ijPPHT
e ISSN-2231-6426
Volume 8 | Issue 2 | December, 2017 | 83-88
■ Visit us: *www.researchjournal.co.in*
International Journal of Processing and Post Harvest Technology
RESEARCH PAPER
DOI: 10.15740/HAS/IJPPHT/8.2/83-88

Development of thermal conductivity measuring device using single operational amplifier and its modeling by artificial neural network (ANN)

■ SHIVMURTI SRIVASTAV
Department of Food Processing Technology, A.D. Patel Institute of Technology, ANAND (GUJARAT) INDIA
Email: shivmurtis@gmail.com

■ **Research chronicle : Received :** 01.05.2017; **Revised :** 04.11.2017; **Accepted :** 18.11.2017

SUMMARY :

Thermal conductivity is one of the important thermal properties of food materials. It is essential during the calculation of heat transfer process through conduction. The setup was constructed by installing a single operational amplifier LM741, precision centigrade temperature sensors LM35, series 3-terminal negative regulators LM7915C, series voltage regulators LM7815C and LM7805C. LM741. The input to the setup was AC mains supplies 220V, 50 Hz which is transformed to 24V by step-down transformer. LM35 were used as a temperature sensor which gives output of 10mV/^{o}C. To convert mV into V inverting amplifier LM741 has been used. The required voltage values can be read from digital multi-meter by connecting the positive and negative terminal. After successful development, calibration and testing of the setup, it has been utilized to calculate the thermal conductivity of wheat, sorghum and rice. The initial moisture content of all three different grains was found 7.88, 10.33 and 14 per cent wet basis, respectively. Thermal conductivity of wheat, sorghum and rice was found in the range of 0.199-0.115W/mK, 0.202-0.139 W/m K and 0.53-0.48 W/m K, respectively at the temperature range from 40 to 60^{0}C. The performance of the optimal neural network with 15 hidden layers and 20 neurons in each hiiden layer was done by using a different data set. It was found that the sorghum grain gives the minimum M.S.E 1.791×10^{-12} with R^2 value is 0.999.

KEY WORDS : Thermal conductivity, ANN modeling, Operational amplifier

How to cite this paper : Srivastav, Shivmurti (2017). Development of thermal conductivity measuring device using single operational amplifier and its modeling by artificial neural network (ANN). *Internat. J. Proc. & Post Harvest Technol.*, **8** (2) : 83-88. **DOI: 10.15740/HAS/IJPPHT/8.2/83-88.**

Thermal conductivity of the food material is one of the important thermal properties. It is mainly used to calculate the rate of heat transfer through conduction in the field of freezing, sterilization, drying, cooking, frying etc (Maroulis *et al.*, 2002 and Nahor *et al.*, 2001). There are many factors like composition of food, its structure and sometimes processing conditions, which affects the thermal conductivity (Rahman 1992;

Rahman *et al.*, 1997 and Ramesh, 2000). Water content plays a significant role due to relative magnitude of conductivities of water (Cuevas and Cheryan, 1978; Denys and Hendrickx, 1999). Due to this, in most of the cases thermal properties are not immediately known, therefore, usually computed or by simplified assumptions (Singh, 1982). In the line heat source probe method the construction of probe and the short utility time is the major problem. In most of the conditions, the classical characterization methods are very complex and take more time caused expensive instrumentation. In addition, the volume and the complexity of acquired data need precise control on instrumentation are required. There have been many attempts made to develop different measuring instrument for thermal properties of foods but literature still lacking on many of the foods which are consumed day to day life. The development of this alternative instrument will facilitate the experimental process relatively simple, less costly, good precision and user friendly under unsteady state conditions would be the great benefit to the scientific and engineering communities. The objectives of the modeling are to have process control and produce high quality product with minimal cost. All we know that food processes are highly nonlinear which complicates food process automation. To achieve these objectives, on-line control techniques are required. The recent developments in advanced control tools, such as artificial neural network (ANN) to food processing have opened up novel possibilities for processing industries. A number of researchers have worked on ANN as a modeling tool in food technology (Kerdpiboon *et al.*, 2006 and Shrivastav and Kumbhar, 2009, 2011 and 2014). It has been successfully used in several food applications like model for prediction of drying rates, physical properties of dried carrot, prediction of dryer performance, extrusion processing of wheat and wheat-black soybean, energy requirements for size reduction of wheat, grain drying process, dough rheological properties among others (Luo *et al.*, 1999; Mittal and Bhang, 2003; Popescu *et al.*, 2001; Ruan *et al.*, 1995 and Shihani *et al.*, 2004). This study has been undertaken to develop ANN model for prediction of thermal conductivity.

