Optimization of Operating Conditions in Rice Heat Blast Process for Chinese Rice Wine Production by Combinational Utilization of Neural Network and Genetic Algorithms

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ABSTRACT

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The rice heat blast process is a novel technique for gelatinizing raw starch. It uses heated air to replace steam for processing rice under high temperature fluidization in a short time period. This is a new technique for making rice wine with the characteristics of easy storage and zero water pollution. This study focused on three major performance indexes (starch gelatinization ratio, total fat content, and amino nitrogen content in the roasted rice), which largely affect the performance of the rice heat blast process and the rice wine quality. The relationship between these performance indexes and the corresponding operation variables were modeled by an artificial neural network (ANN) via learning sets of experimental data. Based on the ANN models obtained, genetic algorithms were used to optimize the operating conditions of the rice heat blast process. The results showed the power in determination of optimal operating conditions by the combinational utilization of artificial neural network and genetic algorithms.

Key words: Artificial neural network, genetic algorithm, optimization, quality control, rice heat blast process.

INTRODUCTION

Chinese rice wines are traditional alcohol beverages in China, with more than 4,000 years of history and are popular in China, particularly in the southern part of the country. In addition, one of the Chinese rice wines, Shaoxing wine, has a large market in Japan, and more than 7,000,000 liters of Shaoxing wine are imported and consumed annually[1]. In general, production of Chinese rice wines is divided into two major stages: raw rice pre-treatment and alcohol fermentation. The former stage is generally carried out on steamed rice grain where the rice starch is enzymatically hydrolyzed and saccharified. The hydrolysis and saccharification process on the steamed rice grains is an intensive water, energy and labor consuming process. Large amounts of waste water are produced from the process, which in turn causes severe environmental problems.

To overcome these problems, the rice heat blast technique, a novel process for starch gelatinization was proposed and patented by Takara Jozo Co. of Japan[6,21], and has been successfully used for industrial sake brewing in Japan. This new technique uses heated air to replace water steam for processing rice under high temperature fluidization conditions and in a short time period, it breaks the raw rice starch into short chain dextrins, a form that speeds the subsequent hydrolysis and saccharification process. The dextrin formed is hard to denaturalize and easy to store compared with that produced by the traditional water steaming processing. Furthermore, as large amounts of water can be saved, severe water pollution and related environmental problems can be controlled.

In the rice heat blast process for Chinese rice wine production, three factors are considered to be the major indexes which affect the performance of the raw rice pretreatment process and the quality of the final product. These are the starch gelatinization ratio (α-ratio), and the content of the total fat and amino nitrogen in the roasted rice. The starch gelatinization ratio represents the percentage of short chain dextrins formed to the total raw rice starch. The higher the starch gelatinization ratio, the easier it is to implement the subsequent hydrolysis and saccharification process. In other word, the subsequent hydrolysis and saccharification process can be carried out with minimum cost and the raw starch utilization rate can be enhanced. In general, the total fat content should be reduced to the lowest level, since higher fat content remaining in the wine increases the rate of denaturalization. This leads to an increase in unpleasant odors, which are generated by the more rapid rate of denaturalization. The amino nitrogen content is also one of the important performance indexes for Chinese rice wine. It is a comprehensive and balanced index of nutrient (amino acid) content, aroma, astringency and color. All rice wine products in China must conform to the amino nitrogen content standards as set by the National Brewing Standard.

The performance indexes are determined and controlled by the operating conditions of the rice heat blast process. Three principal operating variables dominate and control the three performance indexes: the blast tempera-

