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Design for Bread Baking Temperature Profiles using Neural Network Modeling Approach

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ABSTRACT

Various neural network models were developed to establish the relationship between tin temperature profiles and bread quality. The best model was composed of 6 input neurons, 6 first hidden layer neurons, 4 second hidden layer neurons and 4 output neurons with Log-sigmoid transfer functions. During verification, the correlation coefficient and mean square error were 0.9356 and 53.9229 respectively. To produce sandwich bread with various levels of crust color and weight loss, the best neural network model was used to design the tin temperature profiles for 4 baking zones. To obtain the same crust color and weight loss, the amount of increased tin temperatures for shorter baking time could be estimated. However the pattern of tin temperature profiles was not significantly changed. In contrast, the pattern of tin temperature profiles required for producing light crust color (L-values of 55, 65 and 55) and dark crust color (L-values of 50, 55 and 50) was significantly different. Therefore the neural network model presented the potential to assist industry with designing the baking profile to obtain the desire crust color pattern with shorter baking time and less weight loss.

Key words: modeling, neural network, process design, baking, bread

INTRODUCTION

Normally, baking process of bread was controlled at certain temperature for the whole baking period. But after the baker understood how baking condition in each baking zone affects bread quality, the step baking was introduced. The step baking condition could be optimized to minimize weight loss during baking (Therdthai *et al*., 2002). To describe the baking process which is based on heat and mass transfer mechanisms, several studies have been conducted. The change during baking process could be explained by mathematical models (Zanoni *et al*., 1994; Baik *et al*., 2000; Broyart and Trystram, 2002), computational fluid dynamic models (De Vries *et al.*, 1995; Therdthai *et al.*, 2003; 2004; Mirade *et al.*, 2004), kinetic models (Zanoni *et al*., 1995a, 1995b) and neural network models (Zhou and Fong, 2002). A neural network is an information processing technique, using a computer to simulate a human nervous system. A large number of sample data including input and output is required to train the neural network. The network structure includes input layer, output layer and hidden layer. Each layer is composed of a number of neurons connected together by weights. Combined weighted input factors are used to estimate the output factors, using an iterative, trial and error procedure (Horimoto *et al*., 1995). Although the neural network is purely based on a

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black box approach, it could improve the accuracy to predict bread quality from various process conditions, compared to the statistical models (Zhou and Fong, 2002). However, in order to design appropriate process conditions for various bread quality attributes, the model expressing the reverse relationship is required. Therefore the objective was aimed to develop a neural network model to predict baking temperature profiles in accordance with the desired product quality.

METHODOLOGY

Neural network modeling

Training: 96 Data sets of inputs (weight loss, crumb temperature, top crust color, side crust color, bottom crust color and baking time) and outputs (average tin temperature in Zone 1, Zone 2, Zone 3 and Zone 4) were normalized into the range of 0 and 1. The normalized data sets were then used to train a neural network using the back-propagation method (Matlab®6.5). Various four layer neural network models with Tan-sigmoid and Log-sigmoid transfer functions were developed. As shown in Figure 1, Tan-sigmoid transfer function can be used to generate the outputs within the range of -1 and 1 whereas Log-sigmoid transfer function can be used to generate the outputs within the range of 0 and 1.

The model performance was determined by the correlation coefficient (R) and mean square error (MSE) between the modeled tin temperature in Zone 1, Zone 2, Zone 3 and Zone 4 and the corresponding measured values.

Verification: New 29 data sets of input and output were normalized and introduced into the model developed during training. To determine the predictability of the model, the predicted tin temperature in Zone 1, Zone 2, Zone 3 and Zone 4 were compared to the actual values. Rs and MSEs were calculated to verify the model performance.

RESULTS AND DISCUSSION

Four-layer neural network models with different numbers of hidden neuron and transform function (Tan-sigmoid and Log-sigmoid) were established. Their performances are shown in Table 1.