EXPERIMENTAL METHODS

Experimental setup :

The setup is constructed by installing a single operational amplifier LM741, precision centigrade temperature sensors LM35, series 3-terminal negative regulators LM7915C, series voltage regulators LM7815C and LM7805C. LM741 is intended for a wide range of analog applications. The high gain and wide range of operating voltage provide superior performance in integrator, summing amplifier and general feedback applications. The LM35 series are precision integrated-circuit temperature sensors, whose output voltage is linearly proportional to the centigrade temperature. The LM35 thus, has an advantage over linear temperature sensors calibrated in Kelvin, as the user is not required to subtract a large constant voltage from its output to obtain convenient centigrade scaling. The LM7915 is capable of supplying 1.5A of output current. These regulators employ internal current limiting safe area protection and thermal shutdown for protection against virtually all overload conditions. The LM7815C is available with several fixed output voltages making them useful in a wide range of applications. LM7805C is not available with several fixed output voltages making necessary to bypass the output. The LM35 can be applied easily in the same way as other integrated-circuit temperature sensors. It can be glued or cemented to a surface and its temperature will be within about 0.01^{o}C of the surface temperature. This presumes that the ambient air temperature is almost the same as the surface temperature; if the air temperature were much higher or lower than the surface temperature, the actual temperature of the LM35 die would be at an intermediate temperature between the surface temperature and the

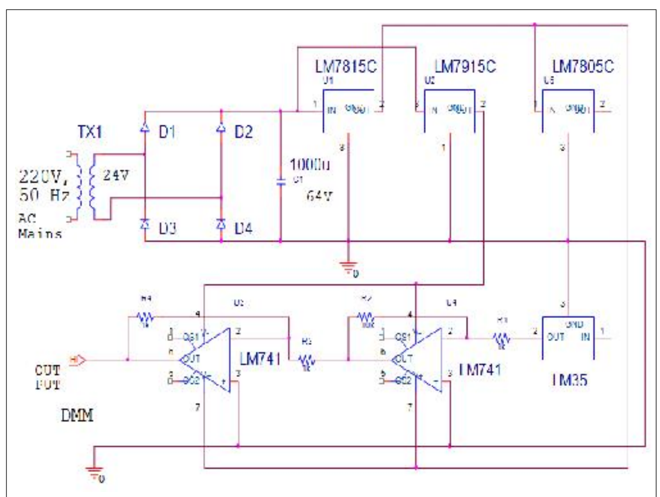

Fig. A : Schematic representation of thermal conductivity measurement set-up

air temperature.Fig. A shows the schematic representation of thermal conductivity measurement set-up.

Design of equipment :

The experimental circuit was made on analog digital trainer to obtain the respective voltage values at a given temperature. After the success of the trial circuit on analogue digital trainer, final circuit was made. The circuit shown below is the schematic representation of the final thermal conductivity measurement set-up. The input to the setup is AC mains supplies 220V, 50 Hz which is transformed to 24V by step-down transformer. Voltage passes through the full-wave rectifier to convert AC voltage into DC voltage. LM7815C supplies +15V and LM7915C supplies -15V to the amplifier LM741. Whereas LM7805C supplies 5V to LM35. Finally as LM35 is the temperature sensor which gives output of 10mV/^{o}C. To convert mV into V inverting amplifier LM741 has been used. The required voltage values can be read from digital multi-meter by connecting the positive and negative terminal. After successful development, calibration and testing, it has been utilized to calculate the thermal conductivity of different food grains. The equation used for the calculation of thermal conductivity is (Sablani *et al.*, 2002a).

$$\alpha = \frac{q.\ln\left(\frac{t_2}{t_1}\right)}{4\pi\left(T_2 - T_1\right)} \quad ....(1)$$

where,

α = Thermal conductivity of sample (W/mK)

q = Generated heat per unit length of sample/time (W/m)

t_1 and t_2 = Initial and final time (s)

T = Temperature (K).

Sample preparation :

Wheat, sorghum and rice grains were procured from local market. All grains were cleaned manually to remove stones, dirt, unmatured grains and other foreign materials. The initial moisture content of all the grains was found out with hot air oven methods, which were 7.88, 10.33 and 14 per cent wet basis, respectively. Cleaned samples were ready to load to find out thermal conductivity. All experiments were run in triplicate.

