Aseptic Packaging of Wheat Bun and the Prediction of Shelf Life Using a BP Neural Network

Xuemeng Xu*, Long Wang, Zhicong Sun, and Ligen Wu

Abstract—**The aim of this study was to investigate a wheat bun aseptic packaging technology and to develop a BP neural network to predict shelf life. This study can be considered to be a technical reference for the industrial production of bun. After cooling and ultra-violet sterilization, steamed buns were packaged aseptically. Then buns were exposed to 3.0 kGy doses of Cobalt-60 gamma irradiation for 120 seconds. The aseptically packaged buns were then stored at 4℃ and 15℃ respectively. The bacterial count, textural characteristics, and color of samples under different storage conditions were measured at different times. The results showed that the shelf life of bun stored at 15℃ and 4℃ was 10 days and 20 days, respectively. A predictive shelf-life model based on back-propagation neural network predicted the shelf lives of aseptically packaged bun stored at 4℃ or 15℃ with 99.4% accuracy. This BP neural network provides a theoretical basis for the prediction of shelf life of industrial produced bun.**

Index Terms—**Aseptic packaging, back propagation (BP) neural network, shelf life, wheat bun.**

I. Introduction

Bun, the Chinese steamed bun, is a traditional and popular staple food in the Chinese diet. The bun has a very generous moisture content, and is also easily deteriorated due to its vulnerability to microorganisms. Therefore, it has short shelf life. These factors directly restrict the circulation, storage, and industrial production of bun [1,2]. With the technological development and increasing market demand, bun production needs to be upgraded from the procedures currently used in local restaurants and small workshop to efficient industrial production. However, elongated shelf life is a prerequisite for industrial production and an extended circulation chain. Therefore, methods to estimate shelf life are of importance to enhance production.

Packaging is a critical step for the food logistic cycle. Aseptic packaging is a technology commonly used for fresh food packaging that consists of the filling and sealing commercially sterile products into sterile containers under aseptic conditions [3]. Aseptic solutions ensure commercial sterility and extend the shelf life of food, without using preservatives.

Shelf life is defined as the length of time that food can be stored and transported. During the period of time, the quality of the food must remain acceptable under the expected (or specified) conditions of distribution, storage, and display. These qualities include sensory quality, physical and chemical properties, desired microbial properties, and the preservation of the nutrients stated on the label. Shelf life is one of the important indicators that consumers use to understand the food quality they are purchasing. An accurate determination of shelf life is pivotal for minimizing waste and eliminating potential quality and safety risks of food [4]. Shelf life depends on the degradation mechanism of the specific product, the packaging material and technology, and the environmental impact of logistics.

Most studies that have investigated bun production have focused on the composition of the raw materials, processing technology, sensory quality, and quality changes during the period of storage [5-8]. Some studies have examined processes that would keep bun fresh during storage and logistics. For example, several studies reported on the effects of preservatives on the delay or minimization of the aging process of the steamed bread [9-11]. Wu et al. and Sheng et al. showed that the shelf life of bun at room temperature could be extended by using packaging gas [12,13]. However, it lacks of enough studies on the use of aseptic packaging to extend bun shelf life. In this study, we investigated aseptic packaging technology for bun and developed a model based on back propagation (BP) neural network to predict the shelf life of aseptically packaged bun. The aim of this study is to provide a technical reference for the industrial production and logistics of bun, and to present a method to predict the shelf life of bun for manufacturers and the food administration.

II. Methodology

A. Materials, Instruments, and Experimental Design

Materials

The all-purpose flour used for this study (Teyifen (Shen Xiang Brand, Zhengzhou Haijia Food Co., Ltd.), had a moisture content of 13.5%, a protein content of 13.5%, and an ash content of 0.51%. Highly active yeast was purchased from Angel Yeast Co., Ltd (Liuzhou, Guangxi, China). The packaging material was acrylic coated $BOPP_{20}/PVDC_4$ composite film with an oxygen permeation rate of 3.158 $cm^3/m^2 \cdot 24$ h and a water vapor permeation rate of 1.53 $g/m^2 \cdot 24$ h (Xinghuo Packing Machinery, Zhengzhou, Henan, China). A hydrogen peroxide solution (30%) was purchased from Longzhong Chemical Glass Company (Zhengzhou, Henan, China). Other reagents included sodium hydroxide, ethanol, and sodium chloride, which were purchased from Sinopharm Chemical Reagent Co., Ltd (Shanghai, China).