The Log-sigmoid transfer function was found to be slightly better than the Tan-sigmoid transfer function, in contradictory to Zhou and Fong (2002). This was possibly because the relationship between input and output parameters was presented in the reverse direction in this paper. According to the model performance during training and verification, the best model structure was composed of six and four neurons in the first and second hidden layers, respectively. During modeling, R value and MSE were 0.9473 and

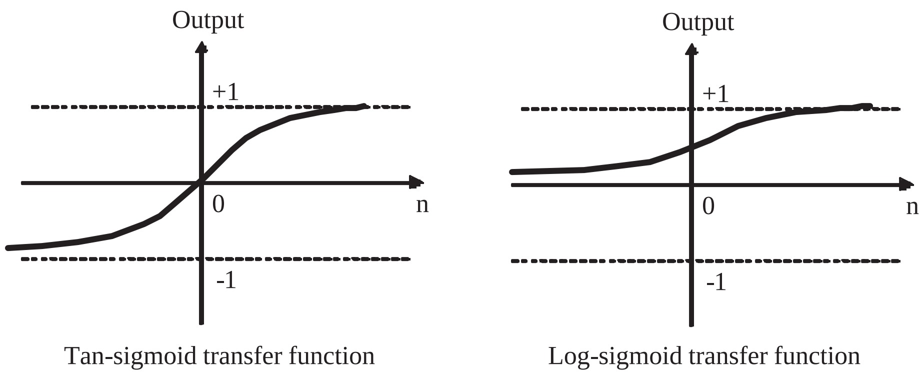

Figure 1 Characteristics of Tan-sigmoid and Log-sigmoid transfer functions.

Table 1 Model performances during modeling and verification.

Model	Number of neurons		Function		Modeling		Verification	
	First hidden layer	Second hidden layer	First hidden layer	Second hidden layer	R	MSE	R	MSE
1	6	2	Tan	Tan	0.9326	60.0409	0.9221	64.7608
2	6	4	Tan	Tan	0.9413	52.6842	0.9337	56.8383
3	7	2	Tan	Tan	0.9034	84.6287	0.8842	94.0541
4	7	4	Tan	Tan	0.9204	71.1397	0.9007	82.6938
5	6	2	Log	Log	0.9439	50.1778	0.9334	55.7298
6	6	4	Log	Log	0.9473	47.2813	0.9356	53.9229
7	7	2	Log	Log	0.9442	49.9011	0.9364	53.3232
8	7	4	Log	Log	0.9426	51.3693	0.9345	55.5478

47.2813 respectively. Similar model performance was also found during verification. Therefore the 6-6-4-4 neural network model was trained properly and could reasonably predict tin temperature profiles in four baking zones.

Process design using the neural network model

After several models had been established, the best neural network model (the 6-6-4-4 neural network model) was selected to design the baking tin temperature profiles for different baking times and bread characteristics including crust colors and weight loss. For a baking index, the starch gelatinization extent could be used to represent the progression of baking. It was found that the maximum starch gelatinization extent was obtained after the crumb temperature met 95°C (Zanoni *et al.*, 1995a). In this paper, the desired crumb temperature was therefore set to 97°C to ensure the completion of bread baking.

According to the prediction of the neural network model (Fig. 2), producing of bread crust color with different patterns of L-value required different tin temperature profiles in four zones. L-values of commercial sandwich bread crust are normally in the range of 50-56, 55-72 and 50-60 for top, side and bottom crust respectively. Higher L-value indicated lighter crust color. To obtain sandwich bread with L-values of 55-65-55 (top-side-bottom crust) within 24 minutes, a high heating rate should be applied at the beginning. Therefore tin temperatures in Zones 1 and 2 were very high to enhance crumb temperature. To obtain the desired crust colors, Zone 3 and Zone 4 temperatures had to be decreased. Otherwise crust colors could be too dark. This coincided with the results of Therdthai *et al.* (2002) that temperatures in Zones 3 and 4 significantly enhanced crust colors. To obtain the same crust color by using a longer baking time, Zone 1, Zone 2 and Zone 3 temperatures could be reduced, comparing with the 24 minute baking process. To reduce weight loss from 9% to 8%, the pattern of baking profile was not significantly changed. However lower temperatures should be applied in Zones 1, 2 and 3. Temperature in Zone 4 should be increased to develop the same crust color with L-value of 55-65-55. Therefore the pattern of temperature profile to produce sandwich bread with 8-9% weight loss and light crust color (L-value of 55-65-55) within 24-26 minutes tended to increase from Zone 1 to Zone 2 before decreasing from Zone 3 to Zone 4.

