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Exploitation of Artificial Neural Networks Approach To Predict The Thermal Conductivity of Food Products In Nigeria

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Abstract: - The application of neural networks in predicting the thermal conductivity of food (bakery) products as a function of moisture content, temperature and apparent density is presented herein. Bread, bread dough, cake, and whole-wheat dough were among some of the bakery products considered in this work. After several configurations had been considered and evaluated in the development of the ANN model, the results of this work showed that the optimal ANN model was a network with 8 neurons in each of the 2 hidden layers. Consequently, this optimal model was capable of predicting the thermal conductivity values of the considered bakery products for a wide range of conditions with MRE of **4.878 X 10^{-2} %**, MAE of **0.0054 W/mK** and SE of **0.0015 W/mK**. In addition, the simplest ANN model was found to be a network with 1 hidden layer and 10 neurons, and it predicted thermal conductivity values with MRE of **3.388 X 10^{-2} %**, MAE of **0.0034 W/mK** and SE of **0.0011 W/mK.** The MRE, MAE and SE are the estimated errors between the predicted and desired (or targeted) thermal conductivity values of the bakery products for both the optimal ANN and simplest ANN models. These errors are approximately equal to zero (i.e., 0 W/mK) and could, therefore, be regarded as a good result for the prediction. Since the simplest ANN model had the least values of all three errors (MRE, MAE and SE) when compared with other configurations, including the optimal ANN model, it is, however, regarded as the best ANN model and is thus,recommended.

Keywords: - *thermo-physical properties of biological products, thermal conductivity of bakery products, back-propagation, artificial neural network, mean absolute error, mean relative error, standard error*

I. INTRODUCTION

In a typical baking process, bakery products undergo physical, chemical and biochemical changes that cumulatively result in expansion of bulk volume, evaporation of water, formation of a porous structure, denaturation of protein, gelatinization of starch, formation of crust and browning reactions respectively. During such processes, ovens powered by gas, electricity, firewood, charcoal, or microwaves are used for generating the required heat.

Accordingly, heat is transferred mainly by convection from the heating media, and by radiation from oven walls to the product surface and then by conduction to the geometric centre. At the same time, moisture diffuses outward to the product surface [1, 2, 13].

The problem of interest in the design of bakery ovens is concerned with the promotion of the required rate of heat transfer with the minimum possible surface area and temperature difference. And from the engineer's point of view, it is usually sufficient to know the total quantities of energy emitted and absorbed by the material at various temperatures [18]. As such, it is frequently necessary to establish the rate at which heat will be conducted through a solid if a known temperature difference exists across the solid. For such purposes, and especially if the process varies with time, sophisticated mathematical techniques are required to establish this, the phenomenon being known as transient-heat conduction. A knowledge of the product properties, including thermal conductivity as a function of processing conditions is needed in order to predict the temperature and water distribution in the product during baking [2, 3, 15]. The temperature and moisture distribution within the porous product can be predicted using diffusion equations of heat and water.

II. LITERATURE REVIEW

Neural networks have been trained to perform complex functions in various fields including pattern recognition, identification, classification, speech, vision, and control systems. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Commonly, neural networks are adjusted (or trained) so that a particular input leads to a specific target output. Typically, many such input/target pairs are needed to train a neural network.

Linko and Zhu also stated that of all the various modelling approaches of predicting the thermal conductivity of a wide range of foods, including bakery products, the neural network-based models have proven to be excellent. Among the major benefits of using ANN are excellent management of uncertainties, noisy data and non-linear relationships. Neural network modelling has generated increasing acceptance and is an interesting method in the estimation, prediction and control of bioprocesses [5, 6].

Review of past work showed that Ruan et al. applied ANN modelling to predict the rheological properties of dough in 1995 [6]. Fang et al. also applied the ANN modelling to predict the physical properties of ground wheat in 1998 [7, 9, 10, 11] while Hussain and Rahman, in 1999, predicted the thermal conductivity of fruits and vegetables with the application of ANN modelling [8]. Similarly, ANN modelling was applied by Myhara et al. in 1998 for the prediction of isotherms of dates [9], Ni and Gunasekaran in 1998 [10] and Xie and Xiong in 1999 [16] also applied ANN modelling differently for the prediction of food quality. Recently, Sablani and Shayya in 2001 applied ANN modelling for the prediction of heat penetration parameters in Stumbo's method of thermal process calculations [17].