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Instruments

A JHMZ-200 needle mixer and a proof cabinet (Model JXFD-7) were obtained from Beijing Dongfu Jiuheng Instrument Technology Co., Ltd. (Beijing, China). Firmness was measured using a TA.XT plus Texture Analyzer (Stable Micro Systems, Ltd., Godalming, UK). The color of a bun sample was measured using a Chroma meter (Konica Minolta CR-400, Japan). Henan University of Technology manufactured the sterilization and packaging machine. The HSX-150 Constant Temperature and Humidity incubator was purchased from the Shanghai Minconne Instrument Manufacture Co., LTD (Shanghai, China). Other instruments included steaming pots and balance.

Experimental methods and the bun production process

(1) The bun production and cooling process

The following recipe was used for bun production: 1. mix the wheat flour (1000 g), yeast (5 g), and water (500 mL) and knead the dough with a dough mixer at 120 revolutions per minute (rpm) for five minutes, followed by 240 rpm for one minute. 2. Rest the dough for one hour (25℃, relative humidity 85%). 3. Next, add flour (100 g) and knead at 120 rpm for another five minutes. Cut and shape the dough into 80-gram portions, then rest and ferment them for 40 minutes (38℃, relative humidity 85%). 4. After that, steam them in a steamer pot for 25 minutes. The above procedures were repeated until 100 buns were made. 5. Cooling of the bun: the newly steamed buns were placed in a cooling box (18℃, relative humidity 75%) with ultraviolet (UV) light (80 $\mu W/m^2$) for 30 minutes.

(2) Sterilization, packaging, and storage of the bun

After cooling, the buns were packaged aseptically according to the procedures used in the literature [14]. The detailed aseptic packaging protocol is described in Table 1. The packaged buns were divided into Group I and Group II. Both groups were stored in a humidity incubator with 75% relative humidity. Group 1 was stored at a constant temperature of 4℃, and Group II was stored at a constant temperature of 15℃. At pre-determined times, seven buns were removed for analysis. Three of these were used to determine the bacterial count, two were used for color measurement, and two were used for texture analysis.

(3) Measurement of bun surface bacterial count

The number of bacteria on the surface of the bun was determined according to GB/T4789.2-2016. (People's Republic of China standard).

(4) Texture characterization of bun

After cooling, two 15-mm slices were removed from the center portion of the bun and these samples were used for texture analysis. In addition, two buns were analyzed simultaneously in order to ensure standardization in the comparison of bacterial counts. The analysis of the texture was carried out using a TA-XI2i Texture Analyzer with a P/36R cylinder probe in TPA mode. The parameters were as follows: pre-test speed, 3 mm/s; test speed, 1 mm/s; post-test speed, 5 mm/s; and a compression rate of 40%.

(5) Color characterization of bun

The color of a bun sample was measured using a Satake portable colorimeter (Japan) and $L^*a^*b^*$ color space. L^* defined the lightness of the bun, and $\triangle a^*$ and $\triangle b^*$ defined the direction of color shift. Two samples were used for the measurement and six points from each bun were measured. The average values were used for analysis purposes.

B. Results and Analysis

The bacterial counts found on the bun surfaces are shown in Table 2. According to the literature [15], surface bacterial counts less than 4lg CFU/g have been used as the criteria to determine microbial quality. After being aseptically packaged, the shelf life of the bun samples stored at 4℃ and 15℃ was 20 and 10 days, respectively. The results showed that aseptic packaging combined with cold chain logistics, effectively increased the shelf life of bun to 20 days.

As shown in Tables 2 and 3, the elasticity and recoverability of bun stored under both conditions decreased slowly with time, which suggested that aseptic packaging had little effect on the elasticity and recoverability of bun. The hardness of bun increased rapidly during the first two days and peaked at day six, then it increased slowly with time. However, the hardness of bun was satisfactory during the entire length of time in storage. Color is an important indicator of the bun quality. In this study, bun stored at both temperatures had a negative Δa (color shifted to green), a positive Δb (color shifted to yellow), and a decreased ΔL. However, there were no significant changes in the color characteristics. These results showed that aseptic packaging had little influence on the texture and color of bun. Increasing of surface bacterial counts and the lightness of the buns showed a downward trend.

After steaming, a combination of aseptic cooling, packaging, and cold-chain logistics significantly increased the shelf life of bun without compromising the sensory quality. This protocol will facilitate the industrial production of bun.