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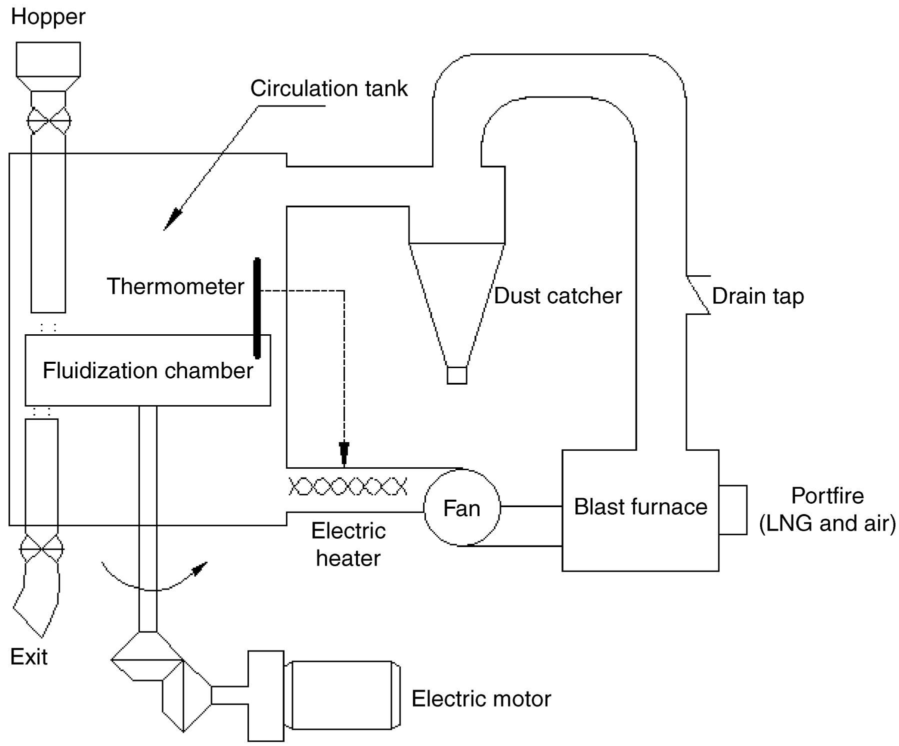

Fig. 1. Flow diagram of rice heat blast processing equipment.

ture, the blast time, and the rice soaking time (representing the water content of the rice). For example, a higher temperature is favorable to a higher starch gelatinization ratio, but if the temperature is too high, the raw rice starch is denaturalized and the pre-treatment process fails. The rice heat blast process is a complex process with the three principal operating variables affecting the performance indexes in a complicated way. Mathematical models with clear physical or chemical meanings are not available to describe the relationships between operating variables and the performance indexes, as well as the complicated nature of the process. It is important to control the operating variables at their optimum to achieve the targeted performance indexes. However, due to the complicated features of the process and lack of suitable mathematical models, process optimization turns out to be a difficult task.

With the rapid developments in computer science and technology, more and more attention has been paid to the utilization of artificial intelligence methodology based on computer techniques. Two typical artificial intelligence techniques, artificial neural networks (ANN) and genetic algorithms (GA), have been widely used in bioprocessing and fermentation fields. Artificial neural network techniques have been applied in many bioprocessing areas such as process control[17,20], optimization[2], pattern recognition[17], state prediction[12], fault detection[5], and modeling[19], for their strong abilities to deal with these processes without precise mathematical models, and with poorly understood and with complicated or non-linear features. Generally, the back-propagation neural network (BP-NN) is the standard tool for these applications for its characteristics of simple, stable, ease of calculation, and accuracy. On the other hand, as a powerful optimization tool, genetic algorithms are superior to many traditional optimization methods such as non-linear programming, etc., for the excellent abilities in searching optimization solutions globally and the characteristics of fast calculation convergence. Many applications on process control[7], dynamic modeling[14], determination of optimal substrate fed-batch strategy[9], and optimization of culture medium[10] have been reported. Recently, reports on the combined application of both neural network techniques and genetic algorithms for optimizing the temperature trajectory of Japanese sake mashing and the Koji making process[4] and other processes[10] have appeared.

In this study, artificial neural network techniques and genetic algorithms have been combined and applied in the optimization of the rice heat blast process for Chinese rice wine production. In addition, this paper attempts to access or test the power of the proposed strategy in the determination of the optimal operating conditions of the process and to demonstrate its potential in a production environment.

MATERIALS AND METHODS

Rice heat blast equipment

The rice heat blast equipment was self-designed and manufactured. It consists of a fan, a blast furnace, an air heating circulation tank, and a fluidization chamber. Fig. 1 shows a flow diagram of the equipment.

