crystallization process, which can be stated as:

$$
\begin{aligned}
&\text{Maximize} \quad J_1 = \mathrm{MA} \\
&\text{Minimize} \quad J_2 = \mathrm{CV} \\
&\text{subject to} \quad g_1(t) = T_m^{\min} \le T_m \le T_m^{\max} \\
&\qquad g_2(t) = \frac{dT}{dt} \ge 0 \\
&\qquad g_3(t) = S_s \le S \le S_m \\
&\qquad g_4(t) = Pur_{\min} \le Pur \le Pur_{\max} \\
&\qquad g_5(t) = v_{\min} \le v \le v_{\max} \\
&\qquad g_6(t) = V_m^{\min} \le V_m \le V_m^{\max} \\
&\qquad g_7(t) = m_0^{\min} \le m_0 \le m_0^{\max} \\
&\qquad g_8(t) = m_1^{\min} \le m_1 \le m_1^{\max} \\
&\qquad g_9(t) = m_2^{\min} \le m_2 \le m_2^{\max} \\
&\qquad g_{10}(t) = m_3^{\min} \le m_3 \le m_3^{\max} \\
&\qquad g_{11}(t) = M_{seed}^{\min} \le M_{seed} \le M_{seed}^{\max}
\end{aligned}
\tag{33}
$$

In accordance with modeling the sugar crystallization process, a method is put forward to make the optimization achievable by dividing the formulation into two sub-formulations, which are shown as

$$
\begin{aligned}
&\text{Maximize} \quad J_1 = \mathrm{MA} \\
&\text{Minimize} \quad J_2 = \mathrm{CV} \\
&\text{subject to} \quad g_1(t) = m_0^{\min} \le m_0 \le m_0^{\max} \\
&\qquad g_2(t) = m_1^{\min} \le m_1 \le m_1^{\max} \\
&\qquad g_3(t) = m_2^{\min} \le m_2 \le m_2^{\max} \\
&\qquad g_4(t) = m_3^{\min} \le m_3 \le m_3^{\max} \\
&\qquad g_5(t) = M_{seed}^{\min} \le M_{seed} \le M_{seed}^{\max}
\end{aligned}
\tag{34}
$$

$$
\begin{aligned}
&\text{Maximize} \quad J_1 = \mathrm{MA} \\
&\text{Minimize} \quad J_2 = \mathrm{CV} \\
&\text{subject to} \quad g_1(t) = T_m^{\min} \le T_m \le T_m^{\max} \\
&\qquad\qquad g_2(t) = \frac{dT}{dt} \ge 0 \\
&\qquad\qquad g_3(t) = S_s \le S \le S_m \\
&\qquad\qquad g_4(t) = Pur_{\min} \le Pur \le Pur_{\max} \\
&\qquad\qquad g_5(t) = v_{\min} \le v \le v_{\max} \\
&\qquad\qquad g_6(t) = V_m^{\min} \le V_m \le V_m^{\max}
\end{aligned} \tag{35}
$$

What's more, in order to connect the two sub-formulations together, an improved algorithm named TNSGA-II is proposed in this paper.

IV. MULTI-OBJECTIVE OPTIMIZATION BY TNSGA-II

a. NSGA-II

Non-dominated genetic algorithm (NSGA) was proposed by Srinivas and Deb [26] in 1994 for solving the problems of multi-objective optimization. Thereafter, an improvement of the algorithm, namely, NSGA-II, was developed by Deb et al [27].

NSGA-II which is similar with genetic algorithm (GA) is a search-based evolutionary optimization technique inspired from the Darwin's survival principle. Different with GA, the members of the population in NSGA-II are categorized based on their rank of Pareto-optimal solutions (expressed by Pareto front) and crowding distance. Fitness is assigned to them based on their rank of non-domination and dispersion corresponding to their neighboring solutions. The mainly parameters of NSGA-II are initial population size (the number of initial chromosome) S_z, generation number of times N_g, length of chromosome (include the decision variables, objective functions, Pareto front and crowding distance) L_c, size of matching pool (the number of selecting parent chromosome) S_p, probability of crossover P_c and mutation P_m. Fig. 1 shows the basic flow of NSGA-II.

