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Baking of Flat Bread in an Impingement Oven: Modeling and Optimization

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An artificial neural network (ANN) was developed to model the effect of baking parameters on the quality attributes of flat bread; i.e., crumb temperature, moisture content, surface color change and bread volume increase during baking process. As the hot air impinging jets were employed for baking, the baking control parameters were the jet temperature, the jet velocity, and the time elapsed from the beginning of the baking. The data used in the training of the network were acquired experimentally. In addition, using the data provided by ANN, a multi-objective optimization algorithm was employed to achieve the baking condition that provides the quality of the bread in all aspects simultaneously.

Keywords ANN; Baking; Flat bread; Genetic algorithm; Impinging jets; Neural network; Optimization; Quality

INTRODUCTION

About one third of world population consumes various kinds of flat bread. Few research studies, however, have been conducted on these types of bread in comparison with those on thicker ones. Various traditional methods have been employed for baking of flat breads. These methods are not necessarily optimal in terms of bread texture and appearance as they are derived empirically over the years.

Using hot air impinging jets for baking of flat breads can provide a good compromise between texture and appearance. Impinging jet heat transfer systems are used in a wide range of industrial processes. Mujumdar[1] has given a concise but comprehensive summary of impingement drying. So far, various research studies have been conducted on the use of impingement heat transfer in food processing but almost nothing on bread baking. For example, Xue et al.[2] examined the effect of ambient relative humidity (RH) on the volume change of a special cake under impinging jets medium. Sarkar et al.[3] studied the effects of geometry of impinging jets on food processing generally. Wahlby et al.[4] studied the effect of impinging jets on baking time and color quality of meat. This study constitutes the first time that impinging jets are proposed to be employed for flat bread baking.

The purpose of this study is to investigate and then quantify the effect of impinging jets on the quality parameters of baked flat bread, which is characterized by different parameters for texture and appearance. Bread texture is chiefly developed by starch gelatinization. Starch gelatinization is the most important quality attribute of the bread, which contributes to the sensory acceptability. On the other hand, Zanoni et al.[5] indicated that starch gelatinization completes at crumb temperature of about 100°C. Thus, crumb temperature was chosen as the first parameter representing the bread quality.

Another parameter considered is bread moisture content (ratio of bread water mass to total mass), which not only influences the bread texture but is a significant factor from a staling viewpoint; i.e., lower water content downgrades the bread quality, whereas higher water content postpones the staling of the bread. In addition, for bread producers, the lower the weight loss, the higher the profit margin. Bread thickness is another factor contributing to flat bread acceptability. The maximum increase in bread volume is desirable, particularly in flat breads.

None of these three parameters are directly related to bread appearance. The key factor that contributes to consumer preference, of course, is its surface color. Hence, these four quality attributes—i.e., bread crumb temperature, moisture content, volume increase, and surface color—represent bread acceptability in terms of various aspects. The objective of this study is to develop a model that predicts these attributes as a function of the baking conditions continuously; that is, not just in discrete values of the input

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variables acquired experimentally. An earlier paper presented the experimental results of the variation of quality attributes as the baking control parameters were changed.[6] However, the experiment does not provide continuous information required for more detailed analyses such as finding the optimum point at which all of the quality indexes are satisfied.

In this study, an artificial neural network (ANN) was used to obtain such a model of bread quality attributes during baking in an impingement oven. As the physicochemical principles governing the bread baking process (e.g., surface color and volume change during baking) are not completely illuminated and understood, the ANN modeling is an appropriate method to relate the oven condition with bread quality attributes without requiring prior knowledge on the mechanisms involved in the process.[7]

ANN modeling has been employed in drying related researches for two decades. Huang and Mujumdar[8] were of possibly first researchers who used ANN for modeling of an industrial dryer. They used ANN to model drying of tissue paper in an industrial-scale Yankee dryer, which uses high-temperature, high-velocity air jets for rapid drying.

ANN has been employed earlier for modeling of many different food applications. Sablani et al.[9] used ANN to predict the heat conductivity of the bread as a function of moisture content, temperature, and apparent density of the bread. Their model estimates the conductivity with mean relative error (MRE) of 10%. Broyart et al.[7] used ANN to model the qualitative parameters of biscuit; that is, color and thickness. The baking parameters included sample temperature, RH, and speed of air recirculation inside the oven; 540 data series were obtained experimentally, which were applied in ANN training and testing.

In all of these earlier works (including studies that did not used ANN for modeling; e.g., Therdthai et al.[10]), various models were developed to describe only one of the quality attributes individually as a function of baking control parameters. If two or more quality attributes were to be predicted, two or more separate ANN models were developed, respectively. Although these models are not pointless, the second aim of this study, as mentioned before, is acquiring the specific baking condition that causes all of the quality attributes to lie in the acceptable range. This ANN model provides the required data for optimization algorithm.

In this study, a multi-objective genetic algorithm (GA) was employed to find the optimum baking control parameters that satisfy all of the quality indexes. The GA uses an ANN model to produce the required input data. Multi-objective optimization means that two or more objectives (here, four baking parameters) are optimized simultaneously. Otherwise, that is, if a multi-objective optimization was not applied, one of the quality indexes should be optimized using a single objective optimization algorithm while the other quality attributes have to be constrained to some predefined limits (as in the paper by Therdthai et al.[10]). Indeed, this method resulted in one of the possible solutions rather than the best solution. However, using multi-objective optimization algorithms, a set of different solutions is provided from which the best one is selected due to the designer preference.