Rice heat blast experiment and data collection

The soaking rice was continuously added through the hopper and placed in the fluidization chamber. The fluidization chamber was rotated at a set speed by the electric motor, and the roasted rice was dropped down from the chamber and drained out of the circulation tank after a 330° rotation. The temperature of the fluidization chamber (blast temperature) was monitored by the thermal meter and controlled by the internal electric heater. The blast time was controlled by the rotation speed. By orthodox experiments, 33 data sets with different blast temperatures, blast times and soaking times, each corresponding to different resultant performance indexes, were collected for the subsequent process modeling and optimization verification.

Measurement of performance indexes of the rice heat blast process

The starch gelatinization ratio was determined using the glucoamylase method described below. Roasted rice (1 g) was taken in equal amounts as sample A and B, and crushed into powder and dissolved in water. Glucoamylase (1 mL) (100,000 units/mL, Genencor Biotech Co., Wuxi, China) was added to the solution of sample A for saccharification at 55°C and pH 4.4–4.6 for 4 h. Sample B solution was first heated in a boiling water bath for 1 h to completely hydrolyze the unconverted (non-dextrin form) starch, and then the solution was saccharified in the same way as sample A. The saccharified solutions A and B were diluted to 100 mL and the residual solid filtered. A 5 mL aliquot of the filtered solution was diluted to 50 mL, and the reducing sugar concentration measured using a SBA-40B biosensor (Biochemical Research Institute of Shandong Science Academy, Shandong, China). The starch gelatinization ratio was determined by the concentration of the reducing sugar measured, C_A and C_B, as C_A/C_B.

The total fat content in the roasted rice was measured by the Soxhlet extraction method[11].

Amino nitrogen content (AG) in the roasted rice was determined by the neutral formaldehyde titration method. Roasted rice powder (25 g) in a 500 mL flask, was dissolved with 250 mL water. Neutral proteinase GC710 (0.375 g) (1600 AU/g, Genencor Biotech Co., Wuxi, China) and 0.050 g acidity proteinase GC106 (1000 SAPU/g, Genencor Biotech Co., Wuxi, China) were added and reacted with the sample at 30°C and pH 4.4 for 4 h to suit the conditions for the subsequent fermentation process. After centrifugation, 10 mL supernatant (V) was transferred into a 150 mL beaker and diluted with 50 mL water. The pH was adjusted to 8.2 by titration of 0.01N NaOH (C_{NaOH}), and 10 mL formaldehyde was added. The titration was continued to pH 9.2, and the NaOH volume consumed (V_2) was recorded after the addition of formaldehyde. The amino nitrogen content in the roasted rice can be determined from the following formula, where V_1 indicates the NaOH volume consumed after the addition of formaldehyde for 10 mL water (blank sample).

$$\mathrm{AG\ (g/L)} = \frac{(V_2 - V_1) \times C_{\mathrm{NaOH}} \times 0.014}{V} \times 1000$$

Artificial neural network model (ANN)

Three standard three-layer feedforward ANNs were used for modeling of the rice heat blast process. The input layer consists of three neurons, and a set of operating variables, the blast temperature, the blast time, and the rice soaking time. These were input into each of the corresponding neurons as the input variables. The output layer had only one neuron, where one of the three major performance indexes corresponds to the set of the operating conditions, the starch gelatinization ratio, or the total fat content, or amino nitrogen content in the roasted rice. This was used as the learning signal for the output unit. The neuron numbers in the hidden layer were set at 10 through trial-and-error method, by evaluating the computation accuracy and the convergence speed. The standard back-propagation algorithm[16] was used for the determination of the associated weights between neurons in different layers (ANN model parameters). The 33 experimental data sets were divided into two groups: 23 data sets were used for ANN models learning, and the remaining 10 sets were used for evaluation of the models' accuracy and the performance of the genetic algorithms for searching the optimal operating conditions. The ANN modeling and evaluations were performed using a Matlab Ver.6.5 software package (The Math Works, Inc., Natick, MA, USA).