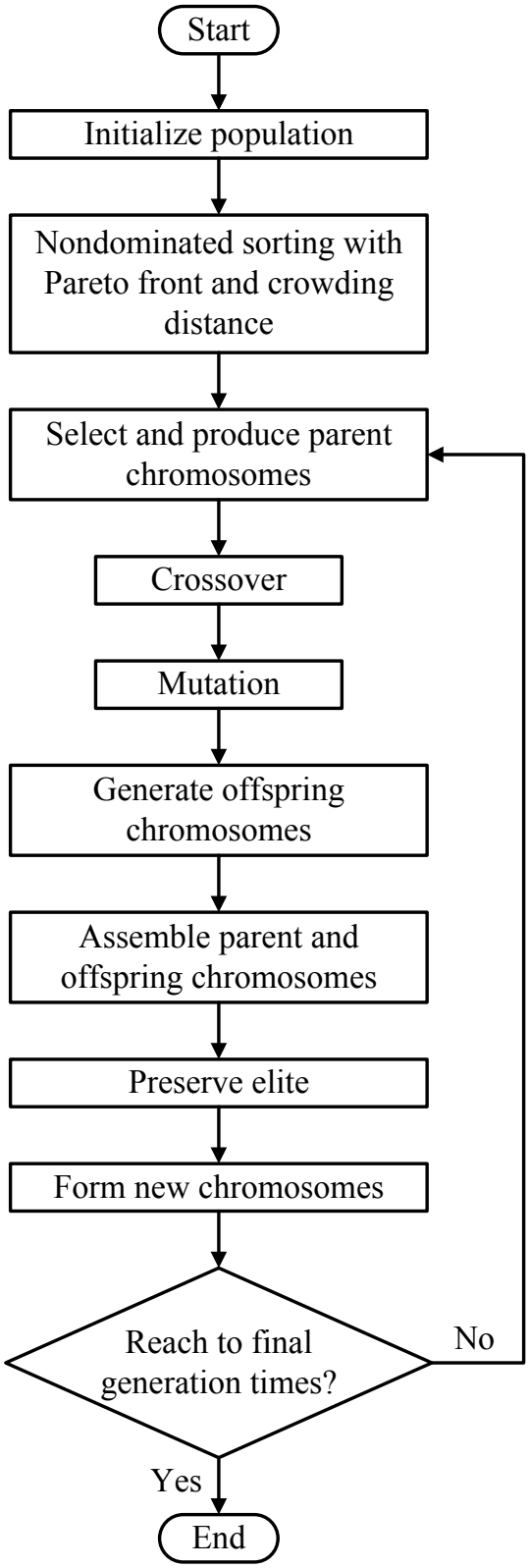


Fig. 1 NSGA-II flow

b. Modeling TNSGA-II

b.i TOPSIS

Before describing the detail of TNSGA-II, knowledge about TOPSIS is presented in this section for smoothly implementing TNSGA-II.

The TOPSIS developed by Hwang and Yoon [28] is a feasible and convenient approach for solving the problem of multiple attribute decision making (MADM), which is easy to implement. Its main purpose is to select out the final solution with the best performance which is output by a multi-objective optimization. In TOPSIS, each attribute corresponds to an objective function which is obtained from the Pareto-optimal solutions. It includes a relative decision variable vector that can be stated as $X^* = (x_1^*, x_2^*, \cdots, x_d^*)$ where d is the number of decision variables. Hence all the attributes can be represented by a $m \times n$ dimensional matrix called decision-making matrix

$$\begin{bmatrix} f_1(X_1^*) & f_1(X_2^*) & \cdots & f_1(X_n^*) \\ f_2(X_1^*) & f_2(X_2^*) & \cdots & f_2(X_n^*) \\ \cdots & \cdots & \cdots & \cdots \\ f_m(X_1^*) & f_m(X_2^*) & \cdots & f_m(X_n^*) \end{bmatrix} \tag{36}$$

Where $n = S_z$ and m is the number of objectives. Then the main procedure of TOPSIS can be followed as:

(1) Standardize decision-making matrix

The purpose of standardizing the decision-making matrix is to have the attributes with a uniform evaluation. One method to calculate each attribute value while standardizing the decision-making matrix is followed by

$$s_{ij} = \frac{f_i(X_j^*)}{\sqrt{\sum_{j=1}^{n} \left[f_i(X_j^*) \right]^2}} \tag{37}$$

Where $i = 1, 2, \cdots, m$ an $j = 1, 2, \cdots, n$. By the way, we call the decision-making matrix after standardization as standard matrix.

(2) Weight standard matrix

The element in the standard matrix after weighting is set as

$$r_{ij} = w_i s_{ij} \tag{38}$$

Before determining the value of w_i, an entropy concept based on information theory, developed by Shannon and Weaver [29], is applied in this paper to assign different weight values to different attributes. Then each attribute can be measured as

$$e_i = -\frac{1}{\ln n}\sum_{j=1}^{n} s_{ij} \ln s_{ij} \tag{39}$$

The average degree of the divergence intrinsic information can be then calculated by

$$d_i = 1 - e_i \tag{40}$$

The determined weight for each attribute is thus given by

$$w_i = \frac{d_i}{\sum_{i=1}^{m} d_i} \tag{41}$$

(3) Calculate Euclidean distance

After determining performance of each alternative and weight of each attribute, an aggregation for producing an overall performance is defined based on the positive ideal solution and the negative ideal solution:

$$\begin{aligned} \mathrm{I}^{+} &= \left(\max(r_{1j}) \quad \max(r_{2j}) \quad \cdots \quad \max(r_{mj})\right) = \left(r_1^{+} \quad r_2^{+} \quad \cdots \quad r_m^{+}\right) \\ \mathrm{I}^{-} &= \left(\min(r_{1j}) \quad \min(r_{2j}) \quad \cdots \quad \min(r_{mj})\right) = \left(r_1^{-} \quad r_2^{-} \quad \cdots \quad r_m^{-}\right) \end{aligned} \tag{42}$$

The overall performance of each alternative is determined by its distance to I^{+} and I^{-}, which can be measured by the n-dimensional Euclidean distance. Euclidean distance of the positive ideal solution is stated as

$$V_j^{+} = \sqrt{\sum_{i=1}^{m}\left(r_{ij} - r_i^{+}\right)^2} \tag{43}$$

And negative ideal solution is stated as

$$V_j^{-} = \sqrt{\sum_{i=1}^{m}\left(r_{ij} - r_i^{-}\right)^2} \tag{44}$$

(4) Obtain the final solution

After determining the Euclidean distance, the relative degree between the ideal solution and each vector can be defined as

$$C_j = \frac{V_j^{-}}{V_j^{+} + V_j^{-}}, \quad j = 1, 2, \cdots, n \tag{45}$$

According to the Eq. (43) and Eq. (44), it's obvious that $V_j^+ \geq 0$ and $V_j^- \geq 0$, and $C_j \in [0,1]$. Besides an alternative that is closer to the positive ideal solution approaches will be nearer to 1. Therefore, it's clear that of the alternative X_j^* whose C_j is the closest to 1 will be selected as the final solution. And the basic procedure of TOPSIS is followed by Fig. 2.

