Technical paper

Artificial Neural Network–Genetic Algorithm to Optimize Yin Rice Inoculation Fermentation Conditions for Improving Physico-chemical Characteristics

Kaiqun HU^{1,2#}, Cheng DING^{1,3#}, Mengzhou ZHOU^{1,2#}, Chao WANG^{1,2}, Bei HU⁴, Yuanyuan CHEN^{1,2}, Qian WU^{1,2*} and Nianjie FENG^{1*}

¹Hubei University of Technology, Wuhan, Hubei 430068, China

²Key Laboratory of Fermentation Engineering (Ministry of Education), Hubei Key Laboratory of Industrial Microbiology, Hubei Provincial Cooperative Innovation Center of Industrial Fermentation, Wuhan, Hubei 430068, China

³State Key Laboratory of Environmental and Biological Analysis, Department of Chemistry, Hong Kong Baptist University, Hong Kong SAR, China

⁴College of Food Science and Technology, Huazhong Agricultural University, Wuhan, Hubei 430070, China

Received August 18, 2017 ; Accepted April 2, 2018

In this research, a nonlinear model describing the relationship between the inoculation fermentation parameters and the quality of yin rice were investigated based on artificial neural network and genetic algorithm (ANN-GA) model. The ANN-GA model had excellent potential for predicting the viscosity property of yin rice, and fermentation parameters were optimized by using genetic algorithm. Through ANN-GA model, the optimized inoculation fermentation parameters were: 0.05 % lactic acid bacteria, 0.05 % *Saccharomyces cerevisiae*, 0.2 % *Rhizopus oryzae*, then fermenting for 48 h at 25 °C. The results were further validated by experiments. Moreover, it revealed that inoculation fermentation not only effectively improved physico-chemical characteristics of yin rice, but also shorten period of fermentation about 14 days compared to the natural fermentation. These results indicated that the accuracy and reliable of fermentation parameters optimized by ANN-GA model.

Keywords: yin rice, fermentation, artificial neural network and genetic algorithm (ANN-GA) model, optimal parameters, physico-chemical properties

Introduction

Cereal grains are considered to be one of the most important sources of dietary proteins, carbohydrates, vitamins, minerals and fiber for people all over the world. For Asian peoples, rice is the main staple food of them. It has many unique properties, such as bland taste and hypoallergenic properties (Kadan *et al.*, 2001). However, the nutritional quality of cereals and the sensorial properties of products are

sometimes inferior or poor in comparison with milk and milk products. The reasons behind this are the lower protein content, the deficiency of certain essential amino acids (lysine), the low starch availability, the absent of determined antinutrients (phytic acid, tannins and polyphenols) and the coarse nature of the grains (Wang *et al.*, 2016). Fermentation as a biological technology is widely used in food processing. It is a prospective technology, which can achieve the proposed

*To whom correspondence should be addressed.

E-mail: Nianjie Feng ; fengnianjie@hotmail.com

Qian Wu ; qianwill2007@163.com

Kaiqun Hu, Cheng Ding and Mengzhou Zhou have contributed equally to this work.

purpose without adding foreign materials which have health hazards (Lu *et al.*, 2005). So it is widely to use waxy rice to get yin rice or “yinmi” in Chinese, which is a kind of the traditional rice food in south of china by natural fermentation in order to improve the shelf-life, digestibility and nutritional properties of waxy rice. Moreover, like china, there are many natural fermented rice foods in other countries, such as “cauim” beverage produced by Brazilian Amerindians (Almeida *et al.*, 2007), “boza” beverage from Turkish, South Africa (Botes *et al.*, 2007; Hancioğlu and Karapinar, 1997), “koji”, traditional fermented rice product in Japan (Hamajima *et al.*, 2016), “banh deo”, yeast rice cakes from Vietnamese and so on (Thanh *et al.*, 2016).

Accumulating evidence has identified that natural fermentation can enhance physico-chemical characteristics of rice, such as major chemical components, digestibility and intrinsic viscosity (Lu *et al.*, 2005; Yang *et al.*, 2011). However, natural fermentation yin rice is produced in small, labour-intensive factories, and the quality of natural fermentation yin rice varies with processing conditions. Thus, it is significant to use inoculation fermentation to shorten fermentation time and get stable quality yin rice. But there are few literatures about the inoculation fermentation and its effects on the properties of yin rice. The predominant microorganisms isolated from naturally fermented yin rice have been reported. The main fermenting strains are species of lactic acid bacteria (*Lactobacillus plantarum*, *L.paracasei*, *L.pentosus*), *Saccharomyces cerevisiae* and *Rhizopus oryzae* (Blandino *et al.*, 2003; Rahayu, 2003). The viscosity of yin rice was decreased significantly after natural fermentation. Additionally, the value of viscosity reflected the composition of yin rice for a certain extent (Yang *et al.*, 2011).