Genetic algorithms (GA)

Once the process models were established, the optimal operation conditions (blast temperature, blast time, and rice soaking time) corresponding to a targeted performance index could be determined by using several multivariable optimization methods. The genetic algorithm was chosen in this case, because of its global optimization ability as well as its high convergence speed[4,9,14] over other non-linear programming, such as the Simplex Method. In the latter case, the initial conditions are crucial for the optimization performance. The improper selection of initial conditions always causes optimal search trapping into a local optimal solution, instead of the global optimal one.

The genetic algorithm is a biological evolutionary method inspired by Darwin's theory of "survival of the fittest". The biological evolution itself can be regarded as an optimization process where simple reproductive elements are optimized by mutation, crossover, selection, and then evolved to highly complex beings. Genetic algorithms are generally operated through a simple cycle of the following procedures, and the systematic descriptions and details of genetic algorithms can be referred to the relevant literature[3,18].

1) Each operating variable was coded as a binary string with certain length called gene, and all the genes were combined to construct a complete chromosome. In this case, one chromosome consists of 3 genes with a total binary string length of 26 bits, each gene corresponding to one particular operating variable. The selection of binary string length depends on computational accuracy and load, as well as convergence speed required. A total of 50 initial chromosomes (population size) were randomly generated. 2) The generated chromosomes were then decoded through a preset decoding program, and then the decoded values were input into the ANN models, and the output values (estimated performance indexes) were calculated. 3) Based on the output values obtained, the fitness of every chromosome was calculated as $f_j = 1 - \mathrm{ABS}\{(y_j - y^*)/y^*\}$ (j = 1,50), where f_j represents the fitness of the j-th chromosome, y_j is the estimated performance index for the j-th chromosome, and y^* is the desired (targeted) value. The fitness calculation can also be easily extended to the multiple objectives cases, for example, using the

starch gelatinization ratio, the total fat and amino nitrogen contents of the roasted rice as the multiple objectives simultaneously. 4) After calculating the fitness of all chromosomes, chromosomes with higher fitness were selected by a combinational selection method based Roulette wheel fitness proportional model and Elitist preserving model[3,18]. With this selection rule, the chromosomes with higher fitness get more copies, the average remains even, and the worst dies off. The Elitist model keeps the chromosome with the highest fitness to the next generation unconditionally, to avoid the possibility of it being ruined by the next crossover and mutation manipulations[18]. 5) With an active pool of chromosomes looking for mates, one-point crossover between a pair of chromosomes was done. The pairs of chromosomes and the bit point subject to crossover were randomly chosen with a crossover possibility P_C of 0.6. If a randomly generated value (ranging from 0 to 1) exceeded P_C, crossover operation was implemented otherwise no crossover manipulation occurred. The similar measures could also be adopted for the next mutation manipulation. 6) As the last operation, mutation was performed. The chromosome and the bit point subject to mutation were also randomly decided by a mutation possibility P_M of 0.2. The mutation operation is necessary to ensure the optimal search not trapping into a local optimal solution. However, if an unsuitable large mutation possibility rate was chosen, the optimal search tended to be a "random search", the search would not be possibly convergent and eventually fail. As generation iterates, dominant chromosomes increased and the performance indexes converged to their targeted values. Steps 2–6 were repeated until the pre-determined generation number (50) was reached and the chromosome with the highest fitness in the final generation pool was then selected as the optimization solution. All of the GA manipulations and calculations were implemented by a Matlab Ver.6.5 software package (The Math Works, Inc., Natick, MA, USA).

RESULTS AND DISCUSSION

The changing pattern of performance indexes at different blast temperatures

Fig. 2 shows the basic change patterns of the process performance indexes at different blast temperatures while the blast time and the rice soaking time were fixed (at 45 s and 5 min). The starch gelatinization ratio increased with the increase of blast temperature, and the value reached ~ 90% at 300°C. However, the increase speed tended to be saturated when temperatures exceeded 250°C. Amino nitrogen content increased slightly with the increase of temperature to 150°C, then it began to decline with the increase of temperature. As fat was evaporated from the surface of the rice with the heated airflow during the course of the blast, the total fat content continuously decreased in relation to the increased temperature. The values became "saturated" at the range of 0.32% to 0.36% as temperatures reached ~250°C. The behavior of the starch gelatinization ratio and amino nitrogen content, with regard to the blast temperature could be explained in the following way. The rate of molecular vibration increases as temperature increases, and weak interactions such as