An experimental setup equipped with an online data acquisition system was developed to provide the required data. Some of the design parameters of an impinging jet oven such as the jet configuration, the nozzle diameter (D), and the ratio between diameter and nozzle-to-bread distance (H/D) were taken reasonably based on literature.[11–13]

However, the experimental setup was designed such that the air jet temperature and velocity, as two important factors influencing on impingement heat transfer, could be changed. Thus, the effect of these parameters on four quality attributes was investigated experimentally.

In this context, the first aim of this article is to develop an ANN model that quantifies the bread quality using the four main quality attributes simultaneously. Consequently, this model enables one to investigate the effect of oven design factors (jet temperature and velocity) and the baking time on the quality attributes continuously. The required data for ANN training are provided earlier by experiments. The second aim is to optimize the baking control parameters—i.e., jet temperature, jet velocity and time—such that the best quality of the bread is provided at the end of the baking. The required data for the employed optimization algorithm is supplied by the previously developed ANN model.

EXPERIMENTS AND ANN MODEL

Baking Experiments

After complete mixing of the dough, it was divided into 250 g pieces and kept for 15 min under ambient conditions. Then, the dough was shaped, punched with the fingers (to obtain small and spatially uniform gas distribution), and placed into an incubator for 35 min at a relative humidity of 80% at 35°C until its thickness reached 2 cm. Each loaf of bread was composed of 135 g (54%) wheat flour, 100 g (40%) water, and 15 g (6%) salt, sugar, dry yeast, and flavors.

An experimental oven in which jets of high-velocity hot air impinge perpendicularly onto the dough surface was designed and constructed. The nozzles are 1.2 cm in diameter and are fixed above the product surface with (H/D) equal to 7. The jet temperature is strictly controlled using a PID controller. A motor inverter was used to change the motor speed and, subsequently, the fan speed of the oven, which in turn makes it possible to acquire different jet velocities. A schematic of the oven is presented in Fig. 1.

Accurate measurements of the baking parameters made the model developed in this study greatly reliable and

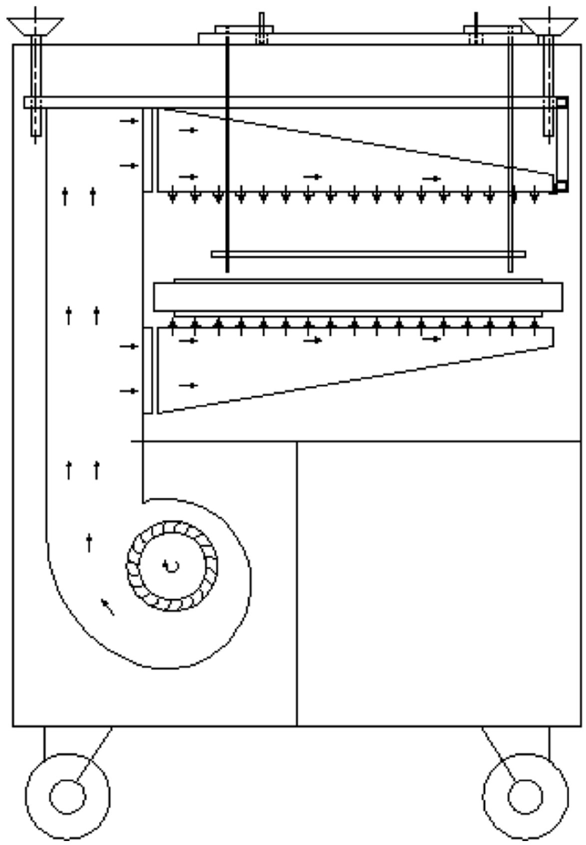

FIG. 1. Schematic of the impingement oven (all dimensions in cm).

effective, as will be seen later. Pt-100 probes were used for temperature measurement. A new measurement system was developed for the on-line measurement and recording of bread weight.

Thickness and color of the bread surface were measured using an image processing technique with two digital cameras. The change of the front side of the bread was used to determine the change in bread thickness.

The average surface color of the bread was first calculated using MATLAB® software in an RGB system from photos of another camera and then converted to L*, a*, b* system using correlations presented in Macdougall.[14] The color change (ΔE) was calculated from the following equation:

$$\Delta E = \left(\left(l^* - l_0^* \right)^2 + \left(a^* - a_0^* \right)^2 + \left(b^* - b_0^* \right)^2 \right)^{\frac{1}{2}} \quad (1)$$

where L_0^*, a_0^*, and b_0^* are the initial values of L*, a*, b*.

To monitor and record the measured data, an on-line data acquisition system was provided with a software package exclusively developed for this study. More details of the constructed oven, measurement methodology, and data acquisition system may be found in previous papers by the same authors.[6,15]

All of the baking experiments lasted for 25 min, which provided comprehensive information to investigate the baking process until combustion or charring occurred.

Other oven control variables—i.e., jet temperature and velocity—were changed such that different baking conditions were experienced. The jet temperature was increased from 150 to 250°C with 25°C increments. The jet velocity was adjusted at 1, 2.5, 5, 7.5, and 10 m/s. Preliminary experiments had shown that the required input variables that result in acceptable values for quality attributes lies in these chosen ranges.

Also, the color and thickness of the bread were recorded 51 times during 25 min (every 30 s). Therefore, in total 1275 (5 jet temperatures × 5 jet velocities × 51 recording times) sets of data were acquired experimentally, each of them containing three input variables and four output quality parameters. These data were acquired as 25 (5 jet temperatures × 5 jet velocities) baking tests were conducted. Table 1 shows samples of acquired datasets.