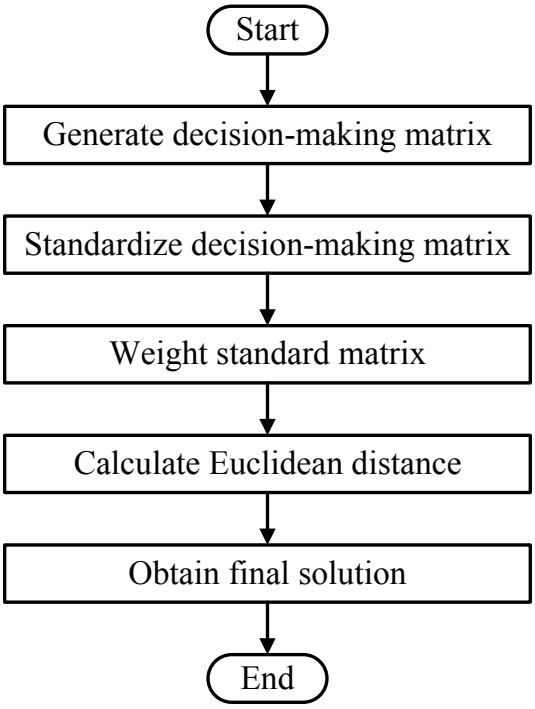


Fig. 2 TOPSIS flow

b.ii TNSGA-II

At this point, the procedure of NSGA-II and TOPSIS has been clearly implemented. This paper will combine them together to connect the two sub-formulations mentioned in section III for optimizing sugar crystallization process.

As we know, both the process variables and the seeding characters have a significant influence on the final product quality. However, we also mentioned earlier that it was difficult or even impossible to consider them simultaneously to implement the multi-objective optimization. Fortunately, the two divided sub-formulations stimulate a resolvable scheme for us and thereby an approach to connect them can be implemented by the three basic ideas:

(1) run NSGA-II for the first time by defining seeding characters as part of the genes,

(2) execute TOPSIS to obtain the final seeding characters,

(3) run NSGA-II again by defining the process variables as part of the genes. And the three basic ideas is shown in Fig. 3.

The first step in implementing TNSGA-II is to set mode of the two branching programs, which is marked with m=1 and m=2 and the initial mode is set as m=1. Thereafter a procedure of NSGA-II is first conducted and then its second time proceeding is done after the implementation of TOPSIS. The two NSGA-II procedures involve the whole basic operators and they almost have the same steps in the course of implementation. Meanwhile the two objective functions of MA and CV, Pareto-front and crowding distance are the common members of chromosomes.