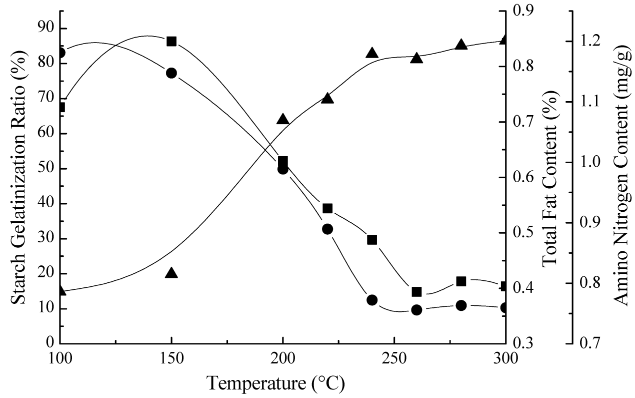

Fig. 2. Basic change patterns of the starch gelatinization ratio and content of total fat and amino nitrogen in roasted rice at different blast temperatures (with blast time and rice soaking time fixed). Starch gelatinization ratio (▲); total fat content in roasted rice (●); amino nitrogen content in roasted rice (■).

hydrogen bonds are disrupted and the protein in the roasted rice unfolds[8]. This promotes the formation of dextrin and the hydrolysis ability of proteinase, and therefore a higher starch gelatinization ratio and amino nitrogen content. As temperature rises further the nonenzymatic deamidation of protein, and Maillard reactions, which lead to the formation of favorable aromas, as well as the brown colors in rice[13,15], take place and dominate the rice blast process. In addition, some dextrin formed is denaturalized due to the high temperature. As a result of these reactions and the overheating effect offsetting the temperature promoting effect on the starch gelatinization ratio at the high temperature range, there is a decrease in the hydrolysis ability of proteinase to cause a decrease of amino nitrogen content. The decrease of amino nitrogen content reduces the nutrient index of the rice wine. However, it is beneficial in the promotion of aromas and astringency, as well as in reduction of bitterness of the products. Thus, the amino nitrogen content should be recognized as a comprehensive index between nutrient components and aromas. In general, roasted rice with a high starch gelatinization ratio, low fat content, and suitable amino nitrogen content is considered to be favorable for the downstream rice wine brewing process. Therefore, a powerful estimation and optimization tool is strongly desirable for this particular process with its many complicated and poorly understood reactions and characteristics.

Estimation performance of ANN models

Fig. 3 shows the estimation performance of three ANN models for starch gelatinization ratio, total fat content, and amino nitrogen content, respectively. All of the output data exhibited are actual values, where the open circles show the learning data (data used for ANNs modeling) and the filled circles show the evaluation data (data used for prediction based on the ANNs models established). If the models are accurate, all data points should lie on the diagonal straight lines. Almost all data plots matched the lines, while there were still some evaluation data plots scattered away from the lines, particularly in the case of the starch gelatinization ratio. The estimating discrepancy in the starch gelatinization ratio model may account for, or reflect that a more complicated relationship exists between the starch gelatinization ratio and the operating variables in comparison with those for fat and amino nitrogen content. To further improve the estimation performance, more data pairs of the starch gelatinization ratio and the operating conditions need to be collected and re-learnt through the ANN model. Nevertheless, it was concluded that, the three ANN models based on the 23 data sets could estimate the relationships between the process performance indexes and the operating conditions with a reasonably high degree of accuracy. Therefore, the ANN models acquired were expected to be applicable in the subsequent operating variables optimization process by GA.