Modeling

As explained earlier, an ANN was developed to model the quality attributes of the bread after baking. The four attributes were bread crumb temperature, moisture content, surface color change, and volume change. The independent variables were baking time, oven jet temperature, and oven jet velocity.

Neural networks are information processing techniques offering solutions to problems that have not been explicitly formulated. The parallel structure of the ANNs distinguishes them from traditional serial processing computers

TABLE 1
Typical acquired experimental data

	Jet temp. (°C)	Jet velocity (m/s)	Baking time (s)	Crumb temp (°C)	Moisture content	Relative volume	Color change (ΔE)
1	150	5	10 × 60	87.44	0.373	1.31	10.69
2	175	7.5	5 × 60	94.51	0.360	1.55	6.37
3	200	10	15 × 60	131.3	0.324	1.37	30.35

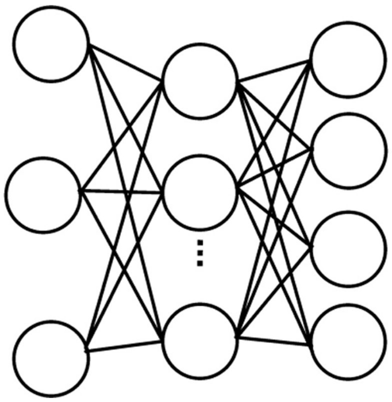

FIG. 2. Neural network schematic diagram.

and results in some of the fundamental properties of neural networks.[15] For example, in contrast with conventional modeling approaches, ANN is capable in dealing with uncertainties, noisy data, and nonlinear relationships.[7]

The acquired datasets were divided into three subsets. Sixty percent of data sets were used in training, 20% in validation process, and 20% in testing. The training data are used to train the network, which means acquiring appropriate weights and biases of the neurons. The validation data are used during the training process, avoiding the network, to memorize the given data so be unable to predict the proper outputs for the new fed inputs. This enhances the generalization power of the network.[16] The testing data are not used in the training process. These are used just to verify the network performance with the new and previously not used data.

A multi-layer perceptron feed forward (MLPFF) network was used to model the quality attributes of the baked flat bread. These types of networks are one of the most popular and successful neural network architectures that are suited to a wide range of applications such as prediction and process modeling.[16] An MLPFF network comprises a number of identical units named neurons organized in layers, with those on one layer connected to those on the next layer so that the outputs of one layer are fed forward as inputs to the next layer. Any input is multiplied by the connection weight and then a bias (a constant number) is added to the product before introducing to the next layer. The output of each neuron is calculated through a transfer function.

Once the network weights and biases are initialized, the network is ready for training. The training process

TABLE 2
ANN weights and biases

From inputs to hidden layer								
Weights					From hidden layer to output layer			
From 1st input: time	From 2nd input: jet temp.	From 3rd input: jet vel.	Biases		To 1st neuron: crumb temp.	To 2nd neuron: moisture content	To 3rd neuron: color change	To 4th neuron: relative volume
−2.48	−0.56	−2.65	3.67	Weights	−0.59	−0.12	−0.95	0.75
1.93	1.26	−2.86	−3.24		0.22	−0.59	0.04	−0.89
1.11	−2.70	−2.23	−2.81		0.72	−0.11	0.10	0.13
2.54	1.41	2.24	−2.37		0.36	−0.26	−0.84	−0.09
−3.59	−0.70	−0.30	1.94		−0.90	0.48	−0.92	0.91
2.90	2.21	0.43	−1.51		0.48	0.87	0.03	−0.52
0.30	−3.65	−0.17	−1.08		−0.48	0.52	0.99	−0.29
0.87	−1.38	−3.29	−0.65		0.51	−0.78	0.19	−0.14
−1.03	2.73	2.23	0.22		0.46	−0.48	−0.81	−0.10
−2.98	1.54	−1.49	−0.22		0.28	−0.74	−0.09	0.30
3.00	−0.74	−1.98	0.65		0.65	−0.38	−0.20	0.77
−2.40	−2.71	0.63	−1.08		0.40	−0.52	0.52	−0.42
−1.77	3.20	−0.33	−1.51		−0.45	−0.99	−0.25	−0.13
1.99	2.23	−2.14	1.94		−0.39	−0.42	−0.51	0.87
2.71	−2.32	0.85	2.37		0.72	−0.21	−0.04	0.13
0.11	−2.40	2.77	2.81		−0.02	−0.46	0.98	−0.63
2.58	2.53	0.63	3.24		0.72	−0.93	−0.34	0.50
−2.87	−0.03	−2.28	−3.67		0.29	−0.66	0.90	0.09
				Biases	−0.50	0.16	0.83	0.79

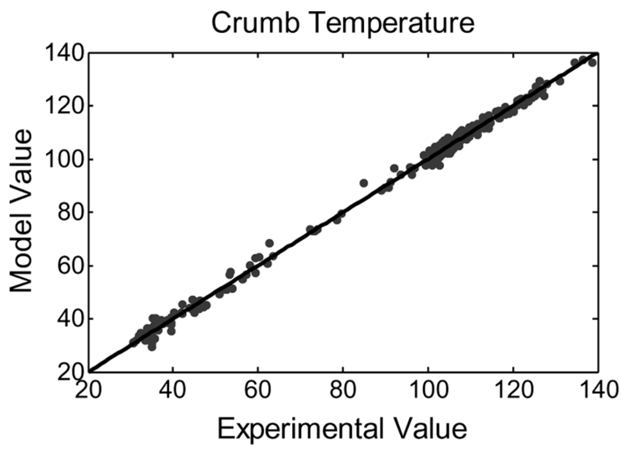

FIG. 3. Correlation between experimental value and model output for crumb temperature.