During inoculation fermentation processing, fermentation conditions are the crucial factors. Therefore, in order to reveal the relationship between inoculation fermentation parameters and properties of yin rice, artificial neural network and genetic algorithm (ANN-GA) model is developed.

Traditional modeling and optimization approaches for such as response surface methodology present restrictions for modeling highly complex systems (Rafigh *et al.*, 2014). However, artificial neural network (ANN) is powerful tool to deal with the nonlinear and multiple processing systems (Ding *et al.*, 2017). As artificial neural networks possess excellent ability of high learning and identifying, it can carry out complicated non-linear relationships between the input and output of a system with an appropriate choice of free parameters or weight easily (Watanabe *et al.*, 2014). In the last decade, the ANN has already been successfully applied to chemistry (Cristea *et al.*, 2003; Sun *et al.*, 2011), food processing (Ding *et al.*, 2016), microbiology (Ferrari *et al.*, 2017), medicine (Amato *et al.*, 2013), psychology (Levine, 2007) as well as various other fields. On the flip side, genetic algorithms (GA) mimic biological evolution process to choose

the optimal value of a complex objective, and it is a global optimizing algorithm (Erenturk and Erenturk, 2007). Experiments show that GA can effective improve the productivity of fermentation (Kumar *et al.*, 2015).

The aim of this present work was to build ANN-GA model to optimize the fermentation conditions of yin rice and the effects of inoculation fermentation on the physico-chemical properties of yin rice were discussed.

Materials and Methods

2.1 Materials Waxy rice (Zhongnuo 2055) was harvested from the Chuhe farm (Hanchuan, Hubei, China). The lactic acid bacteria which were obtained from Beijing Chuanxiu science and technology limited company contained *L. plantarum*, *L. paracasei*, and *L. pentosus* (3:1:1), *S. cerevisiae* was from yellow rice wine yeast and *R. oryzae* was from rice wine starter. Both yellow rice wine yeast and rice wine starter were obtained from Hubei Angel Yeast stock limited company. All other chemicals used were analytical grade. Distilled water was used.

2.2 Preparation of yin rice flours by natural and inoculation fermentation 250 g (14.22 %, wet basis) dehulled waxy rice was fermented at 25 °C for 16 days in 750 mL distilled water which was changed once every 5 days (Yang *et al.*, 2011). After fermentation, the rice grains were washed four times with distilled water, and dried at 40 °C for 12 h, then milled using a grinder (JP-100A, Shanghai Jiupin limited company, Shanghai, China). The rice flours (80 %, dry basis) were sieved through 100 meshes sieve (Shangyu Jinding Standard Sieve Factory, Zhejiang, China), packed and sealed in polyethylene bags and stored at 4 °C in the dryer until use. The yin rice which was got in this process named natural fermentation yin rice.

In this study, lactic acid bacteria (*L.plantarum*, *L.paracasei*, *L.pentosus*), *S.cerevisiae* and *R.oryzae* were chosen as fermentation strains and viscosity value was selected as the major index. The viscosity of natural fermentation yin rice was served as control. Lactic acid bacteria (1.45×10^8 CFU/g: 0.05 %, 0.1 % and 0.15 %), *S.cerevisiae* (2.69×10^7 CFU/g: 0.05 %, 0.1 % and 0.15 %) and *R.oryzae* (3.01×10^{10} spore/g: 0.1 %, 0.2 % and 0.3 %) were added into dehulled waxy rice in 750 mL distilled water before fermentation. Fermentation temperatures were controlled at 22, 25, 28 and 35 °C and the fermentation time were 42, 45, 48 h. After fermentation, the flours were prepared as above.

All flours samples were stored at low temperature (4 °C) for the following analysis. A schematic illustration representing the inoculation fermentation yin rice was shown in Figure 1A.