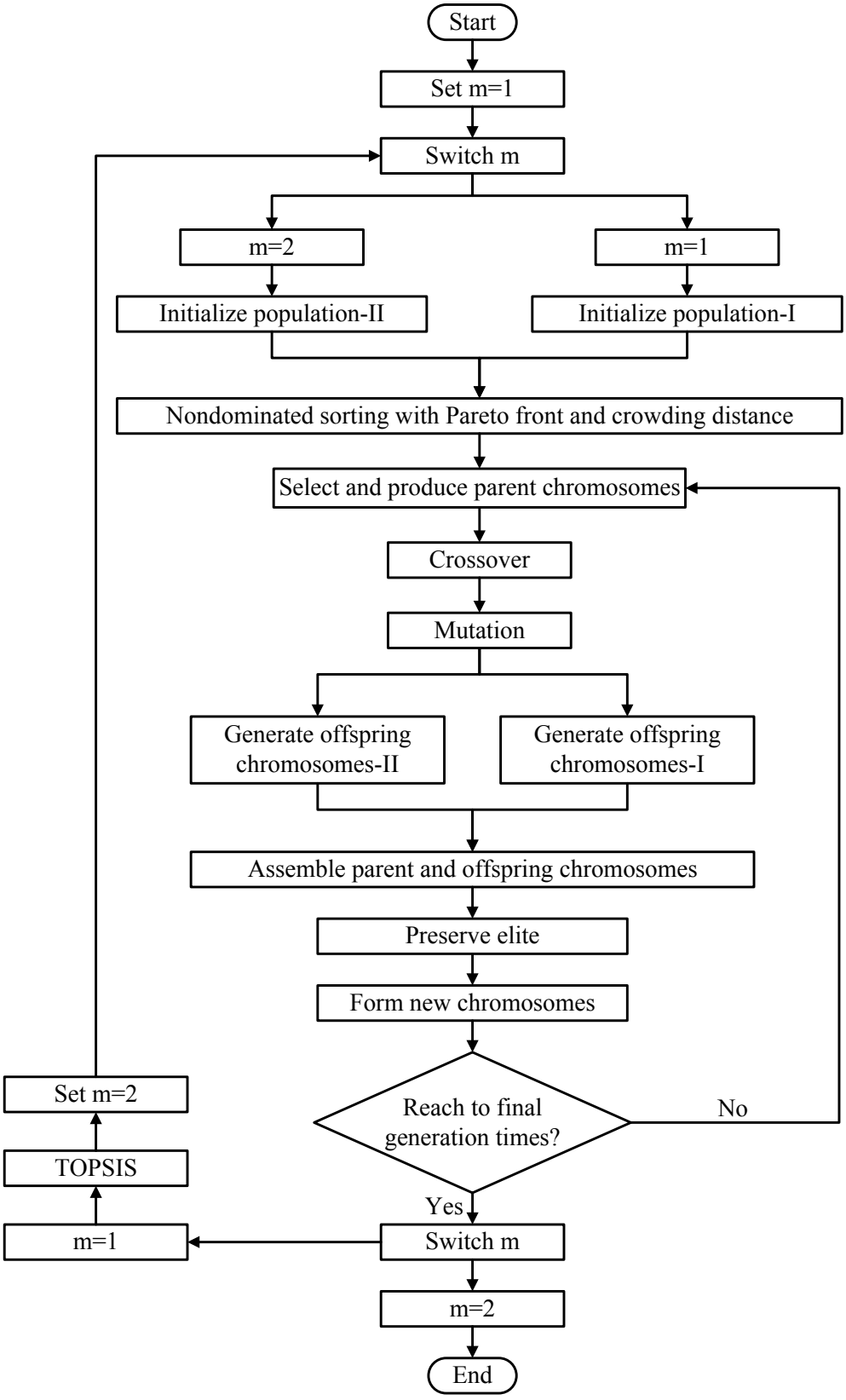


Fig. 3 TNSGA-II flow

Nevertheless, there also exist several differences between the NSGA-II. From Fig. 3, we know that one difference is the step in initializing population distinguished with *initialize population-I* and *initialize population-II*. When m=1, *initialize population-I* is determined by encoding the initial first four moments and seed mass as strings which are referred to as chromosomes. They are generated randomly in the initial population between suitable lower and upper bounds. While m=2, *initialize population-II* is done by deciding the five process variables--massecuite temperature, syrup supersaturation, syrup purity, crystal volume and massecuite volume, as the members of chromosomes, and these are generated randomly in initial population between lower and upper bounds of admissible values. Another difference is the step in generating offspring chromosomes discriminated by *generate offspring chromosomes-I* and *generate offspring chromosomes-II*. In *generate offspring chromosomes-I*, the objective functions are calculated under a series of the process variables, and they were obtained from production, while the seeding characters are produced through crossover and mutation. However, in *generate offspring chromosomes-II* the values of process variables are generated after crossover and mutation and the seeding characters are given from the final solution after implementation of the first NSGA-II.

It is obvious that there are several constraints and bounds on variables of TNSGA-II. There are two of types: constraints of seeding characters ($g_7(t) \sim g_{11}(t)$ in Eq. (33)) and process variables ($g_1(t), g_3(t) \sim g_6(t)$ in Eq. (33)). The genetic operators (crossover and mutation) are so designed that solutions are always created within the specific lower and upper bounds. Thus the variables bounds will never be violated by TNSGA-II during the course of optimization. Apart from the lower and upper bounds, there is an additional constraint on the massecuite temperature profiles: $g_2(t) = dT/dt \geq 0$. This constraint needs to be satisfied at all times if the massecuite temperature profile is always in ascending order. Generation of initial population as well as crossover and mutation operations can lead to nonordered set of massecuite temperature variables. Therefore, an order maintaining procedure needs to be done after finishing TNSGA-II which is aimed at preserving the ascending nature of the massecuite temperature.

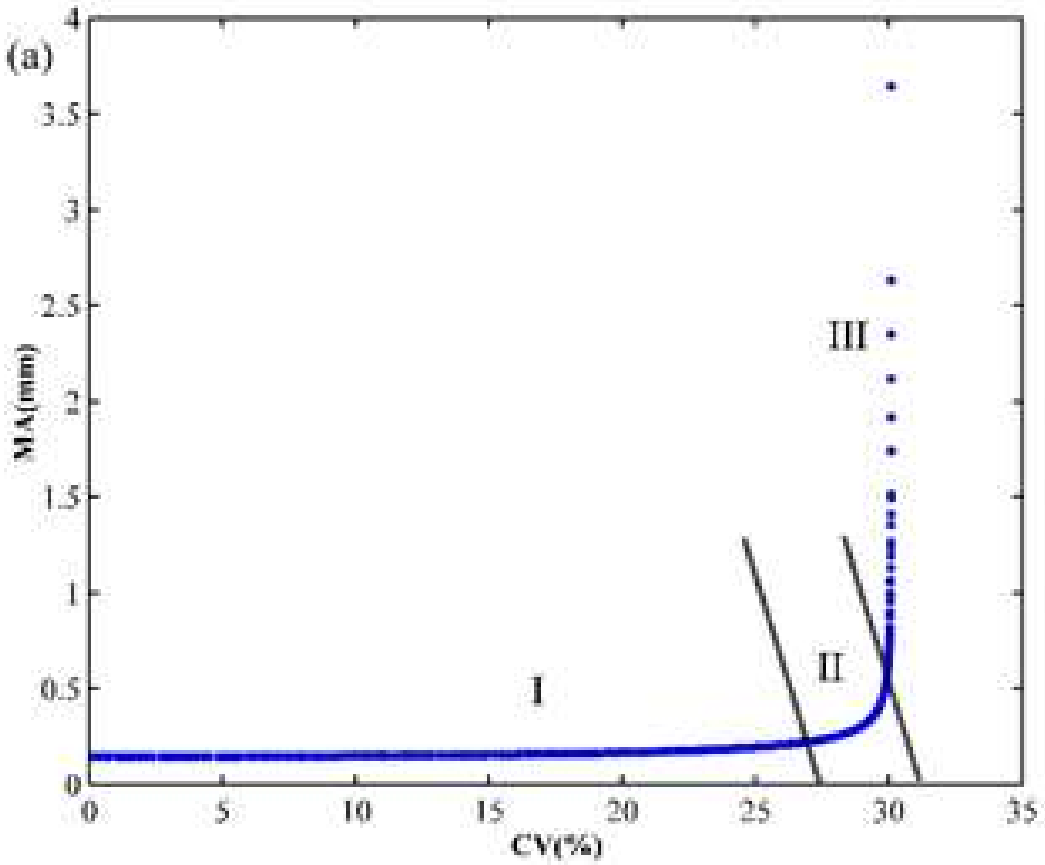
In the process of multi-objective optimization, we chose a population size of 300 for sugar crystallization process. The simulated binary crossover and polynomial mutation operators were used with the probabilities of 0.9 and 0.1 respectively. The distribution indexes for the crossover and mutation operators were both selected as 20. Simulation was carried out by predefining 1000

generations as the maximum number of iteration. The final time of generation obtained were taken as the Pareto-optimal solutions. TNSGA-II simulation was executed on a Windows 7 personal computer in MATLAB language.