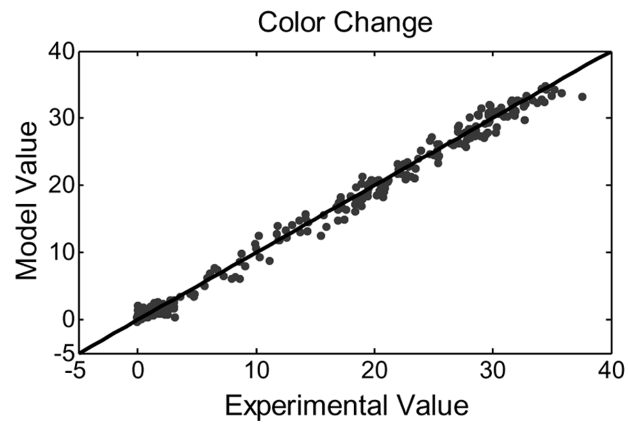

FIG. 5. Correlation between experimental value and model output for color change.

requires a set of previously acquired data of proper network behavior (e.g., obtained experimentally). During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function.

After investigating various NN structures, the best case containing one hidden layer with 18 neurons was obtained. A Levenberg-Marquardt algorithm was used in network training. Mean absolute error (MAE) was selected to evaluate the NN performance during the training process. A hyperbolic tangent sigmoid transfer function was used in the hidden layer and linear transfer function for the output layer. As mentioned before, this model consists of three input neurons including baking time, oven jet temperature, and oven jet velocity and four output neurons as bread crumb temperature, moisture content, surface color change, and relative volume (Fig. 2).

Optimization

Using the trained neural network model, the quality attributes of the bread during baking can be calculated using any arbitrary values for the inputs; i.e., oven jet temperature and velocity and baking time. However, the objective here is to obtain the input values for which the quality attributes lie in the acceptable range. In other words, to provide the appropriate condition for the optimum baking, all of the four quality parameters must be as close as possible to the desired values; that is, the following objective functions should be minimized:

$$\begin{aligned} g_1(x) &= |f_1(x) - d_1| \\ g_2(x) &= |f_2(x) - d_2| \\ g_3(x) &= |f_3(x) - d_3| \\ g_4(x) &= |f_4(x) - d_4| \end{aligned} \tag{2}$$

where f_1, f_2, f_3 & f_4 are the bread crumb temperature, moisture content, color change, and relative volume,

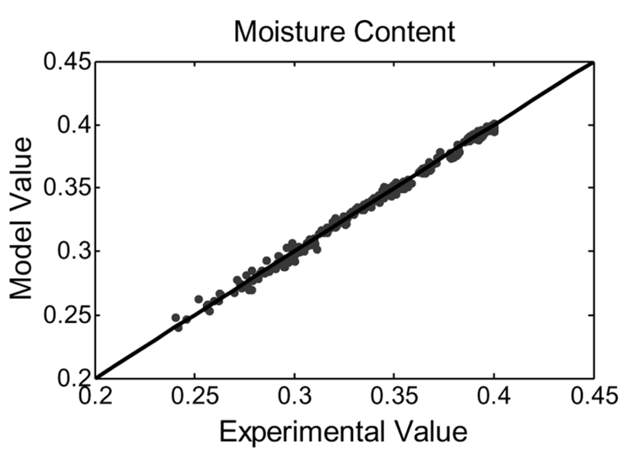

FIG. 4. Correlation between experimental value and model output for moisture content.

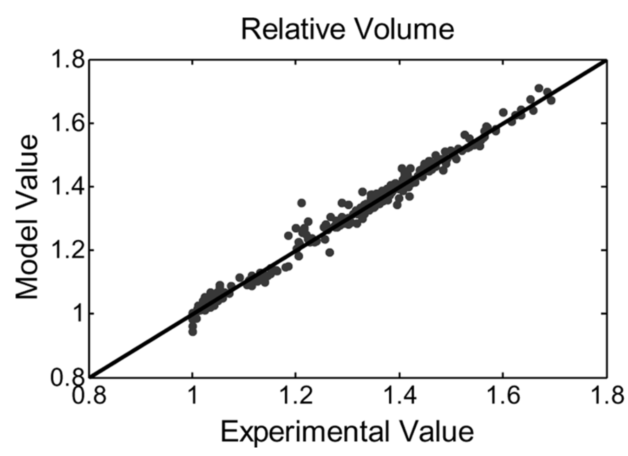

FIG. 6. Correlation between experimental value and model output for relative volume.

TABLE 3
ANN model performance

	Performance	Crumb temperature	Moisture content	Color change	Relative volume
Training data set	R	0.9983	0.9975	0.9959	0.9924
	MAE	1.481	0.002339	0.8464	0.01529
Testing data set	R	0.9979	0.9973	0.9956	0.9922
	MAE	1.510	0.002342	0.8926	0.01571

respectively, and $x = \{x_1, x_2, x_3\}$ is a vector comprised of input variables; i.e., time, oven jet temperature, and oven jet velocity. d_1, d_2, d_3 & d_4 are the desired values for the quality attributes of the bread after baking.