2.3 Artificial neural networks (ANN) analysis

2.3.1 Modeling of artificial neural network Artificial neural network, as a novel information processing technique, which is widely applied to various fields, consists of three layers: input, hidden, and output layers. Input layer consisting

Fig. 1. Schematic of inoculation fermentation yin rice (A) and optimization procedure of ANN-GA (B)

of a group of processing units which are responsible for acceptance of data imported to the network. Then hidden layers of data from previous layer and the processing of each layer data by them corresponding weights, value of the sum, results using the nonlinear or linear activation function and accretion basis (Eq. 1):

$$y = \sum_{i=1}^n f(w_{ij}x) + b_j \quad \text{.....Eq. 1}$$

Where x and y are input and output, respectively; n is the number of input layer neurons; and w_{ij} and b_j are associated with weight and bias, respectively. In the study, was used in the hidden layer was operated by the hyperbolic tangent function (Eq. 2), whereas a linear function was applied in the output layer. The Levenberg-Marquardt algorithm was used as training algorithm because of different ranges of input and output. According to Eq. (3), the inputs and outputs were normalized to $[-1, 1]$ prior to entering the network.

$$\tan \operatorname{sig}(x) = \frac{2e^{2x}}{1+e^{2x}} - 1 \quad \text{.....Eq. 2}$$

$$\text{Normalized input} = \left(\text{input} - \frac{\min - \max}{2} \right) \times \frac{2}{\min - \max} \quad \text{.....Eq. 3}$$

The input layer consisted of five variables in the process, namely, lactic acid bacteria, *S.cerevisiae*, *R.oryzae*, fermentation temperature, fermentation time, and the output layer contained one (viscosity) variables. Figure 1B showed a summary of the network topology illustration.

We employed a range of retort processing conditions as listed in Table 1. The total runs of 324 experiments were obtained in accordance to general factorial design ($3 \times 3 \times 3 \times 4 \times 3$). In this study, the all data points (324) were randomly divided into three groups: training (60 %), validating (20 %), and testing data (20 %). The training data were used to train the network. The weight in the network was developed by the experimental output of the training data. The testing data was used to evaluate the predictive ability of the network.

Training continued as long as the computed error between the actual and predicted outputs for the test set was decreased.

Compared with other algorithms such as Bayesian regularization, gradient descent, Levenberg-Marquardt and BFGS quasi-Newton methodology, it showed that back-propagation (BP) network was effective, stable and consistent (Singh *et al.*, 2009). Thus, we chose BP network to obtain the minimum sum of squared errors. Meanwhile, the BP neural network was trained from the vectors of input and corresponding target until it could approximate a prediction function (Anonymous, 2005). In the ANN, BP topology network had been greatly applied to the complex fermentation process modeling (Ma *et al.*, 2011; Zhang *et al.*, 2014). Hence, BP algorithm as the momentum learning rule was applied to implement supervised training network.

2.3.2 Genetic algorithm to optimize fermentation parameters Genetic algorithm was an optimization method based on the concept of natural selection (Aggarwa *et al.*, 2014). In this study, we used the GA-ANN model linking input layer (lactic acid bacteria, *S.cerevisiae*, *R.oryzae*, fermentation temperature and fermentation time) to output layer (viscosity). Genetic algorithm was a parameter searching and optimization technique based on emulation of natural evolutionary processes. According to the selection, crossover and mutation operation, GA could discover the optimal fitness individual. Selection was the first operation that can be chose to be the best individual through roulette wheel and fitness function. Then the two randomly individuals transform into two new individuals. Finally, based on the mutation probability, the composed of each individual of the chromosome randomly alters through the mutation operation. After the ANN model was established, according to the input variables, GA could continuously optimize the fermentation parameters, until get the optimal solution, as shown in Figure 1B. The operation parameters of genetic algorithm were assigned as follows: number of individuals: 60, maximum number of generations: 100, number of variables: 5, crossover probability: 90 %, mutation probability: 0.01. The optimization process was run several times with various initial populations to avoid local optimum.

2.4 Viscosity determination The viscosity was measured with rotary viscosimeter (NDJ-8S, Shanghai, China). The 5 % (w/w) rice paste was prepared by kneading well with distilled water. The samples were heated at 100 °C for 10 minutes to gel. Then they were cooled for 20 minutes, and measured the viscosity with rotary viscosimeter (Ohishi *et al.*, 2007). The parameter of measuring viscosity was rotor 4, 60 r/min.

$$\text{Viscosity} = K * \eta \quad \dots\dots\text{Eq. 4}$$

When the parameter of measuring viscosity was rotor 4, 60 r/min, the conversion factors $K = 100$. η was value of the shear rate.