C. Predicting the Shelf Life of Aseptically Packaged Wheat bun

Selection of a Shelf Life Forecasting Model

There are two commonly used methods to predict food shelf life. The first method is to investigate the changes of representative food quality indicators according to related chemical or microbiological principles. Results are then extrapolated to determine the changes in food quality and to predict the remaining shelf life. The second uses a mathematical algorithm to forecast shelf life based on the relationship between environmental factors and overall food quality changes, without an investigation of specific chemical reactions or other intrinsic factors that occur during food deterioration. There are five types of commonly used models that are currently used to predict shelf life: a chemical kinetics-based model, a microbial growth kinetics-based model, an artificial intelligence-based model (e.g. BP neural network), a statistical model, and a temperature based model. In this study, experimental data were utilized to develop a BP neural network to predict the shelf life of aseptically packaged bun [16-18].

The BP neural network-based model for the prediction of wheat bun shelf life

TABLE 1
PROTOCOL FOR ASEPTIC PACKAGING OF BUN

	Sterilization of bun	Sterilization of packaging materials	Sterilization of environment and packaging equipment
Temperature and humidity	The temperature of the sterilization room was 4℃ or 15℃, relative humidity was 75%, and 1 standard atmospheric pressure	The temperature of the packaging environment and equipment were maintained at 20℃, with relative humidity 75%.	
Sterilization methods	Low-dose (3 kGy) Co-60 irradiation for 120 s	UV (wavelength 250 nm) irradiation at 80 μW intensity.	H_2O_2 (35%, 20℃)

TABLE 2
THE SURFACE BACTERIAL COUNT OF BUN STORED AT DIFFERENT TEMPERATURES

Storage temperature/ ℃	Days in storage							
	2	4	6	8	10	15	20	25
15	1.1	1.8	2.3	3.1	3.8	-	-	-
4	1.1	1.6	2.0	2.3	2.3	3.3	3.5	-

TABLE 3
THE TEXTURE AND COLOR MEASUREMENTS OF ASEPTICALLY PACKAGED WHEAT BUN STORED AT 4℃

Storage days	Texture characteristics			Color characteristics		
	Hardness	Elasticity	Recoverability	Red and green ($\triangle a^*$)	Yellow and blue ($\triangle b^*$)	Lightness (L)
2	3462.4 ± 347.28^{c}	0.9133 ± 0.008^{a}	0.2430 ± 0.007^{a}	-0.2933 ± 0.15^{bc}	14.47 ± 0.806^{ab}	-9.370 ± 0.680^{bc}
4	3951.2 ± 498.81^{bc}	0.91250 ± 0.010^{a}	0.2252 ± 0.020^{b}	-0.3152 ± 0.12^{bc}	14.853 ± 0.455^{a}	-9.305 ± 0.352^{a}
6	4435.6 ± 293.03^{ac}	0.8768 ± 0.029^{b}	0.2036 ± 0.012^{bc}	-0.3461 ± 0.020^{b}	15.32 ± 0.506^{b}	-9.253 ± 0.493^{b}
8	4051.2 ± 352.88^{bc}	0.8868 ± 0.019^{b}	0.1892 ± 0.008^{cd}	-0.3567 ± 0.015^{a}	15.50 ± 0.604^{a}	-9.022 ± 0.980^{a}
10	4203.9 ± 510.70^{bc}	0.8881 ± 0.009^{b}	0.1801 ± 0.017^{de}	-0.3405 ± 0.009^{b}	14.93 ± 0.455^{a}	-8.843 ± 1.0914^{b}
15	4152.8 ± 342.00^{ab}	0.8778 ± 0.005^{c}	0.1630 ± 0.001^{e}	-0.3200 ± 0.015^{a}	13.43 ± 0.256^{b}	-8.584 ± 3.438^{b}
20	3803.9 ± 510.70^{bc}	0.8853 ± 0.003^{bc}	0.1621 ± 0.01^{bcd}	-0.2900 ± 0.985^{c}	13.29 ± 0.326^{bc}	-8.314 ± 0.6397^{b}
25	3558.5 ± 169.40^{ab}	0.8786 ± 0.005^{c}	0.1620 ± 0.00^{bcd}	-0.2493 ± 0.179^{ab}	13.25 ± 0.522^{ab}	-8.010 ± 0.0365^{b}

Note: The measurement unit used in this table is lg (CFU/g); "-" indicated the bun was stale.