Therefore, the optimization problem was formulated as follows:

$$Minimize \quad g(x) = \{g_1(x), g_2(x), g_3(x), g_4(x)\} \tag{3}$$

while

$$\begin{aligned} 0 < x_1 < 25 \\ 150 < x_2 < 250 \\ 1 < x_3 < 10 \end{aligned} \tag{4}$$

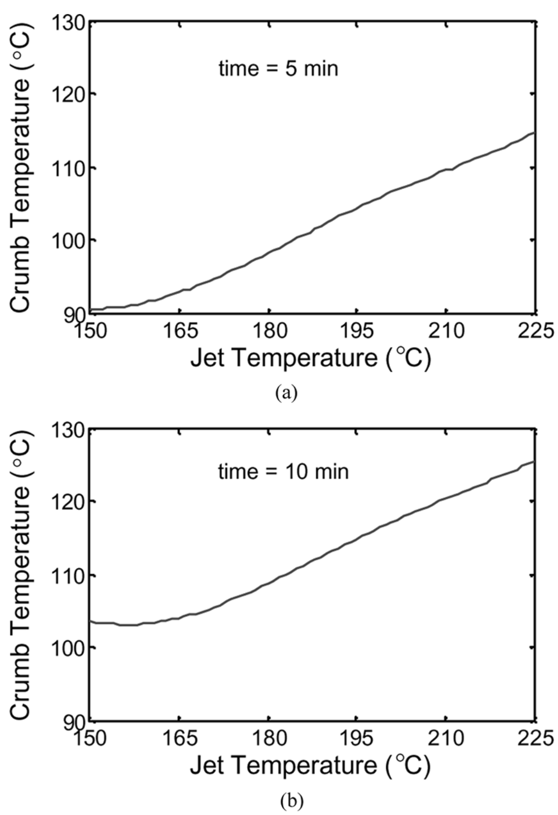

FIG. 7. Crumb temperature vs. jet temperature at $V_j = 10\,m/s$ and (a) time = 5 min, (b) time = 10 min.

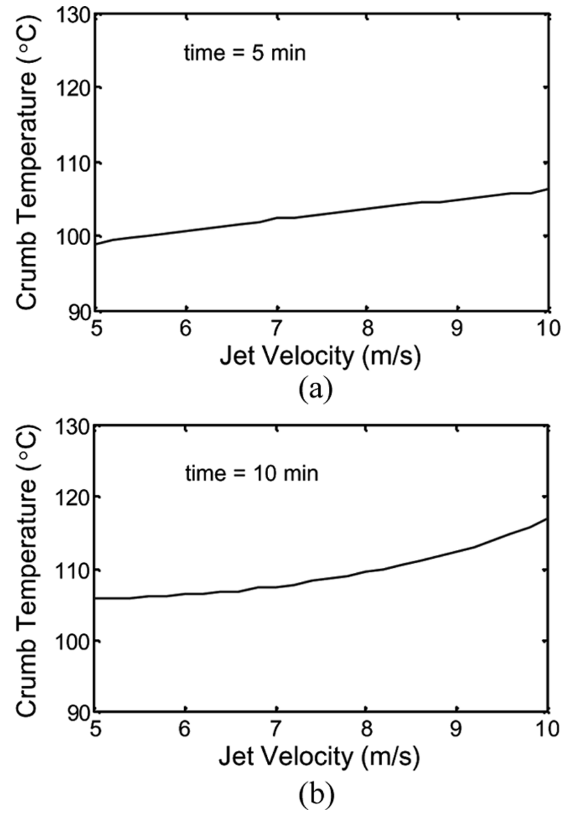

FIG. 8. Crumb temperature vs. jet velocity at $T_j = 200°C$ and (a) time = 5 min, (b) time = 10 min.

This is an unconstrained and bounded multi-objective optimization problem. Most optimization problems naturally have several objectives to be achieved normally conflicting with each other. It is rarely the case that there is a single point that simultaneously optimizes all the objective functions. Therefore, we normally look for trade-offs rather than single solutions when dealing with multi-objective optimization problems. These sets of solutions are called Pareto optimal sets.[17]

So far, different methods have been used to solve the multi-objective optimization problem. In this study, the genetic algorithm was employed to find the Pareto set. This GA uses the previously developed ANN model to calculate the quality attributes from the randomly selected input variables. After processing and refining the data, a new generation of input variables is provided by GA; that is, applying these values of input variables will give a better quality of the bread at the end of the baking. This process continues until the optimum solution is acquired.

RESULTS AND DISCUSSION

Table 2 shows the final weights and biases of the ANN after training is accomplished. Figures 3 to 6 evaluate the performance of the neural network for prediction of the

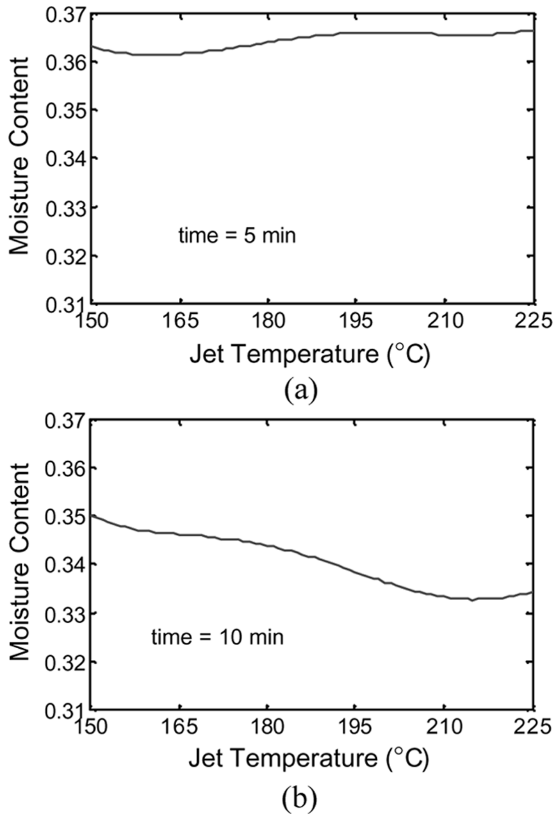

FIG. 9. Moisture content vs. jet temperature at $V_j = 10\,m/s$ and (a) time = 5 min, (b) time = 10 min.