2.5 Chemical analysis The moisture content, ash content

and lipid content of native rice flours, natural fermentation yin rice flours and inoculation fermentation yin rice flours were determined. The amylose content was examined using the method of Xie *et al* (2014). The total starch content and resistant starch content were examined using the method of Jiang *et al* (2013). Crude protein ($n \times 5.95$) was determined by the Shaikh *et al* (2014). The results were expressed on a dry basis except for amylose content, which was based on total starch. Total sugar was examined using the method of Miller (1959).

2.6 Size distribution A laser particle size analyzer BT-9300H (Bettersize, China) was used to determine the size distribution of rice flours. A mount of rice flours were dispersed in ethanol regularly for the analysis of size distribution (Wang *et al.*, 2012).

2.7 Scanning electron microscopy Scanning electron micrographs were obtained with a scanning microscope (JSM-6390/LV, Japan). The rice flours were set to the mold and then observed. Micrographs were taken at 1000 $\times$ magnification.

2.8 X-ray diffraction and relative crystallinity Rice flours were equilibrated in a relative humidity (5 % RH) at room temperature. X-ray diffraction analysis was performed with a D/max-RA III X-ray diffractometer (Rigaku Corporation, Tokyo, Japan). Rice flours were tightly packed into the sample holder. The diffractometer was operated at 40 kV and 50 mA with the Cu K α radiation. The diffraction data were collected over an angular range from 3 to 50° (2 θ). Step width 0.02°, and a scan rate of 15°/min (Wang *et al.*, 2012). The crystallinity (%) of the rice flours were calculated following the method of Woranuch *et al* (2017) using a computer program (Origin 6.0, Microcal, Northampton, MA).

2.9 Differential scanning calorimetry (DSC) Thermal properties of rice flours were measured using a differential scanning calorimeter (DSC 200F3, Suzhou Kaidi Deri instrument limited company, Europe). Rice flours (5 mg, db) were weighed into an aluminium specimen box with 10 μ L of distilled water. The samples were sealed and equilibrated at room temperature for 12 h, and then heated from 30 to 130 °C at a rate of 5 °C/ min (Chung *et al.*, 2011).

2.10 Statistical analysis All statistical analyses were performed using Origin software 8.0. All data were presented as means $\pm$ standard deviation (SD) and calculated using one-way ANOVA of SPSS 17.0 followed by the Tukey's multiple-range test. The statistical significance was defined as $p < 0.05$ or $p < 0.01$.

Results and Discussions

3.1 Evaluation of artificial neural network Based on the fermentation parameters and viscosity, the reliable back-propagation ANN model was established. According to widely accepted empirical rule, as follows, the maximum number of hidden layer was obtained (Nagata and Chu, 2003).

Fig. 2. Regression plots of training, validation and test data of artificial neural network

Table 1. A range of retort processing conditions of GA-ANN model

Parameter	viscosity
Mean square error	0.0387
Normalized mean square error	0.2481
Mean absolute error	0.0762
Minimum absolute error	0.0195
Maximum absolute error	19.8581
Linear Correlation coefficient	0.9746

$$N \leq \frac{N^{\text{TR}}}{N^{\text{Inputs}} + 1} \quad \dots\dots \text{Eq. 5}$$

Where N^{TR} and N^{Inputs} were the number of training samples and input nodes output of neurons, respectively. Therefore, in the network, the maximum value for hidden layer was 32. Further, the regression plots of the ANN model were depicted in Figure 2, which presented the prediction values versus experimental values for training, validation and test data.

The ANN results showed that correlation coefficient of training, validation and test were 0.9777, 0.9889, and 0.9746,

respectively. Table 1 showed the mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), minimum absolute error, maximum absolute error and the linear correlation coefficient from the testing process. In the GA-ANN model, the values of the linear correlation coefficient, MSE, NMSE, and MAE were found to be close to 1, 0, 0, and 0, respectively, which represented the optimum of GA-ANN model (Sahoo and Ray, 2006). These results indicated that GA-ANN model provided an accurate prediction method for viscosity based on fermentation parameters. A sensitivity