Rahman's model [21] (data considered only above 0°C) predicted thermal conductivity with mean relative errors of 24.3 and 81.6%, respectively. This model was able to predict thermal conductivity with a mean relative error of 12.6% and a mean absolute error of 0.081 W/mK. The model can be incorporated in heat transfer calculations during food processing where moisture, temperature and apparent porosity dependent thermal conductivity values are required.

In Shyam et al's work,the optimal ANN model was found to be a network with 6 neurons in each of the 2-hidden layers. This optimal model was capable of predicting the thermal conductivity values of various bakery products (such as bread, bread dough, French bread, yellow cake, tortilla chip, whole wheat dough, baked chapati and cup cake) for a wide range of conditions with a mean relative error of 10%, a mean absolute error of less than 0.02 W/m K and a standard error of about 0.003 W/m K. The simplest ANN model, which had 1-hidden layer and 2 neurons, predicted thermal conductivity values with a mean relative error of less than 15%. [20, 21, 22] All these work were successfully carried out with satisfactory results obtained using ANN modelling.

In predicting thermal properties of a material at desired conditions, several modelling approaches have been proposed and none of them was found suitable for use over a wide range of foods. According to Murakami and Okos (1989) the most promising approach is based on chemical composition, temperature and physical characteristics [4]. More recently, Baik et al. in 2001 reviewed common and new measurement techniques, prediction models and published data on thermo-physical properties of bakery products [19]. The series model of specific heat, density and thermal diffusivity has been successfully applied to many food materials including porous materials such as baking products. However, for the prediction of thermal conductivity of porous food, there is still some theoretical argument for the use of the structural models [4]. Murakami and Okos (1989) evaluated nine different structural models with specific types of porous foods and found that parallel and perpendicular models showed 12–97% and 18–61% standard errors respectively.

Among the models, Keey's model was found to be the best prediction model for porous grains and powders. The model produced standard errors of <28% for full fat dry milk and <10% for other food materials. In addition, all structural models neglect interactions between components, phase transition and distillation heat transfer, which may be significant in the baking process [1]. Hence, most thermal conductivity models reported are usually empirical rather than theoretical.

III. MATERIALS AND METHODS

3.1 MATERIALS

Depending on the specific type of bakery product to be produced and associated production process, a wide variety of raw materials are available to the baker. In addition to the basic Raw materials (flour, water, salt and yeast) various other ingredients can be used. The ingredients used have an influence on the characteristics or technological aspect of the dough.

FLOUR

Flour account for the main portion of the raw materials involved in baked product production and the thermal conductivity of flour need to be considered while applying the neural network. Flour used is mainly those extracted from two basic cereals – wheat and rye. Flour from other grains which do not contain gluten-forming proteins is usually blended with wheat flour for the production of bakery products. The quality of flour is basically dependent on its intended use. The flour quality depends on the following factors:

- Wheat variety
- Growing conditions
- Grain storage
- Flour production technique
- Flour storage

Table 1 Example of a requirement profile for various baking flours (REF)

	Patent Flour	gluten % Flour	High-Ash Flour	whole-Grain Flour
Moisture %	13.0-15.0	13.0-15.0	13.0-15.0	11.0-13.0
Ash % DM	0.38-0.60	0.64-0.78	1.05-1.15	1.75-1.95
Protein %	12.0-14.0	13.5-15.0	14.0-15.5	13.5-15.0
Wet gluten %	28.0-33.0	31.0-35.0	32.0-36.0	29.0-33.0
Falling N umber sec	320-410	300-390	280-380	300-380
Sedimentation ml	38-45	38-43	25-30	NIL
Water Absorption %	60-64	61-65	65-70	66-71
Weakening FU	20-70	60-90	60-90	60-90
Dough energy cm^2	90-130	80-110	55-85	60-90
Max. viscosity AU	500-1000	350-800	300-550	250-500