TABLE 4
THE TEXTURE AND COLOR MEASUREMENTS OF ASEPTICALLY PACKAGED WHEAT BUN STORED AT 15℃

Storage days	Texture characteristics			Color characteristics		
	Hardness	Elasticity	Recoverability	Red and green ($\triangle a^*$)	Yellow and blue ($\triangle b^*$)	Lightness (L)
2	3540.4 ± 40.73^{a}	0.9133 ± 0.005^{a}	0.2462 ± 0.002^{a}	-0.3400 ± 0.026^{b}	13.54 ± 0.922^{b}	-8.933 ± 0.365^{a}
4	4032.5 ± 338.7^{bc}	0.9042 ± 0.019^{a}	0.2182 ± 0.036^{ab}	-0.3567 ± 0.050^{a}	15.77 ± 0.592^{a}	-10.32 ± 0.210^{b}
6	4311.2 ± 597.3^{a}	0.9026 ± 0.0164^{a}	0.2051 ± 0.015^{ab}	-0.3633 ± 0.111^{b}	15.473 ± 0.535^{a}	-11.48 ± 0.450^{b}
8	3755.6 ± 509.8^{a}	0.8952 ± 0.224^{bc}	0.1887 ± 0.025^{b}	-0.4008 ± 0.521^{c}	15.0167 ± 0.375^{a}	-11.55 ± 0.554^{b}
10	3673.9 ± 712.1	0.8843 ± 0.010^{a}	0.1702 ± 0.051^{bc}	-0.4767 ± 0.153^{b}	14.85 ± 0.455^{a}	-7.284 ± 0.558^{a}

Note: Data in Table 3 and 4 are the mean ± standard deviation. The different superscripts a, b, c in one cell indicates significant difference ($P<0.05$), while the same lower-case letters indicate no significant difference.

A BP neural network (abbreviated to BP network) uses an Error Back Propagation algorithm in an artificial neural network. A BP network usually includes an input layer, a hidden layer, and an output layer. There are connections between layers, but no connection between the neurons within the same layer [19,20]. The transfer functions usually have a sigmoid shape, which maps the input from negative infinity to positive infinity in the $(-1, 1)$ or $(0, 1)$ intervals, with a non-linear amplification effect. A typical BP network with a sigmoid transfer function can realize any non-linear mapping from input to output [21]. After determining the architecture of the BP network, the network can be trained by using a sufficiently representative set of input-output examples. The weights and thresholds can be adjusted during the training so that the network learns the desired input-output mapping. The trained BP network can map the appropriate output for inputs that are not included in the examples, which is called the generalization function of the network. From the point of function fitting view, the BP network has an interpolation function that we utilized for prediction [22]. The BP network is a good solution to the nonlinear relationship between the various indicators, and therefore its commonly used to build forecast models [23,24].

Construction of shelf life predicting model

In this study, we developed a BP neural network using the Graphical User Interface (GUI) in MATLAB, and we determined the architecture, training functions, and other parameters of the network [25]. These parameters are listed below:

Selection of network architecture: It is well-accepted that BP neural networks that contain a single hidden layer can realize arbitrary non-linear mapping by increasing the number of neural nodes appropriately. Therefore, we adopted a BP neural network in this study.

Determination of number of nodes for the input and output layers: According to the nature of problem presented in this study, we included eight nodes in the input layer; storage temperature, surface bacterial count, texture (hardness, elasticity, recoverability), and color (red-green, yellow-blue, and lightness). There was one node for the output layer, which was used for the remaining shelf life of the bun.

Since the input parameters and output parameters had different dimensions, we normalized all the data to a range between −1 and 1 using the MATLAB default normalization algorithm to minimize the error of the forecast model. The normalization formula used was

$$y = (y_{\max} - y_{\min}) \;\; y = (y_{\max} - y_{\min}) * \frac{x - x_{\min}}{x_{\max} - x_{\min}} + y_{\min} \qquad (1)$$

where y represents the normalized data, x represents the original data, x_{min} represents the minimum value of the original dataset, x_{max} represents the maximum value of original dataset, y_{max} represents the maximum value of the normalized data, with a default value of 1, and y_{min} represents the minimum value of the normalized data, with a default value of −1.