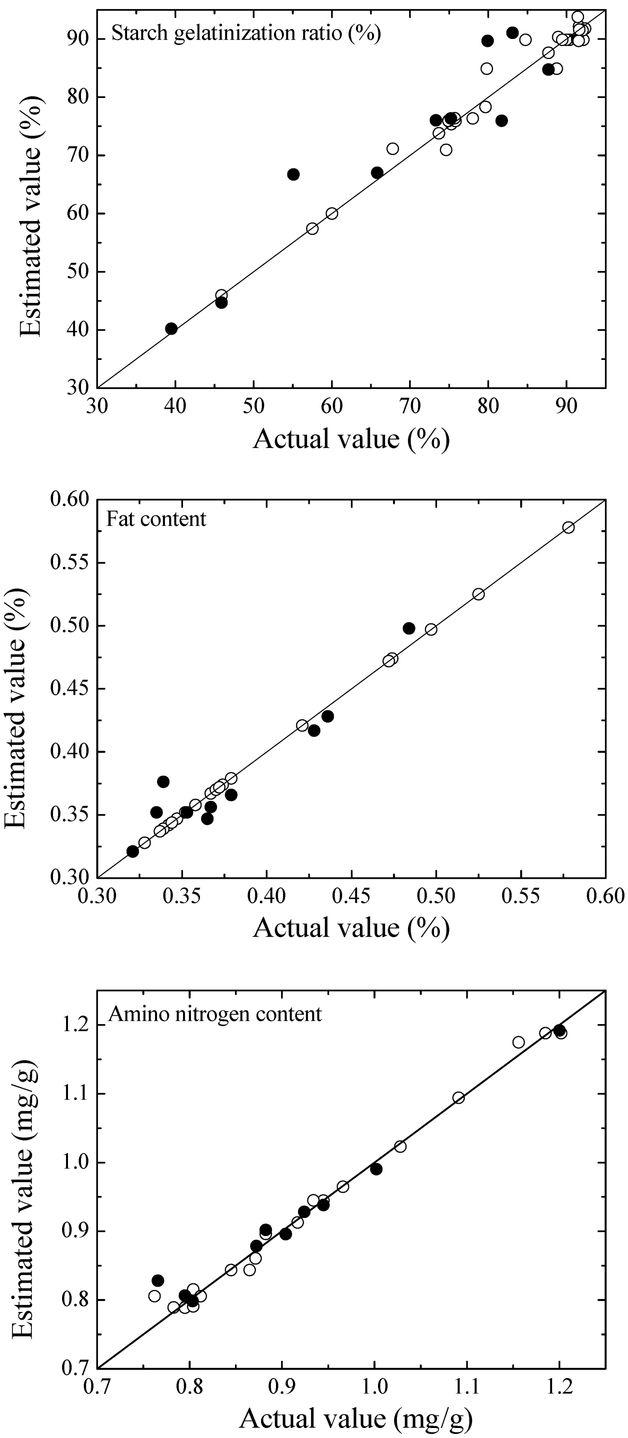

Fig. 3. Estimation of process performance indexes by ANN models: learning data (○) estimating data (●).

Optimization of rice heat blast process by GA

Optimization using the single performance index – starch gelatinization ratio, was first performed using genetic algorithms, as it is the most important performance index of the rice heat blast process. It should be noted that only the starch gelatinization ratio was used as the performance index in this case, and no specifications were imposed on the other two indexes, the contents of total fat and amino nitrogen in the roasted rice. These two indexes were calculated based on the relevant ANN models and the "optimum conditions" for the starch gelatinization ratio. In this case, the targeted starch gelatinization ratio was set as 92.3%. After about 50 generations' calculation, the performance index and the relevant operating variables reached and then stayed at their target and optimum levels. A calculated starch gelatinization ratio of 92.4% was obtained, which is very close to the targeted value (fitness 0.999). However, the calculated amino nitrogen content of 1.16 mg/g, largely deviated from the actual possible value (around 0.75–0.85 mg/g), and was very unrealistic under the operating conditions used. The large deviation might