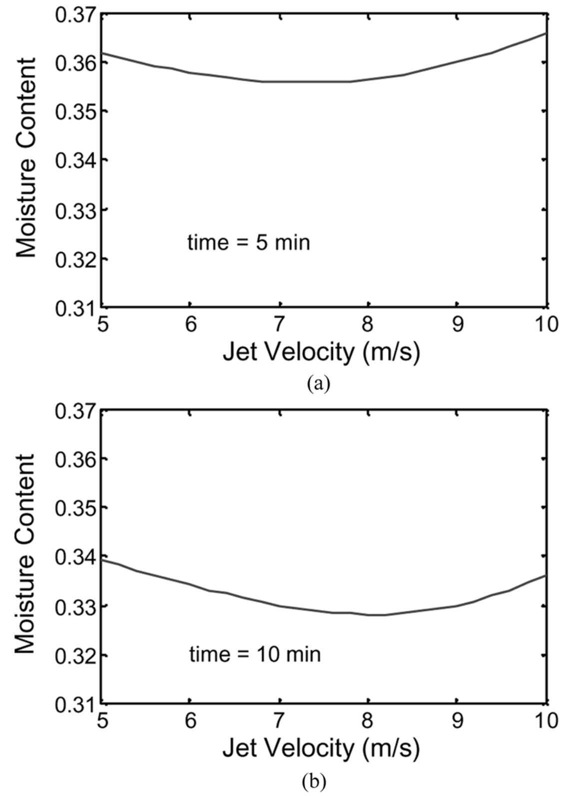

FIG. 10. Moisture content vs. jet velocity at $T_j = 200°C$ and (a) time = 5 min, (b) time = 10 min.

quality attributes using the testing data. As it is clear, the network predicts these parameters with a high accuracy ($R > 0.99$). This may be justified due to the large set of experimental data used in the training process of the network. Table 3 shows the ANN model performance for training and testing data sets.

As explained in the Introduction, developing a model enables us to investigate the quality attributes of the bread as the jet temperature and velocity are changed. Experimental results also provided us with such information but in discrete values of input variables.[6] Therefore, using the modeling results rather than experimental ones, the trade-off between quality attributes was studied more accurately and comprehensively.

However, the acceptable range of quality attributes should be specified experimentally. In an earlier experimental study, these values were discussed thoroughly.[6] The crumb temperature, as stated before, must reach 100°C in order for the process of starch gelatinization to be completed. Starch gelatinization is the most important quality attribute of the bread that contributes to the sensory acceptability in terms of appearance and texture.

For the moisture content, the acceptable range differs for different types of the bread, but a range of 30–35% seems appropriate for the samples used in this study.[6] Therefore, in this study, a moisture content of 35% was taken as target.

For the crust color, the acceptable ΔE ranges from 15 to 20. As stated before, this quantity describes the color as well as lightness of the bread.[6] Therefore, ΔE equal to 17.5 was taken as the most desired for flat breads.

The maximum bread thickness is desirable particularly in Iranian flat breads. Here, as explained before, the relative volume represents the proportional volume change of bread at the end of the baking.[6]

Now, using the modeling results and knowing the desired values of quality attributes, the effect of baking parameters was investigated. Figures 7a and 7b show the variation of bread crumb temperature versus oven jet temperature at the baking times of 5 and 10 min, respectively. Here, the jet velocity is constant at 10 m/s. As can be seen, if the baking time of 5 min is desired, the jet temperature should not exceed 190°C in order that crumb temperature does not go far beyond 100°C. Also, in the case of 10 min for baking time, this temperature should not exceed 170°C. Results of our experimental study show[6] that at the jet velocity of 10 m/s, jet temperature of about 170 to 190°C provides the best condition for baking in terms of the bread interior texture.

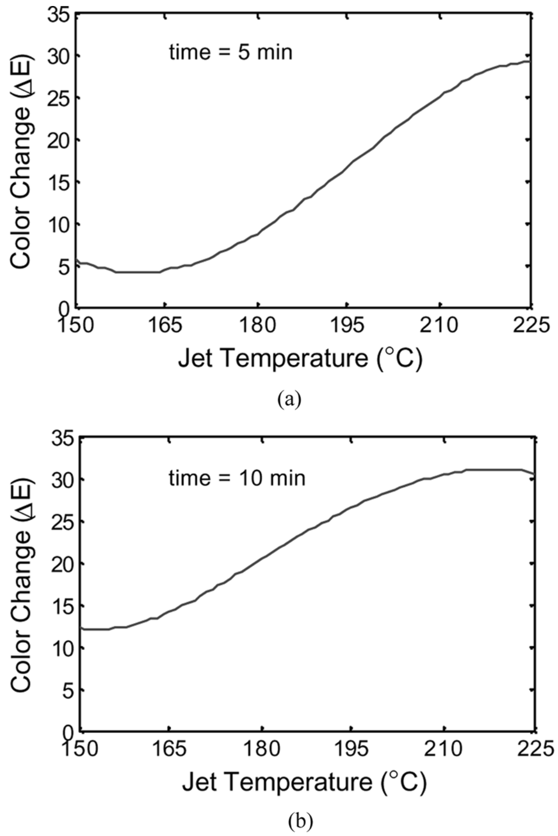

FIG. 11. Color change vs. jet temperature at $V_j = 10\,m/s$ and (a) time = 5 min, (b) time = 10 min.