Determination of the number of nodes in the hidden layer: The number of nodes in the hidden layer affects the non-linear capability of the neural network. The number of nodes in the hidden layer was estimated using the empirical formula:

$$M = \sqrt{n+m} + a \qquad (2)$$

where m represents the number of nodes in the input layer, n represents the number of nodes in the output layer, and a is a constant between 1 and 10.

We tested the neural network performance in the case where the number of nodes in the hidden layer ranged between 4 and 13. The results from multiple tests indicated that the network performance was optimal when the number of nodes in the hidden layer was six. Therefore, six nodes were used for the hidden layer in this study.

The selection of network functions: The functions used in the BP network included a hidden layer transfer function, a training function, a neural network performance function, and a simulation function.

The commonly used transfer functions include the non-linear log-sigmoid transfer function "logsig", the hyperbolic tangent sigmoid transfer function "tansig", and the linear transfer function "purelin". The function logsig constrains the neural network outputs between 0 and 1, the transig constrains the network outputs between −1 and 1, and the input and output for purelin could be arbitrary numbers. In this study, all the input and output parameters had been normalized between −1 and 1. To ensure the non-linearity of the BP neural network, we used the tansig as the transfer function for the hidden layer, and purelin as the transfer function for the output layer.

Commonly used training functions include trainlm, trainrp, trainscg, trainbfg, and traingdx. The selection of the training function was determined by the nature of the problem and the number of training samples. Among these training functions, trainlm converges fast, has less mean square error, and offers a more accurate training outcome. Therefore, we used trainlm as the training function for this study.

We used a BP neural network default network performance function and simulation function, which were the mean squared error (MSE) and the sim function, respectively.

In summary, we developed a BP neural network containing a single hidden layer. The input layer parameters included storage temperature, surface bacterial count, the texture (hardness, elasticity, recoverability), and color (red-green, yellow-blue, lightness). There were six neural nodes in the hidden layer and one node in the output layer, which represented the remaining shelf life of the bun. The transfer functions for the hidden layer and the output layer were tansig and purelin, respectively. The training function, network performance function, and simulation function was trainlm, mse and sim, respectively. The scheme of the BP neural network is illustrated in Fig. 1.

Training of network

After these parameters were determined, a BP neural network was developed using the Neural fitting toolbox (nftool) in MATLAB. After the parameters were established, we conducted training of the network.

During training, the network divided the samples into three subsets randomly, including a training dataset, a validation dataset, and a test dataset. These three subsets of data had different functions. The training dataset was used for network training. The network weights and thresholds were adjusted according to the errors of the training data. The validation dataset was used to validate the generalization function of the network. When the generalization performance could no longer be improved, which suggested the network had been optimized, the training of the network would be terminated. The test dataset was utilized to test the performance of the network. The weights or threshold of the network would not be adjusted based on the results of the test data. In this study, nine sets of data were randomly selected from 12 datasets and these were used for the network training. Therefore, there were nine datasets for training and validation of the network. The three remaining datasets were used for the test.

After repeated training, the optimal mse reached 0.0074, which met our criteria (no greater than 0.01). The training was then terminated. The resulting weights and thresholds are listed in Table 5.

Prediction and Results Analysis

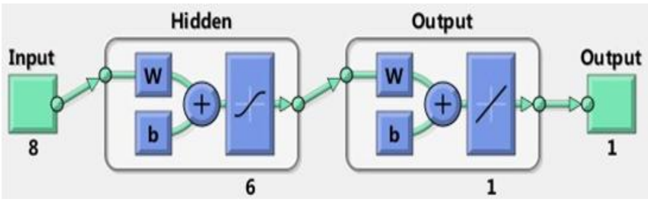

Fig. 1. Illustration of the BP neural network used for the prediction of shelf life of aseptically packaged bun.

TABLE 5
WEIGHTS AND THRESHOLDS OF THE BP NEURAL NETWORK

Categories	A						B
Temperature	0.4612	0.7573	−1.2592	0.6548	0.4087	0.3907	0.6744
Hardness	−0.7286	0.0561	0.982	0.8276	−0.9912	1.0165	−0.4016
Elasticity	1.9744	0.085	0.2455	−0.723	0.54662	1.0871	0.0275
Recoverability	1.7018	1.1576	0.1772	−0.6907	0.5366	0.7371	−0.479
Red-green	0.0689	0.3722	0.3995	0.0452	0.3372	−0.8039	−0.919
Yellow-blue	1.2088	−0.8327	−0.4271	−0.7174	−0.653	0.7553	−0.8393
Lightness	−0.263	−0.3796	0.8991	−0.6331	0.7691	−0.291	-
Number of bacteria	−0.1022	0.411	−0.4708	−0.1366	−0.1371	0.1258	-
Threshold	−1.9303	−1.2452	0.0049	0.8067	1.0703	−2.0734	−0.3436

Note: A: Weights between input layer and hidden layers; B: Weights between hidden layer and output layer.