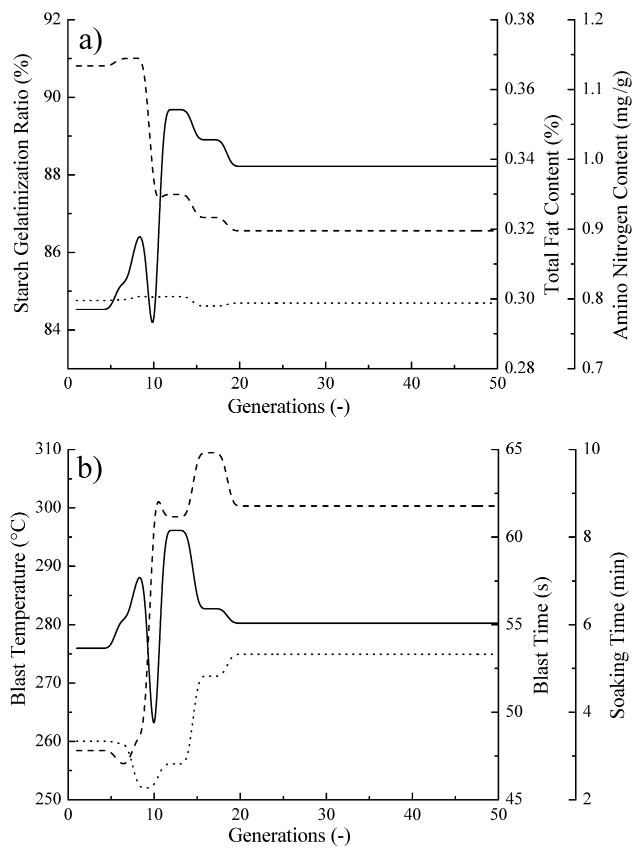

Fig. 4. Optimization of the rice heat blast process by GA, with the starch gelatinization ratio, total fat content and amino nitrogen content as multiple targeted performance indexes. **a.** Starch gelatinization ratio (—); total fat content (– – –); amino nitrogen content (· · ·). **b.** Blast temperature (—); blast time (– – –); soaking time (· · ·).

Table I. Optimization performance of rice heat blast process by genetic algorithms.

Experimental data			Calculated results					
Performance indexes			Performance indexes					
Starch gelatinization ratio (%)	Total fat content (%)	Amino nitrogen content (mg/g)	Starch gelatinization ratio (%) / R.E. (%)	Average R.E. (%)	Total fat content (%) / R.E. (%)	Average R.E. (%)	Amino nitrogen content (mg/g) / R.E. (%)	Average R.E. (%)
39.5	0.484	1.200	39.65/0.38	2.65	0.492/1.65	3.35	1.191/0.75	1.77
45.9	0.360	1.002	49.12/7.01		0.344/4.44		0.996/0.60	
55.1	0.337	0.803	48.85/11.3		0.339/0.59		0.800/0.37	
68.7	0.367	0.945	68.70/0.00		0.347/5.45		0.940/0.53	
74.8	0.428	0.904	74.95/0.20		0.426/0.47		0.930/2.88	
69.8	0.430	0.924	70.60/1.14		0.485/12.8		0.893/3.35	
74.6	0.379	0.882	77.93/4.46		0.371/2.11		0.844/4.31	
78.8	0.347	0.766	77.88/1.17		0.327/5.76		0.791/3.26	
88.9	0.320	0.798	88.2/0.79		0.320/0.00		0.794/0.50	
83.1	0.369	0.795	83.17/0.08		0.370/0.27		0.804/1.13	
Operating variables			Operating variables					
Blast temperature (°C)	Blast time (s)	Soaking time (min)	Blast temperature (°C) / R.E. (%)	Average R.E. (%)	Blast time (s) / R.E. (%)	Average R.E. (%)	Soaking time (min) / R.E. (%)	Average R.E. (%)
150	40	5	151.8/1.2	3.39	41.1/2.8	5.99	5.0/0.0	17.0
180	40	9	171.7/4.6		41.5/3.8		8.3/7.8	
180	50	1	167.8/6.8		50.0/0.0		1.0/0.0	
200	55	5	191.1/4.4		55.5/0.9		4.8/4.0	
220	55	5	217.4/1.2		54.2/1.4		5.2/4.0	
220	45	5	205.2/6.7		51.7/14.8		4.6/8.0	
240	40	7	250.9/4.5		42.9/7.2		4.9/30.0	
260	60	5	256.3/1.4		57.5/4.2		3.9/22.0	
280	50	7	280.3/0.1		61.8/23.6		5.3/24.3	
300	50	1	308.9/3.0		49.4/1.2		1.7/70.0	

be due to the lower estimation accuracy of the starch gelatinization ratio ANN model, and the incomplete description of the whole process when using the starch gelatinization ratio as the sole performance objective, as only the ANN model for starch gelatinization ratio was used in optimization of the operating variables. To overcome the problem, multiple targeted performance objectives were used in the process optimizations, where the targeted starch gelatinization ratio, total fat content, and amino nitrogen content were specified simultaneously.