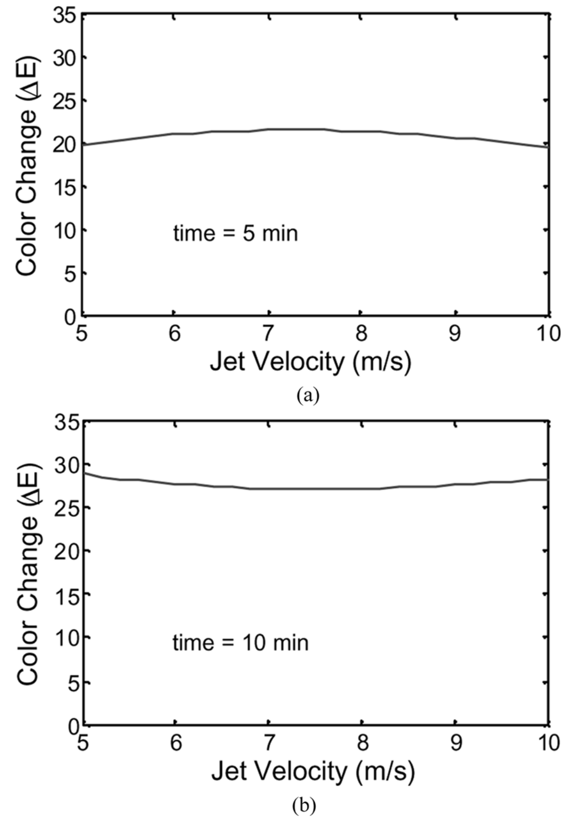

FIG. 12. Color change vs. jet velocity at $T_j = 200°C$ and (a) time = 5 min, (b) time = 10 min.

Figures 8a and 8b illustrate the effect of jet velocity on crumb temperature at the jet temperature of 200°C and baking times of 5 and 10 min, respectively. At the baking time of 5 min, the jet velocity has an insignificant effect on crumb temperature, which allows us to use higher jet velocities. At the baking time of 10 min, however, higher jet velocities may result in undesirable rise in crumb temperature.

Contrary to the initial expectations, moisture content of the bread, as another important factor of the baking process, is not significantly influenced by jet temperature, as is shown in Figs. 9a and 9b. Although it decreases about 3 to 4% at the baking time of 10 min, this rate of decrease intensifies at jet temperatures over than 200°C, which were earlier concluded undesirable for bread texture. In addition, Figs. 10a and 10b show that high jet velocities do not have a destructive effect on bread moisture and may be employed for baking.

Because of the high rate of heat transfer, there is a temperature gradient, albeit small, within the bread. Therefore, maintaining the crumb temperature at about 100°C avoids the surface temperature reaching the required value in which the browning reactions take place. In other words, the surface temperature rise is immediately followed by the increase in crumb temperature, which may lead to excessive increase of internal vapor pressure and, consequently, the collapse of bread interior texture. Therefore, according to Figs. 11a and 11b, the minimum required temperature of the surface to achieve the minimum desired value of the color change is about 185°C at baking time of 5 min and about 170°C at baking time of 10 min. In addition, jet temperatures more than 200°C are not appropriate for baking times more than 5 min, since in that case, the color change does go beyond the maximum desired value ($\Delta E = 20$) and dark spots appear on the bread surface.

As was the case for moisture content, the jet velocity does not affect the color change of the bread considerably (Figs. 12a and 12b). Thus, the higher jet velocities that are associated with higher rates of heat transfer are more likely to be used.

As the jet temperature increases, the relative volume of the bread at the end of the baking decreases. Considering 50% volume increase at the end of the baking, the jet temperature should be 190 and 180°C for the baking times of 5 and 10 min, respectively (Figs. 13a and 13b). However, using the jets with higher velocities brings about larger volume change (Figs. 14a and 14b).

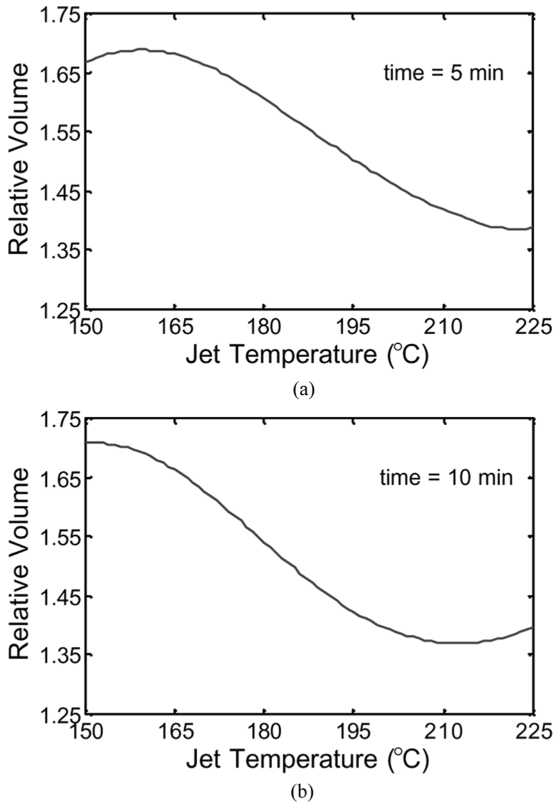

FIG. 13. Relative volume vs. jet temperature at $V_j = 10\,m/s$ and (a) time = 5 min, (b) time = 10 min.