V. RESULTS AND DISCUSSIONS

A. Simulation results and discussion

By this TNSGA-II algorithm, the value of MA can be maximized while the value of CV can be minimized in sugar crystallization process. The application of this algorithm produces the results presented in Fig. 4(a)-4(b).



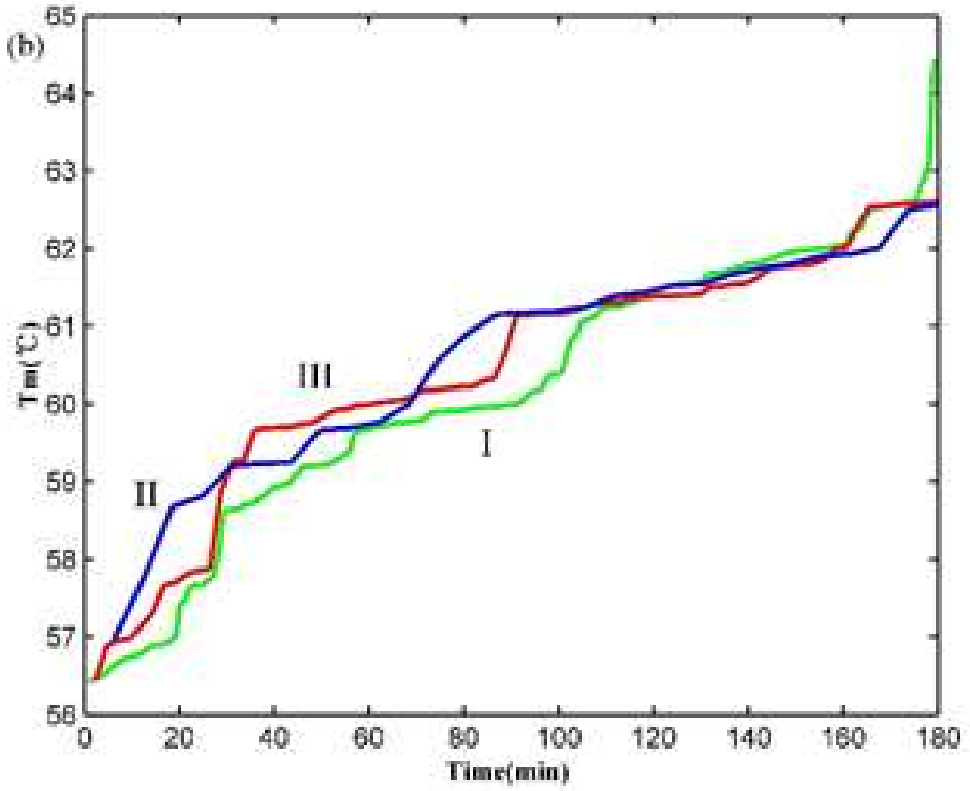


Fig. 4. Pareto-optimal solutions and corresponding massecuite temperature profiles. (a) Pareto-optimal solutions for maximization of MA and minimization of CV, (b) massecuite temperature profiles corresponding to the three different Pareto-optimal solutions(regions I-III)

The Pareto-optimal solutions in Fig. 4(a) clearly indicate the trade-off between MA and CV. The Pareto-optimal solutions in Fig. 4(a) are divided into three different regions indicated by I-III.

It is declared that the MA increases slowly and that the CV increases fast in region I with a limits of CV<27.5%. It is corresponded to wish to minimize the CV alone. And it is characterized that the MA increase rapidly in region III, which is aimed to maximize the MA alone. It is obvious that region II is the transition zone between region I and region III, which is the best zone to obtain the maximum MA and minimum CV of product CSD at the same time. Each point of the Pareto-optimal solutions in Fig. 4(a) indicates a different massecuite temperature profile. And three representative heating profiles taken from the three regions of the Pareto-optimal solutions in Fig. 4(a) are shown in Fig. 4(b). The rate of the three temperature profiles increases approximately at a same speed between 110 and 160 minutes.

But the profile corresponding to the Pareto-optimal solutions in region I keeps in a lower increasingly rate than that associated with the region III at most of time. It is the reason that a low increasingly rate of massecuite temperature can make a slow growth rate of crystals. The results of the algorithm shown in Fig. 4 are correctly in accordance with the nature of the sugar crystallization process.