As shown in Figure 3, to obtain darker and more uniform crust color with L-values of 50-55-50 (top-side-bottom crust), which were still in the commercial crust color range, the pattern of baking profiles was significantly different from the one for producing crust color with L-values of 55-65-55. This was because the process required the significantly higher temperature in Zones 3 and 4

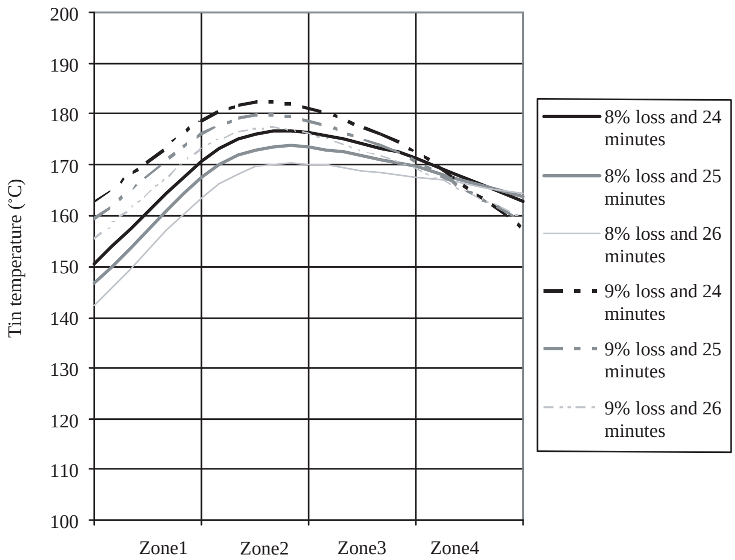

Figure 2 Estimated temperature profiles to develop light crust color with L-values of 55-65-55 (top-side-bottom crust).

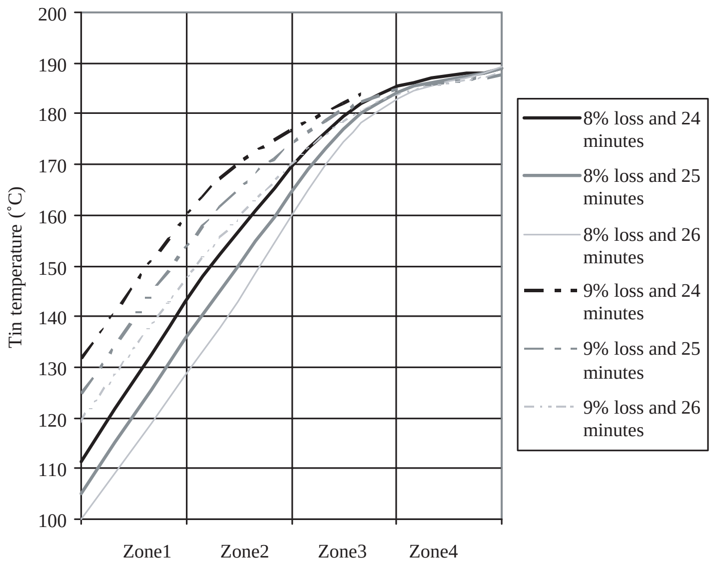

Figure 3 Estimated temperature profiles to develop darker crust color with L-value of 50-55-50 (top-side-bottom crust).

to produce darker bread crust, comparing to the process for crust color with L-values of 55-65-55. Not only the higher temperatures in Zones 3 and 4 could enhance crust color development, but they also possibly increased crumb temperature. As a result, temperatures in Zones 1 and 2 which normally enhanced crumb temperature (Therdthai *et al*., 2002) could be reduced when higher temperatures in Zones 3 and 4 were applied. Therefore the process started with a lower temperature in Zone 1. After that tin temperature gradually increased to Zone 4 which was the highest. For either a longer baking time process or a lower weight loss process, the lower temperature was required in all baking zones, which was similar to the case of the lighter bread (L-values of 55-65-55).

CONCLUSION

Four-layer neural network models were established to predict the baking temperature profiles for white sandwich bread. The best neural network model showed a good agreement between the predicted temperature profile and the actual temperature profile. Therefore the neural network model was applied to assist with the process design. Using the neural network model developed, the required temperature profiles could be estimated in order to produce bread containing different levels of crust color and weight loss within different baking times. Therefore this approach could provide the guidance to design the baking profile in accordance with the specified bread quality.

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