Average patent flour (first grade) is made up of the following:

- Carbohydrates: 73.5%. This includes starch: 71%, soluble sugars 2.4% and cellulose 0.1%.
- Proteins: 11.0 % :This includes gluten-forming proteins 10% & water soluble proteins 1%
- Water :14%
- Fat : 1.0%
- Minerals: 0.5 %

In terms of quantity carbohydrates accounts for the greatest portion in flour which incidentally forms the greater part of bakery products. Starch essentially fulfills the following functions: 1) a source of nutrient for yeast after enzymatic degradation, 2) absorption of free dough water during gelatinization, 3) contribution to crust, crumb and coloration formation.

The content of soluble sugar substances in wheat flour amounts to approximately 1.5 – 3%. The main soluble sugar substances are glucose, maltose and dextrin. They are dissolved during dough production in the available dough liquid. Glucose and Maltose are available as yeast food while Dextrin cannot be fermented by yeasts

Data were obtained at 25°C on thermal conductivities of slurries of starch in a carbon tetrachloride-ethyl benzene mixture having a density equal to that of the starch. The thermal conductivity of granular ordinary corn starch was estimated to be 0.125 B.t.u.-foot per hour-foot$^{2-0}$ F by calculation and by extrapolation from the slurry data. The thermal conductivities of granular corn starches decreased with increasing amylose content.
Thermal properties (thermal conductivity and diffusivity) of gluten and glutenin were measured in the temperature range 60-175°typically used in extrusion processing. Thermal conductivity and diffusivity of gluten decreased with increasing temperature and increased with increasing moisture content. Thermal conductivity and diffusivity of glutenin increased with temperature and moisture content. Thermal conductivity of gluten was 0.06-0.35 W/m-C and glutenin was 0.29-0.49 W/m-C for the temperature range 60-175°and moisture content range of 0-30%.

3.2 METHODS

(i) Mathematical Modelling For Thermal Conductivity Of Bakery Products

Although, the exact mechanism of heat conduction in solids is not entirely understood, it is believed, however, to be partially due to the motion of free electrons in the solid matter, which transports energy if a temperature difference is applied (Refer to Fig.1) and the conceptual representation of Oven dynamics during typical baking process as depicted in figure 2 below .

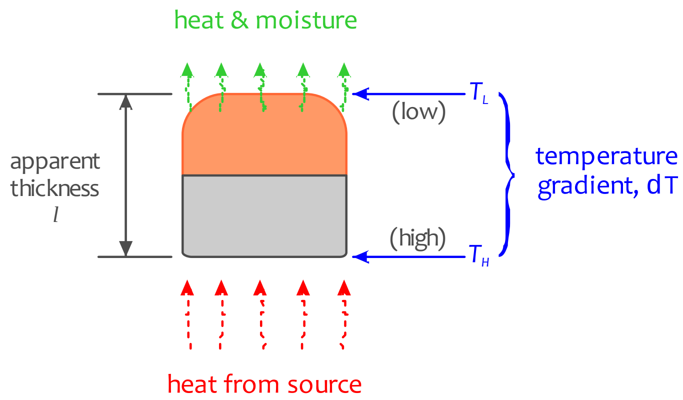

Fig. 1: Conceptualisation of thermal conductivity of a bakery product

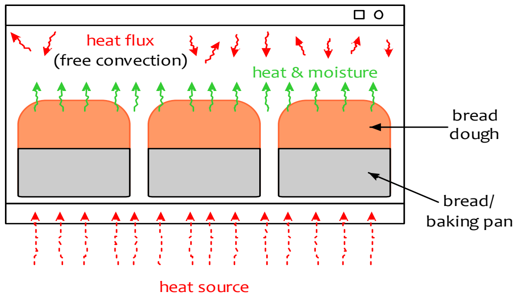

Fig. 2: Conceptual representation of Oven dynamics during typical Baking process

From Fourier's law of heat conduction, the rate at which such heat is conducted through a body per unit cross-sectional area is said to be proportional to the negative of the temperature gradient existing in the body [18]. In other words,

$$Q \propto -\nabla T \qquad (1)$$

The proportionality factor is called the thermal conductivity of the material. By definition, it is the ability of the material to conduct heat and thus, a measure of the rate at which heat flows through a material between points at different temperatures, measured in watts per meter per degree.