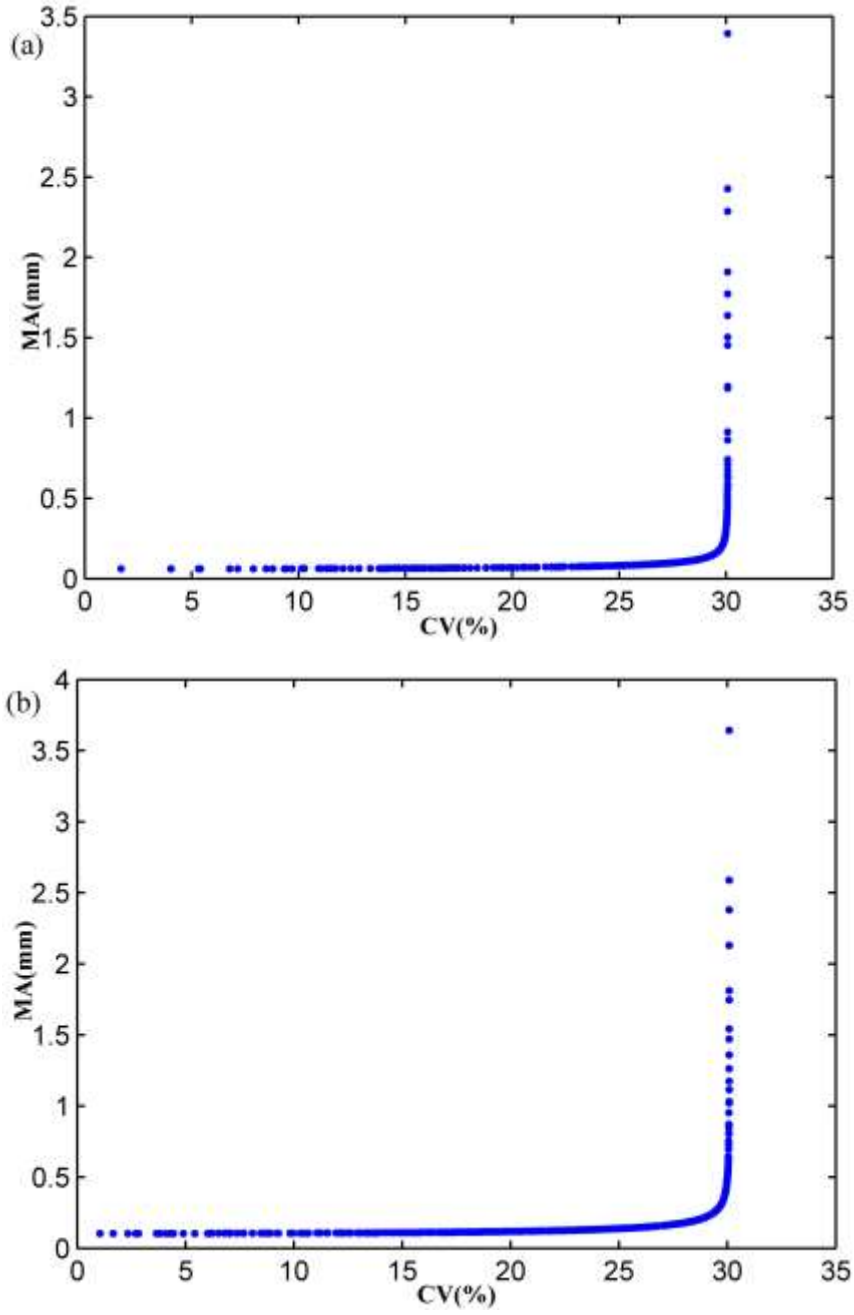


Fig. 5. Evolution of the Pareto-optimal solutions in Fig. 4. (a) distribution of feasible solutions at generation number of 10, (b) distribution of feasible solutions at generation number of 100.

Besides, two different generations progressed by TNSGA-II were taken for the evolution of the Pareto-optimal solutions shown in Fig. 5(a)-(b), where Fig. 5(a) shows the generation number of 10 and Fig. 5(b) shows the generation number of 100. The results of the two subsequent generations state that the algorithm have a quick identification of the defined Pareto-optimal solutions and well capability of keeping a sustainable wide-spread diversity of the population.

In addition, the optimal massecuite temperature profile taken from the region II in Fig. 4(b) were compared with the original one that was obtained from a sugar industry and the result of the comparison is presented in Fig. 6. The optimal heating profile obtained from the algorithm produces a distinct improvement in consideration with the original massecuite temperature profile.