Table 2. Chemical components of rice flours

Rice flours	Native	Natural fermentation	Inoculation fermentation
Moisture (%)	11.97 ± 0.07	8.93 ± 0.08	6.77 ± 0.06**
Total sugar (%)	6.49 ± 0.18	8.52 ± 0.62	8.59 ± 0.67
Total starch (%)	76.76 ± 1.03	73.26 ± 0.60	81.24 ± 0.87*
Amylose (%)	3.56 ± 0.14	4.51 ± 0.11	5.85 ± 0.19**
Resistant starch (%)	7.46 ± 0.15	4.41 ± 0.09	5.06 ± 0.05**
Protein (%)	6.21 ± 0.03	5.10 ± 0.02	4.95 ± 0.06
Lipid (%)	8.89 ± 0.13	6.82 ± 0.05	4.02 ± 0.09**
Ash (%)	0.41 ± 0.01	0.16 ± 0.01	0.27 ± 0.01**
Relative crystallinity (%)	30.39	33.18	35.54

Amylose content was calculated on the basis of total starch. All data are a mean of three values ± standard deviation. * $p < 0.01$; ** $p < 0.05$

Table 3. Physical properties of fermented and control rice flours

Rice flours	Native	Natural fermentation	Inoculation fermentation
Size distribution (µm) %			
0–2.76	12.65 ± 1.61	18.33 ± 0.67	78.12 ± 4.88
2.76–21.12	61.42 ± 0.70	61.15 ± 0.68	16.49 ± 0.38
21.12–40.15	19.64 ± 1.32	15.61 ± 0.71	4.96 ± 0.19
40.15–61.62	5.20 ± 0.48	4.02 ± 0.43	0.23 ± 0.09
61.62–84.96	1.05 ± 0.13	0.86 ± 0.15	0
84.96–94.56	0.04 ± 0.08	0.04 ± 0.07	0
>94.56	0	0	0
Thermal properties			
To (°C)	75.50 ± 0.40	74.01 ± 0.38	75.11 ± 1.51*
Tp (°C)	80.21 ± 0.31	78.80 ± 0.12	80.02 ± 1.30**
Tc (°C)	85.91 ± 0.31	85.01 ± 0.27	87.20 ± 1.14**
ΔH (J/g)	9.62 ± 1.02	10.61 ± 0.88	11.51 ± 0.90
Tp–To (°C)	4.70 ± 0.10	4.73 ± 0.32	4.92 ± 0.27
Tc–To (°C)	10.30 ± 0.15	11.00 ± 0.64	12.13 ± 0.19*

All data are a mean of three values ± standard deviation. * $p < 0.01$; ** $p < 0.05$

analysis was applied to select the largest contribution of output layers in ANN. Figure 3 showed that the variation of each output layers with respect to the variation of each input. Among input variables, fermentation temperature exhibited the most significant effect on viscosity of yin rice, followed by *R. oryzae*, lactic acid bacteria, *S. cerevisiae* and fermentation time.

3.2 Optimization of process parameters by GA Based on fermentation parameters (lactic acid bacteria, *S. cerevisiae*, *R. oryzae*, fermentation temperature and fermentation time), optimization conditions were continuously chosen in the ANN-GA model. The model optimal value of viscosity was 146.8 ± 0.8 , which was nearly to that of natural fermentation yin rice (148.9 ± 1.3). The optimized process conditions were as follow: the content of lactic acid bacteria, *S. cerevisiae* and

Fig. 3. Significance analysis on the optimized neural network sensitivity. L: lactic acid bacteria; Y: *S. cerevisiae*; R: *R. oryzae*; FT: Fermentation temperature; FM: Fermentation time

Fig. 4. Scanning electron micrograph of the rice flour A: native rice flours; B: natural fermentation yin rice flours; C: inoculation fermentation yin rice flours

R.oryzae, were 0.05 %, 0.05 % and 0.2 %, respectively, the fermentation temperature and time were 25 °C and 48 h, respectively. Furthermore, the optimization condition of inoculation fermentation yin rice obtained from ANN-GA model was validated by experiments.

3.3 Chemical components Table 2 showed the chemical components of native rice, natural fermentation yin rice and inoculation fermentation yin rice. After fermentation, the contents of moisture, total starch, resistant starch, protein, lipid and ash in waxy rice decreased, whereas the contents of total sugar and amylose increased. Theoretically speaking, the decrease of resistant starch, protein and lipid content would improve the digestibility of waxy rice. Meanwhile, the contents of total sugar and protein had no significant differences between inoculation fermentation yin rice and natural fermentation yin rice. These results revealed that the optimization of inoculation fermentation could obtain the similar characteristics to natural fermentation yin rice to some extent.