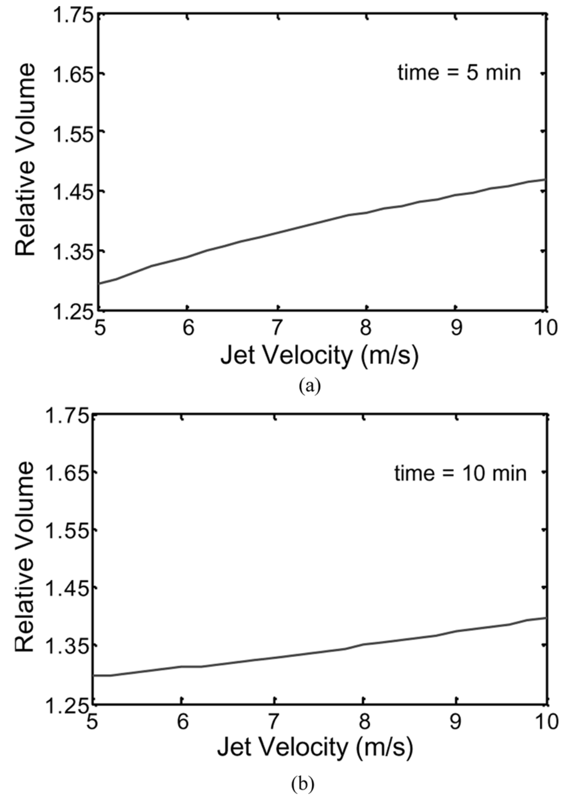

FIG. 14. Relative volume vs. jet velocity at $T_j = 200°C$ and (a) time = 5 min, (b) time = 10 min.

As is clear from the foregoing discussion, finding an optimum combination of jet temperature, jet velocity, and time that provides all the quality attributes may not be achieved intuitively. For this reason, genetic algorithm, as an optimization tool, was employed to find the optimum solution. Based on the experimental results given earlier,

TABLE 4
Optimization solutions (the Pareto optimal set)

No	Independent variables: Jet temperature (°C)	Jet velocity (m/s)	Baking time (min)	Quality attributes: Crumb temperature (°C)	Moisture content (%)	Color change (ΔE)	Relative volume
1	186.43	8.33	8.53	106.39	34.39	19.91	1.45
2	185.94	9.32	7.06	107.9	35.43	17.44	1.51
3	177.80	9.77	4.85	96.21	36.34	7.58	1.61
4	178.24	9.69	5.11	98.19	36.27	8.49	1.60
5	180.92	9.80	5.20	99.96	36.30	9.91	1.59
6	182.93	9.28	5.44	101.85	36.10	11.80	1.56
7	183.59	8.86	5.64	102.65	35.94	12.83	1.54
8	190.08	8.46	5.52	103.86	35.75	16.51	1.48
9	182.98	8.85	6.42	105.09	35.65	14.38	1.53
10	182.46	9.28	5.23	100.42	36.18	10.96	1.56
11	180.97	8.91	7.44	105.98	35.26	15.59	1.53
12	183.92	9.06	5.81	103.74	35.92	13.37	1.54
13	178.31	9.51	5.22	98.90	36.20	8.91	1.60

the objective functions can be rewritten as follows:

$$\begin{aligned} g_1(x) &= |f_1(x) - 100| \\ g_2(x) &= |f_2(x) - 0.35| \\ g_3(x) &= |f_3(x) - 17.5| \\ g_4(x) &= -f_4(x) \end{aligned} \quad (5)$$

As mentioned previously, if the relative volume needs to be maximized, the negative value of the thickness should be minimized. Using GA, the Pareto optimal set was finally acquired as shown in Table 4.

All of the 13 solutions listed in Table 4 are equivalent from the mathematical point of view. Looking practically, however, the solutions may differ. As can be seen, the jet temperature varies from 177 to 190°C, jet velocity from 8.33 to 9.80 m/s, and baking time from 4.85 to 8.53 min. For the mass production purposes, reducing 2 min from the baking time (out of 7.44 min) through an increase of 9°C in jet temperature and a little increase in jet velocity seems desirable (comparing the solutions 8 and 11 in Table 3). As gaining the lower baking time by means of impinging jets is one of the aims of this study, solution 11 was taken as the best answer; i.e., jet temperature of 190°C, jet velocity of 8.46 m/s, and baking time of 5.5 min.

In addition, this solution is of the best ones based on the acquired values for quality attributes. The crumb temperature of 103°C guarantees the starch gelatinization. The moisture content is so close to the desired value; that is, 35%. Color change is in the acceptable range and the volume is increased by about 50%, which is good enough.

CONCLUSION

An ANN model was developed to describe the four main quality parameters of flat bread; i.e., crumb temperature, moisture content, surface color change, and bread volume increase. These parameters describe the quality of the flat bread comprehensively in terms of bread texture and appearance. In the ANN model developed in this study, all of control parameters were unified as a single output of the network. This was achieved through the appropriate structure selected for the network (number of neurons in hidden layer) and also because of enough experimental data used in network training.

Modeling results showed that the jet temperature greatly affects the quality of the bread, while jet velocity has a much smaller effect. Therefore, finding the appropriate jet temperature for baking would require an optimization algorithm to be employed, while the higher (8–10 m/s) jet velocities can be used to speed up the baking process. A multi-objective GA was employed to optimize the jet temperature and velocity as well as the baking time that provide the desired quality of the bread at the end of the baking.

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