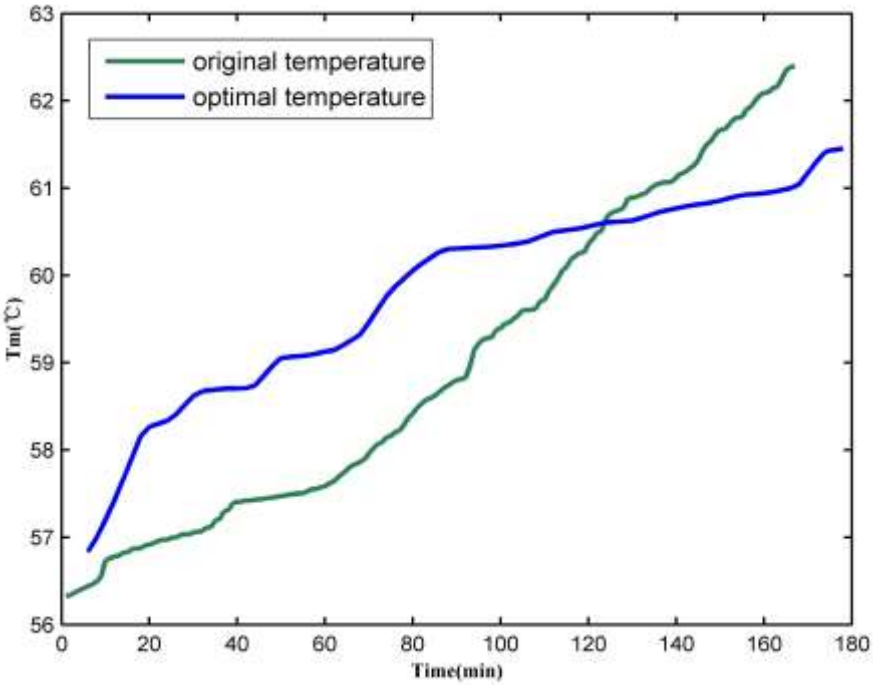
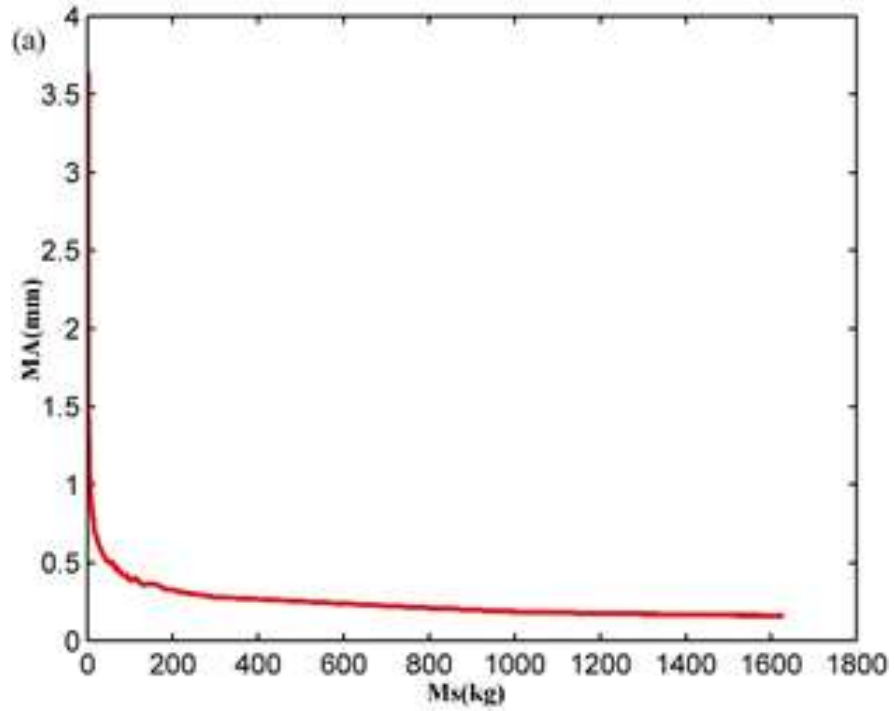
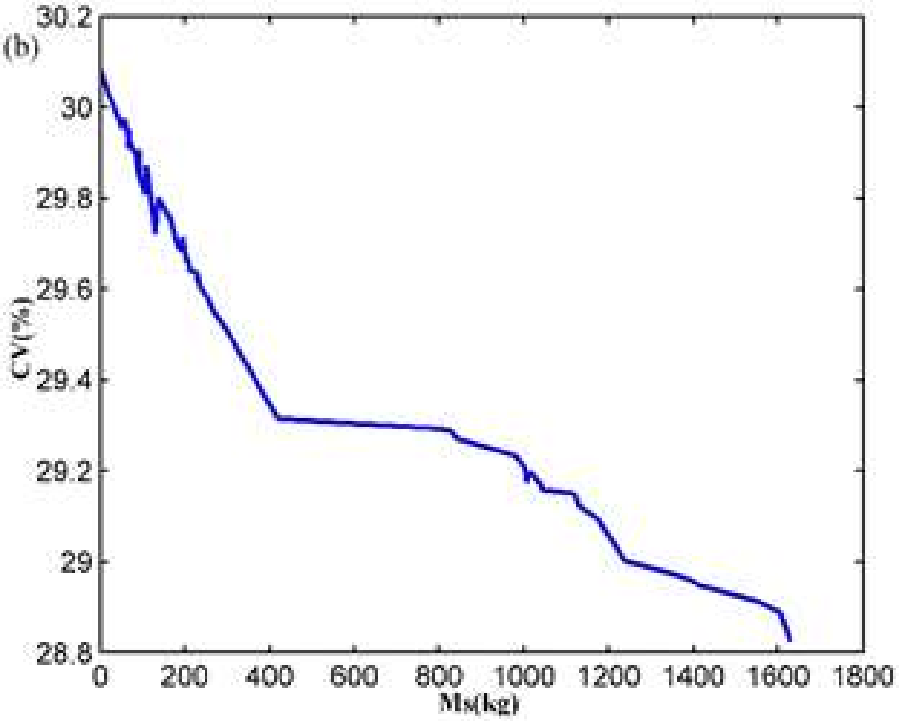


Fig. 6. Massecuite temperature profiles of original and optimal data.


(a)
MA(mm)
Ms(kg)
0
0.5
1
1.5
2
2.5
3
3.5
4
0
200
400
600
800
1000
1200
1400
1600
1800


(b)
CV(%)
Ms(kg)
28.8
29
29.2
29.4
29.6
29.8
30
30.2
0
200
400
600
800
1000
1200
1400
1600
1800