The implementation of multiple performance objectives was both feasible in calculation and realistic in practice, as roasted rice suitable for the rice wine brewing was required with the overall characteristics of high starch gelatinization ratio, low fat content, and reasonable low amino nitrogen content. Fig. 4 shows the changing patterns of the performance indexes and the relevant operating variables with regard to the genetic generations during the optimization with multiple performance objectives. A set of experimental data (real operating conditions: blast temperature, 280°C; the blast time, 50 s; rice soaking time, 7 min) and the performance indexes obtained experimentally (starch gelatinization ratio, 88.9%; fat content, 0.32%; amino nitrogen content, 0.798 mg/g) were used for the optimization evaluation. The experimental values (performance indexes obtained experimentally) were used as the targeted performance indexes during the optimization calculation. The calculated results (performance indexes: 88.2%, 0.320%, and 0.794 mg/g, corresponding operating conditions: 280.3°C, 61.8 s, and 5.3 min), particularly the performance indexes, were very close to their targeted values.

Table I summarizes the optimization performance by comparing 10 sets of experimental data with the calculated results. Here, the performance indexes obtained experimentally were used as the targeted one. A good optimization performance means that the calculated performance indexes, and the corresponding operating variables in particular, must coincide well with the corresponding actual data. Both experimental and calculated data of process performance indexes and operating variables are listed, as well as the relative errors and mean relative errors. The targeted performance indexes could be reached with high accuracy. Small mean relative errors of 2.65%, 3.35%, and 1.77% for starch gelatinization ratio, total fat content, and amino nitrogen content, individually, were obtained for the 10 data sets. The optimized operating variables, the blast temperature and time, also coincided well with the actual data, with the mean relative errors of 3.39% and 5.99% respectively. However, the third optimized operating variable, the soaking time of rice, had relatively large deviations from the actual one, with a mean relative error of 17.0%. In a subsequent study, we found that the water content of rice was nearly saturated after soaking rice for more than 5 min at 20°C, and extra soaking time did not significantly increase the rice water content. The nature of the rice water content saturation beyond certain soaking times would deteriorate the accuracy of the ANN models, and could affect the overall optimization performance to some extent. However, as the effecting intensity of soaking time on the three performance indexes seemed less than those of the blast temperature and time, therefore, the deviation in soaking time did not greatly affect the overall performance indexes obtained. In the industrial rice heat blast processing, the performance indexes need to be frequently varied batch by batch to suit the special requirements for various Chinese rice wines. Therefore, a rapid, simple and convenient method for the determination of the corresponding optimal operation conditions is strongly desired. The results of Table I clearly indicate the power and effectiveness of the combinational utilization of ANN modeling and GA optimization in dealing with the rice heat blast process for many different kinds Chinese rice wine production.

An alternative method for process modeling and optimization might be Response Surface Methodology (RSM). The reason ANN was used for modeling and GA for process optimization instead of using the RSM, was related to the significant estimation performance deterioration when using RSM. Compared with the RSM, ANN has large advantages in modeling the processes with strong non-linear characteristics and complicated natures. This has been reported by a number of researchers[10,22].

CONCLUSION

Although many other factors, such as types of rice, rice feed-in quantity, ventilated air flow rate, etc., also affect the quality of roasted rice, the blast temperature, blast time, and rice soaking time were considered to be the three major operating variables dominating the performance of the rice heat blast process under the condition of full fluidization. Through correlating of the operating variables with the process performance indexes by ANN models, and then optimizing the operating variables corresponding to the targeted performance indexes by GA, optimization of the rice heat blast process for Chinese wine production can easily be carried out. The results shown in this paper clearly indicate the power and effectiveness of the combinational utilization of ANN modeling and GA optimization in the Chinese rice wine brewing pre-treatment process.

As estimating the performance of the ANN models can be continuously modified through the accumulation of production data, the proposed method appears to be very feasible and useful in the supervision and quality control of industrial alcohol production.

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