3.4 Granule size distribution, thermal properties and scanning electron microscopy survey The granule size distributions and thermal properties of rice flours were presented in Table 3. It was clear that the granule distribution of the optimization of inoculation fermentation yin rice flours was more intensive than natural fermentation yin rice flours.

The major range of granule size distribution for inoculation fermentation yin rice flours was just <2.76 μm. Smaller granular size would result in energy efficient when the yin rice was cooked. Within the smaller granular size, the rice flours would be more easily to gel. So it was meaningful to utilize inoculation fermentation yin rice flours to make products, like rice cake.

The gelatinization enthalpy (ΔH) and T_p - T_o (°C) varied no significantly among the optimization of inoculation fermentation rice flours and the natural fermentation rice flours. From the Table 3, it was easy to obtain the result that the T_o and T_p of the fermentation rice flours were decreased, but the gelatinization enthalpy and the range of gelatinization temperature were increased after fermentation. Gelatinization temperatures enhanced with increasing amylose content in various rice starches (Park *et al.*, 2007). During fermentation, the amorphous zone of starch changed and the hydration ability of starch molecular enhanced because of acid and enzyme produced by the microbe, so the gelatinization enthalpy (ΔH) of yin rice flours increased. In addition, the process of fermentation could destruct the combination of fat, protein and starch and might led to the decrease of T_c which was contributed to decreasing the energy during food process.

The granule shapes of different rice flours were presented in Figure 4. From the figure, it could obtain the result that the

Fig. 5. X-ray diffraction patterns of rice flours

optimization of inoculation fermentation rice flours granule would more homogeneous than the natural fermentation rice flours granule. The range of granule size of native rice flours was wider than fermentation rice flours. Meanwhile, granules had slight superficial corrosion after fermentation.

3.5 X-ray diffraction and relative crystallinity The X-ray diffraction patterns of rice flours were showed in Figure 5. The crystallinity level calculated from the ratio of area of crystalline diffraction peak and total diffraction peaks area were given in Table 2. Rice flours exhibited strong diffraction peaks at 2θ with values of around 15.61° , 17.58° , 18.35° , 23.44° and 27° . These results indicated that the crystal type of rice flours was a characteristic A-type. No significant differentia was observed between the X-ray diffraction patterns of different rice flours. As shown in Table 2, the relative crystallinity of different rice flours ranged from 30.39% to 35.54%. So the differences in relative crystallinity among the rice flours could not be attributed to differences in crystallite size since the sharpness in X-ray pattern was identical in all rice flours (Wang *et al.*, 2012).

In the tested rice samples, fermentation yin rice flours showed the higher value of relative crystallinity than the native yin rice flours. During the process of fermentation, the metabolism of microbial might produce acids and enzymes which might influence the amorphous portion of starch granules. As the position of the characteristic peaks of rice flours was quite similar, so it was easy to obtain the result that fermentation hadn't change the crystal type of the rice flours.

Conclusion

In the present work, the excellent predictive capabilities of ANN model were established and optimization of fermentation conditions were carried out by coupling with GA. Optimization of fermentation process parameters based on the ANN-GA, the reliability of network model was further verified by experiments. Results showed that the optimization of inoculation fermentation effectively improved physico-

chemical properties of yin rice compared to the natural fermentation. The results revealed that the optimization of inoculation fermentation may change the crystalline structure of rice flours and amorphous region of the starch granule as well as the chemical components and it may modify the physical properties of yin rice. Therefore, ANN-GA was an optimization method which provided valuable information for inoculation fermentation yin rice.

Acknowledgments The authors wish to acknowledge the National Key Research and Development Program of China (No: 2016YFD0400701-05), Doctoral Start-up Funding of Hubei University of Technology (No: 4301/00047, BSQD2017016), and Nature Science Foundation of Hubei Province (No: 4115/00051).