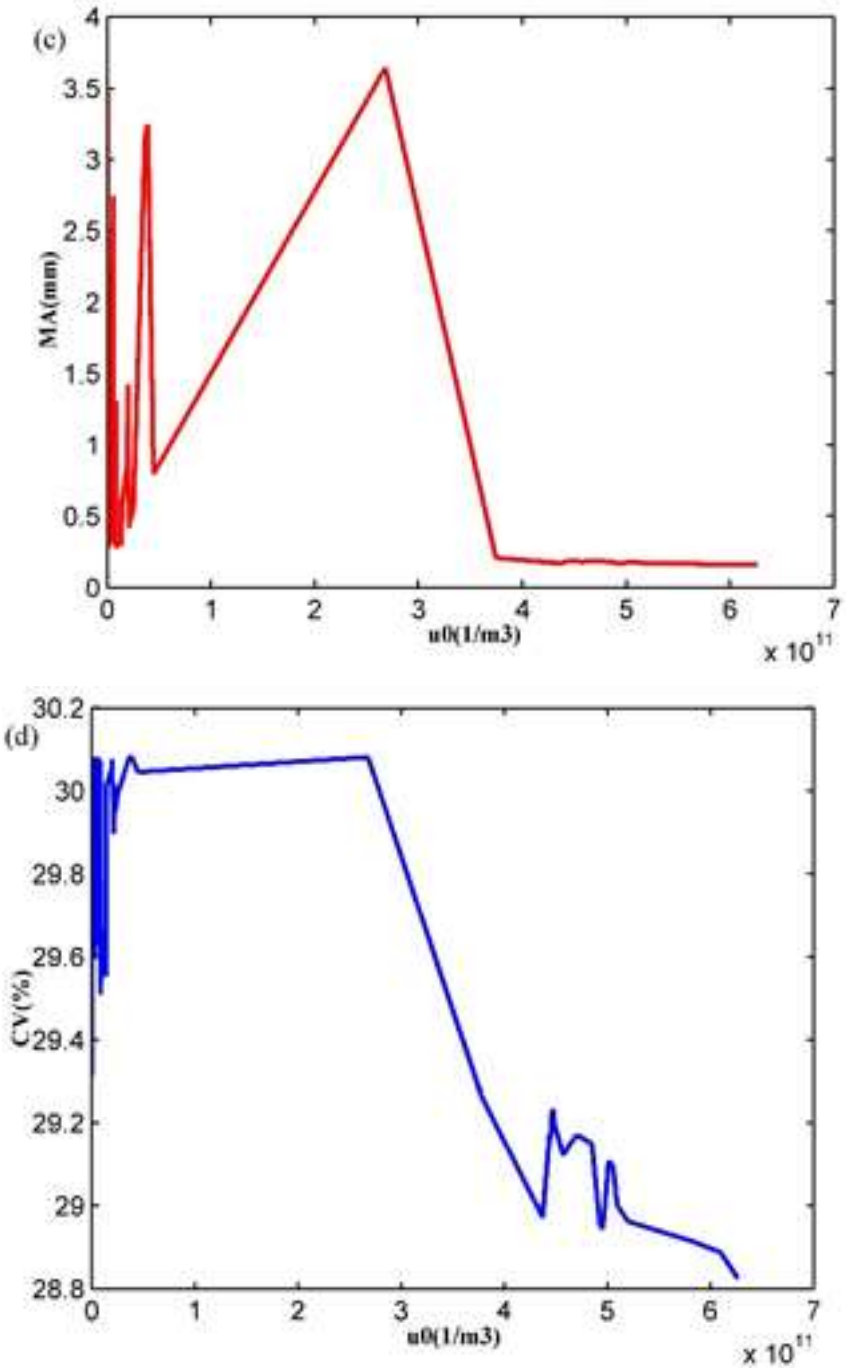


Fig. 7. Effect of seed mass and the first distribution moment on MA and CV. (a) variation of MA with optimal seed mass, (b) variation of CV with optimal seed mass, (c) variation of MA with optimal m_0, (d) variation of CV with optimal m_0

It is shown in Fig. 7(a)-(d) that the effect of the seed mass and the first moment of the crystal number-volume distribution on MA and CV of the product CSD.MA and CV decrease with an increase in seed mass in Fig. 7(a)-(b), but the rate of decrease in MA becomes very sharp while

seed mass maintains at low level. However, MA and CV in Fig. 7(c) and (d) have no monotonicity corresponding to the first moment m_0 in Fig. 7(c) and (d). It is obvious that the seed mass makes a more significant influence than m_0 on MA and CV, which illustrates that m_0 only produces a little fluctuation on MA and CV. Furthermore, the little fluctuation of the MA and CV profiles in Fig. 7(a) and (b) with the increase in seed mass indicates that all of the first four moments have a little effect on MA and CV when the existence of the seed mass at the same time.

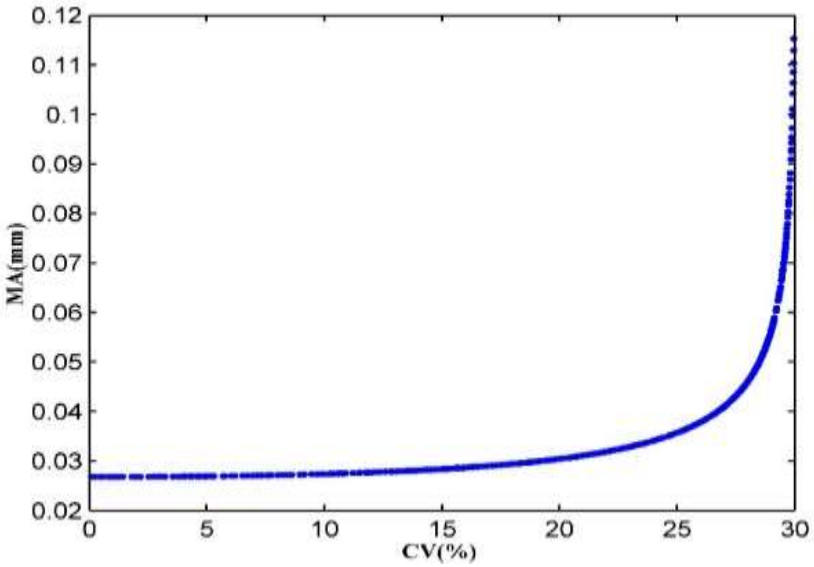


Fig. 8. Pareto-optimal solutions generated by NSGA-II

Finally, there is a comparison between the Pareto-optimal solutions generated by TNSGA-II shown in Fig. 4(a) and these generated by NSGA-II shown in Fig. 8 in the same circumstances (the same population size, predefined number of generations, probabilities of crossover and mutation and their distribution indexes). In the evolution of the NSGA-II algorithm, the quantities of the seeding characters are given by hand with experience. It is noted that the NSGA-II algorithm produces a better diversity of population than TNSGA-II, but the distribution of the Pareto-optimal solutions of NSGA-II are less wide-spread than that which the TNSGA-II generates. The NSGA-II can only make MA get a maximum value of 0.12mm while the value of CV has reached to 30%. But the TNSGA-II can make MA get a maximum value of 3.5mm while the value of CV has reached to 30%. These declare that the TNSGA-II algorithm, involving the effect of the seed characters on MA and CV, makes a better improvement than NSGA-II for the multi-objective optimization of sugar crystallization process.

VI. CONCLUSIONS

One difficulty in crystallization optimizing essentially corresponds to the simultaneous consideration of effects of all seeding characters and the process variables on MA and CV of product CSD. In this paper, a proposed TNSGA-II algorithm is developed for multi-objective optimization of sugar crystallization process. This algorithm produces a sustainable wide-spread diversity of population and is able to achieve better result than NSGA-II. Moreover, the TNSGA-II offers an approach for a quantitative analysis of the optimal seeding characters and process variables corresponding to the trade-off between MA and CV.

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