As a property, the thermal conductivity expresses the heat flux, Q (W/m^2) that will flow through the material if a certain temperature gradient, ΔT (K/m) exists across the material. That is, it is the heat flow per unit area per unit time when the temperature decreases by one degree in unit distance. Thus,

$$Q = -kA\frac{\Delta T}{\Delta x} \qquad (2)$$

or $$Q = -kA\frac{T_H - T_L}{l} \qquad (3)$$

where Q = heat flux, k = thermal conductivity, A = cross-sectional area, T_H = temperature at hot end, T_L = temperature at cold end, and l = thickness of material respectively, and the negative sign indicates that the heat flow is positive in the direction of temperature fall.

(ii) TRAINING THE ANN MODEL USING BACK PROPAGATION ALGORITHM

The back-propagation algorithm was utilized in model training. A hyperbolic-tangent transfer function was also used in all cases. Properly trained back-propagation networks tend to give reasonable answers when presented with unfamiliar inputs that have never been seen earlier. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to those being presented. This generalization properly makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

The back-propagation algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. For a given set of inputs to the network, the response to each neuron in the output layer is calculated and compared with the corresponding desired output response. The errors associated with desired output response are adjusted in the way that reduces these errors in each neuron from the output to the input layer.
In order to avoid the potential problem of over-training or memorization while employing the back-propagation algorithm, the option of saving the best result is adopted during the selected number of training cycles of 2,000.

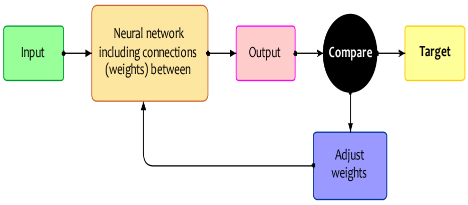

Fig. 3: Adjusting (or training) of a Neural network

(iii) OPTIMAL CONFIGURATION OF ANN MODEL FOR BAKERY PRODUCTS
Upon using the mean relative error (MRE), mean absolute error (MAE) and standard error (SE) as standard criteria, the performances of the various ANN configurations were compared. The mathematical representation of these error parameters are as defined in equations 1 to 3 as follow [11, 14]:

$$\text{MAE} = \frac{1}{n}\left[\sum_{i=1}^{n}(K_D - K_P)\right] \quad (4)$$

$$\text{MRE} = \frac{1}{n}\left[\sum_{i=1}^{n}(K_D - K_P)/K_D\right] \quad (5)$$

$$\text{SE} = \left[\frac{\sqrt{\sum_{i=1}^{n}(K_D - K_P)^2}}{n-1}\right] \quad (6)$$

where n is the number of data points, K_D and K_P are the desired and predicted values of thermal conductivity respectively.

The optimum configuration of the network was chosen by selecting the lower value from the different configuration of the network. It was evidently based upon minimizing the difference between the neural network predicted values and the desired outputs. The datasets of 52 cases obtained from other literature [1] were divided into two sets. The first set consisted of 36 (~70%) cases for training/testing and 16 (~30%) cases for validation (simulation), chosen randomly from the set of 52 cases.

IV. SIMULATION AND RESULTS

4.1 SIMULATION

Computer simulation of ANN was employed for the purpose of this work using the MATLAB version 7.0.4.365 (R14) Service Pack 2 commercial software package with embedded neural network add-in toolbox.
Several ANN models were simulated (or trained) using the thermo-physical properties datasets of Table 1. The feed-forward network structure with input, output and hidden layers were also used and the generalized network structures are as shown in Fig. 5 and Fig. 6 respectively.