References

- Aggarwal, S., Garg, R., and Goswami, P. (2014). A review paper on different encoding schemes used in genetic algorithms. *Int. J. Adv. Res. Computer Sci. Softw. Eng.*, **4**, 596–600.
- Almeida, E. G., Rachid C. C., and Schwan R. F. (2007). Microbial population present in fermented beverage 'cauim' produced by Brazilian Amerindians. *Int. J. Food Microbiol.*, **120**, 146–151.
- Amato, F., López, A., Peña-Méndez, E. M., Vañhara, P., Hampl, A., and Havel, J. (2013). Artificial neural networks in medical diagnosis. *J. Appl. Biomed.*, **11**, 47–58.
- Anonymous (2005). "Matlab Users" Guide. The Math Works, Inc., MA, USA.
- Blandino, A., Al-Aseeri, M. E., Pandiella, S. S., Cantero, D., and Webb, C. (2003). Cereal-based fermented foods and beverages. *Food Res. Int.*, **36**, 527–543.
- Botes, A., Todorov, S. D., Von Mollendorff, J. W., Botha, A., and Dicks, L. M. (2007). Identification of lactic acid bacteria and yeast from boza. *Process Biochem.*, **42**, 267–270.
- Chung, H. J., Liu, Q., Lee, L., and Wei, D. (2011). Relationship between the structure, physicochemical properties and in vitro digestibility of rice starches with different amylose contents. *Food*