TABLE 6
PREDICTION RESULTS OF THE BP NEURAL NETWORK

Actual shelf life	Shelf life predicted using BP neural network	Relative error (%)
14	13.91	0.64
10	10.00	0
2	1.98	1

After training, the test datasets, which included the data obtained at day six and day ten at a 4℃ storage temperature, and data obtained at day eight at a 15℃ storage temperature, were input into the BP neural network for prediction of shelf life. The predicted results were converted back to the original dimensions. As shown in the table, the BP neural network had an error of less than 1%, with average error of 0.54% and an accuracy of 99.4%. The Prediction results are shown in Table 6.

III. CONCLUSION

Fresh-steamed wheat buns were cooled down and sterilized with UV irradiation. To realize aseptic packaging, the entire bun production line was aseptic. The packaging material was UV irradiated, and the buns were sterilized with low-dose Co-60. In addition, the packaging environment and equipment were sterilized using H_2O_2. Aseptic packaging combined with cold-chain logistics significantly increased shelf life of bun to 20 days. This aseptic packing technology is reliable for the industrial production of wheat bun.

A BP neural network containing an input layer, one hidden layer, and an output layer was developed for the prediction of bun shelf life. The input layer parameters included the storage temperature, surface bacterial count, texture (hardness, elasticity, and recoverability), and color (red-green, yellow-blue, and lightness). The output layer parameter consisted of the remaining shelf life of the bun. The training function used for the BP neural network was trainlm. This BP network predicted the shelf life of bun with 99.4% accuracy. This BP neural network provides a theoretical basis for the prediction of shelf life of industrial produced bun. It also can be used to predict the shelf life of other aseptically packaged wheat foods.

REFERENCES

[1] J. Xi, Q. Zhao, D. Xu, Y. Jin, F. Wu, Z. Jin, and X. Xu, “Volatile Compounds in Chinese Steamed Bread Influenced by Fermentation Time, Yeast Level and Steaming Time,” LWT, vol. 141, pp. 110861, 2021.

[2] X.Z. Liu, “Statue and Tendency Analysis of Staple Food of China,” Grain Processing 2014, vol. 6, pp. 1-5.

[3] A.T. Petkoska, D. Daniloski, N.M. D’Cunha, N. Naumovski, and A.T. Broach, “Edible Packaging: Sustainable Solutions and Novel Trends in Food Packaging,” Food Research International, vol. 140, 109981, 2021.

[4] A. Ainsa, P.L. Marquina, P. Roncalés, J.A. Beltrán, and J.B. Calanche M, “Enriched Fresh Pasta with a Sea Bass By-Product, a Novel Food: Fatty Acid Stability and Sensory Properties Throughout Shelf Life,” Foods, vol. 10, no.2, pp. 255-255, 2021.

[5] Y. Shao, C.H. Liu, and X.F. Liu, “Effects of Mixture Food Antibacterialim Prover on Keeping Quality and Freshness of Steamed Bread,” Science and Technology of Cereals, Oils and Foods, vol. 22, no.2, pp. 16-18, 2014.

[6] Y.H. Hu, J. Guo, and Z.X. Guo, “Effect of Heating Tempering on Steamed Bread Quality,” Journal of Henan University of Technology Natural Science Edition, vol. 37, no.5, pp. 64-69, 2016

[7] Z.H. Han, and J. Wang, “Study on Sterilization Technology of Steamed Bread,” Food& Machinery, vol. 29, no.33, pp. 209-211, 2013

[8] H.P. Fan, R. Li, X.L. Zheng, N. Wang, Y.H. Chen, and Z.L. Ai, “Effect of Yeast Products on Fermentation Characteristics of Frozen Dough and Quality of Steamed Bread,” Transactions of the Chinese Society of Agricultural Engineering, vol. 20, no.32, pp. 298-305, 2016.