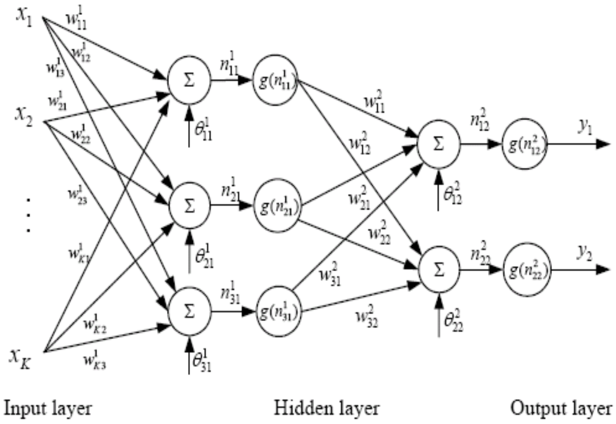

Fig. 5: Generalized multilayer neural network

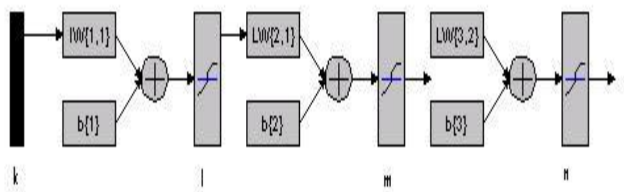

Fig. 6: Generalized multilayer neural network obtained with MATLAB

For the purpose of this work, the input layer consisted of 3 neurons which corresponded to a product's moisture content, temperature and apparent density respectively, while the output layer had 1 neuron representing the thermal conductivity. The number of hidden layers and neurons within each hidden layer can be varied based on the complexity of the problem and dataset. Moreover, the number of hidden layers was varied from 1 to 2. The neurons within each of these layers were varied from 2 to 16 with increments of 2. This resulted in a total of 16 networks.

4.2 RESULTS OF SIMULATION

Once a given ANN configuration was trained using the input data, its performance was evaluated using the same dataset. The analysis was repeated several times. The ANN configuration (out of 16) that minimized the three error measures: MRE, MAR and SE, was selected as the optimum. The error measures associated with different ANN configurations for prediction of thermal conductivity are presented in Table 4.1. The optimal ANN configuration included 2-hidden layers with 8 neurons in each layer. The MAE, MRE and SE for this optimal configuration were 0.0054W/mK, 4.8776 X 10^{-4} W/mK (4.8776 X 10^{-2} %) and 0.0015 W/mK respectively (shown highlighted below).

Table 2: Error parameters in the prediction of thermal conductivity with different neural network configurations

No. of hidden layers	**No. of neurons in each hidden layer**	**MRE** (%)	**MAE** (W/mK)	**SE** (W/mK)
1	2	0.17	0.0199	0.0046
1	4	4.2	0.2212	0.0970
1	6	0.035077	0.0038	0.0011
1	8	0.18	0.0191	0.0050
1	**10**	**0.03388**	**0.0034**	**0.0011**
1	12	0.26	0.0297	0.0073
1	14	0.090897	0.0149	0.0041
1	16	0.12	0.0115	0.0038
2	2	0.24	0.0298	0.0075
2	4	0.41	0.0641	0.0125
2	6	0.37	0.0606	0.0121
2	**8**	**0.048776**	**0.0054**	**0.0015**
2	10	0.29	0.0441	0.0106
2	12	0.22	0.0382	0.0095
2	14	0.17	0.0166	0.0047
2	16	0.22	0.0323	0.0072

Table 3: Error prediction for 1 hidden layer with their corresponding neurons

No. of neurons in each hidden layers	MRE (% x10^{-2})	MAE (W/mK x10^{-3})	SE (W/mK x10^{-4})
2	17	19.9	46
4	420	221.2	970
6	3.5	3.8	11
8	18	19.1	50
10	***3.4***	***3.4***	***11***
12	26	29.7	73
14	9.1	14.9	41
16	12	11.5	38