- Hydrocoll.*, **25**, 968–975.
- Cristea, M. V., Varvara, S., Muresan, L., and Popescu, I. C. (2003). Neural networks approach for simulation of electrochemical impedance diagrams. *Indian J. Chem.*, **42**, 764–768.
- Ding, C., Xu, L., Zhou, N., Chen, Y., Li, D., Xu, N., and Wang, C. (2016). Genetic Algorithm-artificial neural network modeling of capsaicin and capsoybin content of Chinese chili oil. *Food Anal. Methods*, **9**, 2076–2086.
- Ding, B., Li, L., and Yang, H. (2017). An artificial neural network approach to estimating the enzymatic hydrolysis of Chinese yam (*Dioscorea opposita* Thunb.) starch. *J. Food Process. Pres.*, **41**, 1–7.
- Erenturk, S. and Erenturk, K. (2007). Comparison of genetic algorithm and neural network approaches for the drying process of carrot. *J. Food Eng.*, **78**, 905–912.
- Ferrari, A., Lombardi, S., and Signoroni, A. (2017). Bacterial colony counting with convolutional neural networks in digital microbiology imaging. *Pattern Recogn.*, **61**, 629–640.
- Hancioğlu, Ö. and Karapinar, M. (1997). Microflora of Boza, a traditional fermented Turkish beverage. *Int. J. Food Microbiol.*, **35**, 271–274.
- Hamajima, H., Fujikawa, A., Yamashiro, M., Ogami, T., Kitamura, S., Tsubata, M., and Hayashi, N. (2016). Chemical analysis of the sugar moiety of monohexosylceramide contained in koji, Japanese traditional rice fermented with *Aspergillus*. *Fermentation*, **2**, 2.
- Jiang, L., Yu, X., Qi, X., Yu, Q., Deng, S., Bai, B., and Pang, J. (2013). Multigene engineering of starch biosynthesis in maize endosperm increases the total starch content and the proportion of amylose. *Transgenic Res.*, **22**, 1133–1142.
- Kadan, R. S., Robinson, M. G., Thibodeaux, D. P., and Pepperman, A. B. (2001). Texture and other physicochemical properties of whole rice bread. *J. Food Sci.*, **66**, 940–944.
- Kumar, A., Pathak, A. K., and Guria, C. (2015). NPK-10:26:26 complex fertilizer assisted optimal cultivation of *Dunaliella tertiolecta* using response surface methodology and genetic algorithm. *Bioresource Technol.*, **194**, 117–129.
- Levine, D. S. (2007). Neural network modeling of emotion-review. *Phys. Life Rev.*, **4**, 37–63.
- Lu, Z. H., Li, L. T., Min, W. H., Wang, F., and Tatsumi, E. (2005). The effects of natural fermentation on the physical properties of rice flour and the rheological characteristics of rice noodles. *Int. J. Food Sci. Technol.*, **40**, 985–992.
- Ma, Y., Huang, M., Wan, J., Wang, Y., Sun, X., and Zhang, H. (2011). Prediction model of DnBP degradation based on BP neural network in AAO system. *Bioresource Technol.*, **102**, 4410–4415.
- Miller, G. L. (1959). Use of dinitrosalicylic acid reagent for determination of reducing sugar. *Anal. Chem.*, **31**, 426–428.
- Nagata, Y. and Chu, K. H. (2003). Optimization of a fermentation medium using neural networks and genetic algorithms. *Biotechnol. Lett.*, **25**, 1837–1842.
- Ohishi, K., Kasai, M., Shimada, A., and Hatae, K. (2007). Effects of acetic acid on the rice gelatinization and pasting properties of rice starch during cooking. *Food Res. Int.*, **40**, 224–231.
- Park, I. M., Ibanez, A. M., Zhong, F., and Shoemaker, C. F. (2007). Gelatinization and pasting properties of waxy and non-waxy rice starches. *Starch-stärke*, **59**, 388–396.
- Raffigh, S. M., Yazdi, A. V., Vossoughi, M., Safekordi, A. A., and Ardjmand, M. (2014). Optimization of culture medium and modeling of curdlan production from *Paenibacillus polymyxa* by RSM and ANN. *Int. J. Biol. Macromol.*, **70**, 463–473.
- Rahayu, E. S. (2003). Lactic acid bacteria in fermented foods of Indonesian origin. *Agritech.*, **23**, 75–84.
- Sahoo, G. B. and Ray, C. (2006). Flow forecasting for a Hawaiian stream using rating curves and neural networks. *J. Hydrol.*, **317**, 63–80.
- Shaikh, A., Kathe, A. A., and Mageshwaran, V. (2014). Reduction of gossypol and increase in crude protein level of cottonseed cake using mixed culture fermentation. *KKU Res. J.*, **19**, 67–73.
- Singh, R. R. B., Ruhil, A. P., Jain, D. K., Patel, A. A., and Patil, G. R. (2009). Prediction of sensory quality of UHT milk – a comparison of kinetic and neural network approaches. *J. Food Eng.*, **92**, 146–151.
- Sun, S. P., Yi, D. Q., Jiang, Y., Wu, C. P., Zang, B., and Li, Y. (2011). Prediction of formation enthalpies for Al₂X-type intermetallics using back-propagation neural network. *Mater. Chem. Phys.*, **126**, 632–641.
- Thanh, V. N., Thuy, N. T., Chi, N. T., Hien, D. D., Ha, B. T. V., Luong, D. T., Ngoc, P. D., and Ty, P. V. (2016). New insight into microbial diversity and functions in traditional Vietnamese alcoholic fermentation. *Int. J. Food Microbiol.*, **232**, 15–21.
- Wang, L., Xie, B., Xiong, G., Du, X., Qiao, Y., and Liao, L. (2012). Study on the granular characteristics of starches separated from Chinese rice cultivars. *Carbohydr. Polym.*, **87**, 1038–1044.
- Wang, L., Mostaed, E., Cao, X., Huang, G., Fabrizi, A., Bonollo, F., and Vedani, M. (2016). Effects of texture and grain size on mechanical properties of AZ80 magnesium alloys at lower temperatures. *Mater. Design.*, **89**, 1–8.
- Watanabe, K., Kobayashi, I., Matsushita, Y., Saito, S., Kuroda, N., and Noshiro, S. (2014). Application of near-infrared spectroscopy for evaluation of drying stress on lumber surface: A comparison of artificial neural networks and partial least squares regression. *Dry. Technol.*, **32**, 590–596.
- Woranuch, S., Pangon, A., Puagsuntia, K., Subjalearndee, N., and Intasanta, V. (2017). Rice flour-based nanostructures via a water-based system: transformation from powder to electrospun nanofibers under hydrogen-bonding induced viscosity, crystallinity and improved mechanical property. *RSC Adv.*, **7**, 19960–19966.
- Xie, L. H., Tang, S. Q., Chen, N., Luo, J., Jiao, G. A., Shao, G. N., and Hu, P. S. (2014). Optimisation of near-infrared reflectance model in measuring protein and amylose content of rice flour. *Food Chem.*, **142**, 92–100.
- Yang, C., Nan, N., Fu, X. Y., Chen, P., Xie, B. J., and Sun, Z. D. (2011). Effect of natural fermentation on physico-chemical characteristics of Yinmi starch. *Food Sci.*, **11**, 129–136.
- Zhang, R., Xie, W. M., Yu, H. Q., and Li, W. W. (2014). Optimizing municipal wastewater treatment plants using an improved multi-objective optimization method. *Bioresource Technol.*, **157**, 161–165.