[9] O. Parenti, L. Guerrini, B. Zanoni, M. Marchini, M.G. Tuccio, and E. Carini, “Use of the 1H NMR Technique to Describe the Kneading Step of Wholewheat Dough: The Effect of Kneading Time and Total Water Content,” Food Chemistry, vol. 338, pp. 128120-128120, 2021.

[10] M. Houngbédji, S.W. Padonou, C. Parkouda, P.G. Johansen, and M. Hounsou, “Multifunctional Properties and Safety Evaluation of Lactic Acid Bacteria and Yeasts Associated with Fermented Cereal Doughs,” World Journal of Microbiology and Biotechnology, vol. 37, no.2, pp. 1-15, 2021.

[11] R.Y. Martin, and Sophie Boakes, “That Smells Filling: Effects of Pairings of Odours with Sweetness and Thickness on Odour Perception and Expected Satiety,” Food Quality and Preference, vol. 54, pp. 128-136, 2016.

[12] L.G. Wu, A.N. Wang, and L.B. Qu. “Study on Characteristics of Steamed Bread in Vacuum Package During the Period of Storage Under in Door Temperature,” Journal of Zheng Zhou University of Light Industry (Natural Science), vol. 30, no.4, pp. 11-14, 2015.

[13] Q. Sheng, K.X. Zhu, and X.N. Guo, “Effect of Modified Atmosphere Packaging on Quality and Shelf Life Extension of Chinese Steamed Bread,” Journal of the Chinese Cereals and Oils Association, vol.31, no.9, pp. 126-356, 2016.

[14] X.M. Xu, Y. Xu, and L.B. Qu, “Design and Experiment of Aseptic Packaging Line of Staple Wheat Food with Analytic Hierarchy Process Method,” Transaction of the Chinese Society of Agriculture Engineering, vol. 32, pp. 249-255, 2016.

[15] B.M. Prüβ, “Microbes in Our Food, an Ongoing Problem with New Solutions,” Antibiotics (Basel, Switzerland), vol. 9, no.9, 2020.

[16] A.K. Khamis, “Dissolution Time and Shelf Life Quality of Ficus Deltoidea Powder and Granule,” IOP Conference Series: Materials

Science and Engineering, vol. 105, no.1, 012092, 2021.
[17] B. Shen, "Comprehension and Thinking of Complex Network Construction and Clustering Based on Neural Network Algorithm," MATEC Web of Conferences, vol.173, 2018.
[18] X. Liu, Y.M. Li, and J. Liu, "BP Neural Network Based Prediction Model for Fresh Egg's Shelf Life," Transactions of the Chinese Society for Agricultural Machinery, vol. 46, no.10, pp. 28-334, 2015.
[19] M. Jimenez-Martinez, and M. Alfaro-Ponce, "Fatigue Life Prediction of Aluminum Using Artificial Neural Network," Engineering Letters, vol. 29, no.2, pp704-709, 2021.
[20] J. Qian, H.Y. Long, Y. Long, and C.X. Zhao, "Improved NSGA-III Algorithm and BP Fuel-cost Prediction Network for Many-objective Optimal Power Flow Problems," IAENG International Journal of Applied Mathematics, vol. 51, no.2, pp307-320, 2021.
[21] M. Chen, "Matlab Neural Network Principle and Example," Beijing: Tsinghua University Press, 2013.
[22] L. Wang and L. Wang, "BP Network Implementation Based on Computer MATLAB Neural Network Toolbox," Journal of Physics: Conference Series, vol. 1648, no.2, 022134, 2020.
[23] A.V. de Souza, A B. Neto, J.C. Piazentin, B.J.D. Junior, E.P. Gomes, C.D.S.B. Bonini, and F.F. Putti, "Artificial Neural Network Modelling in the Prediction of Bananas' Harvest," Scientia Horticulturae, vol. 257, 108724, 2019.
[24] M.A. Aslam, C.L. Xue, M.H. Liu, K. Wang, and D.X. Cui, "Classification and Prediction of Gastric Cancer from Saliva Diagnosis using Artificial Neural Network," Engineering Letters, vol. 29, no.1, pp10-24, 2021.
[25] Z. Du, H. Yang, W.J. Lv, X.Y. Zhang, and H.L. Zhai, "Prediction of the Inhibitory Concentrations of Chloroquine Derivatives Using Deep Neural Networks Models," Journal of Biomolecular Structure and Dynamics, vol. 39, no.2, pp. 672-680, 2021.