Table 4: Error prediction for 2 hidden layers with their corresponding neurons

No. of neurons in each hidden layers	MRE (% x10^{-2})	MAE (W/mK x10^{-3})	SE (W/mK x10^{-4})
2	24	29.80	75
4	41	64.10	125
6	37	60.60	121
8	***4.88***	***5.40***	***15***
10	29	44.10	106
12	22	38.20	95
14	17	16.60	47
16	22	32.30	72

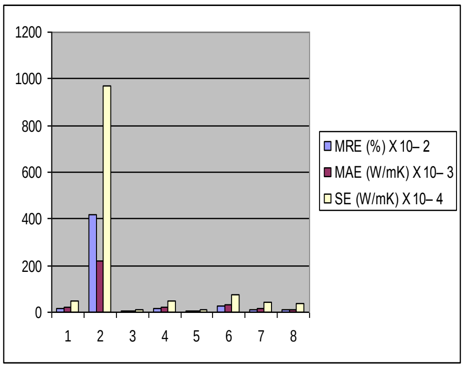

Fig 7: *Corresponding chart showing the error values for 1-hidden layer*

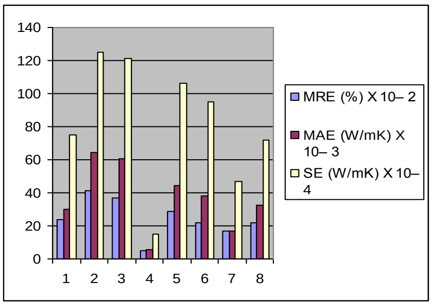

Fig. 8: Corresponding chart showing the error values for 2-hidden layers

4.3 DISCUSSION OF RESULTS

Herein, the thermal conductivity of the bakery products was modelled by simulation. As a result, both the predicted and targeted/desired thermal conductivity values are plotted separately against each of the three dependent variables as a function of moisture content (%), temperature (^{o}C) and apparent density (kg/m^3). The corresponding curves were obtained for the optimal ANN configuration; 2-hidden layers with 8 neurons, and the simplest ANN configuration; 1-hidden layer with 10 neurons .

For each of the corresponding diagrams, there was a considerable and first-rate agreement between the predicted and desired/targeted values of thermal conductivities for different parameters of MAE,MRE and SE.

It can be concluded that the predicted thermal conductivity is good, efficient and credible prediction for thermal conductivity of bakery products

V. CONCLUSION

In this paper, an ANN model was developed for calculating the thermal conductivity of a variety of bakery products under a wide range of conditions of moisture content, temperature and apparent density. The optimal model consisted of 2-hidden layers with eight neurons in each hidden layer, and was able to produce thermal conductivity values with a MAE of 54 X 10^{-4}W/mK, MRE of 4.878 X10^{-4}W/mK and a SE of 15 X 10^{-4}W/mK (see Table 3). However, the simplest ANN model has 1-hidden layer with 10 neurons. This also showed a good prediction with a MRE of about 3.388 X 10^{-4} W/mK, MAE of 34 X 10^{-4} W/mK and SE of 11 X10^{-4} W/mK (see Table 4).

From these values, it can be deduced and concluded that the simplest ANN model (with 1-hidden layer and 10 neurons), when compared with the optimal ANN model (with 2-hidden layers and 8 neurons in each hidden layer) has smaller mean relative error,smaller mean absolute error and lesser standard error. Therefore, this model performs better accordingly.

REFERENCES

[1] **Baik**, O. D., Marcotte, M., Sablani, S. S., and Castaigne, F. (2001): *Thermal and physical properties of Bakery products. Critical Review in Food Science and Nutrition*. CRC Press LLC

[2] Rask, C. (1989): *Thermal properties of dough and bakery products: A review of published data*. Journal of Food Engineering, 9, 167–193

[3] Sablani, S. S., Marcotte, M., Baik, O. D., and Castaigne, F. (1998): *Modelling of simultaneous heat and water transport in the baking process. Lebensmittel* Wissenchaft and Technologie, 31, Germany; 201–209

[4] Murakami, E. G., and Okos, M. R. (1989): *Measurement and Prediction of thermal properties of foods*. In R. P. Singh, and A. G. Medina (Eds.), Food Properties. Computer-aided Engineering of Food Processing System (pp. 3–48). Norwell, MA: Kluwer Academic Publishers

[5] Linko, P., and Zhu. Y. H. (1991): *Neural network programming in bioprocess variable estimation and state prediction.* Journal of Biotechnology, 21(3), 253–270

[6] Ruan, R., Almaer, S., & Zhang, J. (1995): *Prediction of dough rheological properties using neural networks*. Cereal Chemistry, 72(3), 308–311

[7] Fang, Q., Bilby, G., Haque, E., Hanna, M. A., and Spillman, C. K. (1998): *Neural network modelling of physical properties of ground wheat*. Cereal Chemistry, 75(2), 251–253

[8] Hussain, A. M., and Rahman, M. S. (1999): *Thermal conductivity prediction of fruits and vegetables using neural networks*. International Journal of Food Properties, 2(2

[9] Myhara, R. M., Sablani, S. S., Al-Alawi, S. M., and Taylor, M. S. (1998): *Water sorption isotherms of dates: Modelling using GAB equation and artificial neural network approaches*. Lebensmittel Wissenschaft und Technologies, 31(7/8), Germany; 699–706

[10] Ni, H., and Gunasekaran, S. (1998): *Food quality prediction with neural networks*. Food Technology, 52(10), 60–65

[11] Bishop, M. C. (1994): *Neural networks and their applications*. Review in Scientific Instruments, 64(6), 1803–1831

[12] Sweat, V. E. (1985): *Thermal properties of low and intermediate moisture food.* ASHRAE Transaction, 91, 369–389

[13] Bakshi, S. A. and Yoon, J. (1984): *Thermophysical properties of bread rolls during baking.* Lebensmittel Wissenschaft und Technologie, 17, 90–93

[14] Hornik, K., Stinchombe, M. and White, H.(1989): *Multilayer feed-forward network and universal approximator.* Neural Network, 2, 359–366

[15] Baik, O. D., Marcotte, M., Sablani, S. S., and Castaigne, F. (1999): *Modelling the thermal properties of a cup cake during baking.* Journal of Food Science, 64, 295–299

[16] Xie, G. and Xiong, R. (1999): *Use of hyperbolic and neural network models in modelling quality changes of dry peas in long time cooking.* Journal of Food Engineering, 41, (3/4), 151–162

[17] Sablani, S. S. and Shayya, W. H. (2001): *Computerization of Stumbo's method of thermal process calculations using neural networks.* Journal of Food Engineering, 47, 233–240

[18] Rogers, G. F. C and Mayhew, Y. R. (1989): *Engineering Thermodynamics*. ELBS 3/e, 469–502

[19] Baik, O. D., Sablani, S. S. and Marcotte M. (2002): Journal of Food Engineering. Elsevier. Retrieved from sciencedirect.com/science/article/pii/S0260877401001194

[20] Baik, O. D., Marcotte, M., Sablani, S. S., and Castaigne, F. (2006): *Modelling the Thermal properties of a Cup cake during Baking.* Journal of Food Science Volume 64, Issue 2, 295–299. Article first published online: 20 JUL 2006 and retrieved from onlinelibrary.wiley.com/doi/10.1111/j.1365-2621.1999.tb15886.x/abstract

[21] Shyam Sablani, S and Shafiur Rahman, M. (2003), *Using neural networks to predict thermal conductivity of food as a function of moisture content, temperature and apparent porosity*. Food Research International. Elsevier. Volume 36, Issue 6, 2003, 617–623. Retrieved from sciencedirect.com/science/article/pii/S0963996903000127

[22] Christina Rask (1989), *Thermal properties of dough and bakery products: A review of published data*. Journal of Food Engineering. Volume 9, Issue 3, 1989, 167–193. Elsevier. Retrieved from sciencedirect.com/science/article/pii/0260877489900393