ANN description of the process :

The neural network model consisted of an input, a hidden and an output layer was designed. The input layer has two nodes which correspond with processing conditions or independent variables: time of heating, corresponding change in temperature. The output layer consists of one neurons or dependent variables, representing the thermal conductivity. The nodes and the neurons were connected to each other by weighted links, W_{ij}, over which signals can pass. The arriving signals multiplied by the connection weights are first summed (activation function) and then passed through the sigmoid function (transfer function) to produce the corresponding output that may be passed on to other Neurons.

Training and testing algorithms :

MATLAB-10 software was used for Artificial Neural Networks (ANN) modeling. A multi-layer feed forward network structure with input, output and hidden layer (s) was used in this study. Several ANN models were trained using the thermal conductivity data. The back-propagation algorithm was utilized in training of ANN models. A hyperbolic-tangent transfer function was used in all cases. 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 was calculated and compared with the corresponding desired output response (Shrivastav and Kumbhar, 2009, 2011 and 2014). 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. The error minimization process is achieved using gradient descent rule. To avoid the potential problem of over-fitting or memorization while employing the back-propagation algorithm, the option of saving the best configuration was selected where the network with the best result is saved during the selected long number of training cycles of 200,000. The save best option allows running train/test cycles and saving the network with the best result during the run. One of the problems that can occur with the back propagation and associated network is the problem of over-fitting. The symptom of this is when the network is performing well on the training data, but poorly on independent validation data. Save best is one of a number of ways to deal with this. The input layer consisted of four neurons which corresponded to initial and final temperature and time at that temperature. There were fifteen hidden layers with twenty neurons in each hidden layer. The output layer had one neuron representing thermal conductivity. The number of hidden layers and neurons within each hidden layer can be varied on the complexity of the problem and data set.

Optimization of ANN configuration:

The optimized configurations from training and testing of ANN were obtained by the performance of the network. The performance of output is judged by mean square error (MSE) and was less than 0.001. The networks were simulated with the learning rate equal to 0.05. For training, validation and testing different set of data were examined. It was concluded that 70 per cent training, 15 per cent validation and 15 per cent testing predicts the best output.

EXPERIMENTAL FINDINGS AND ANALYSIS

The sample was kept in water bath inside a test tube to maintain the temperature. LM35 sensor was kept inside the grain to find the change in temperature at different time interval. After getting the different set of experimental data, thermal conductivity was calculated. Thermal conductivity of wheat, sorghum and rice was found in the range of 0.199-0.115W/m K, 0.202-0.139 W/m K and 0.53-0.48 W/m K, respectively at the temperature range from 40 to 60^{0}C. It is seen from the observation values that the thermal conductivity of grains decreases with increase in temperature because increase in temperature leads to the evaporation of moisture due to which air gets trapped inside the void. As air is bad conductor of heat thermal conductivity decreases with increase in temperature. The result was supported by Sablani *et al.* (2002b). Thermal conductivity of wheat, sorghum and rice is shown in Fig. 1 at different temperature. The performance of the optimal neural network with 15 hidden layers and 20 neurons in each hiiden layer was done by using a different data set. The network predicted thermal conductivity values of different grains with minimum Mean Square Error and R^2 valus. Correlation of experimental versus neural network values of thermal conductivity with training, validation, testing and combine data set using the optimal network is shown below. To reveal the credibility of prediction (with the training data set and validation) from the optimal

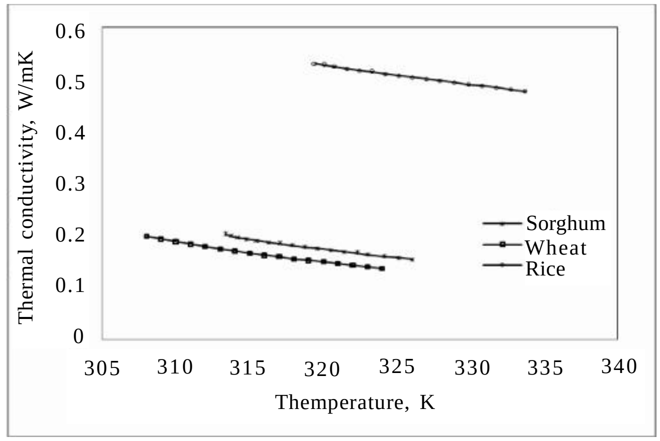

Fig. 1 : Thermal conductivity of grains at different temperature

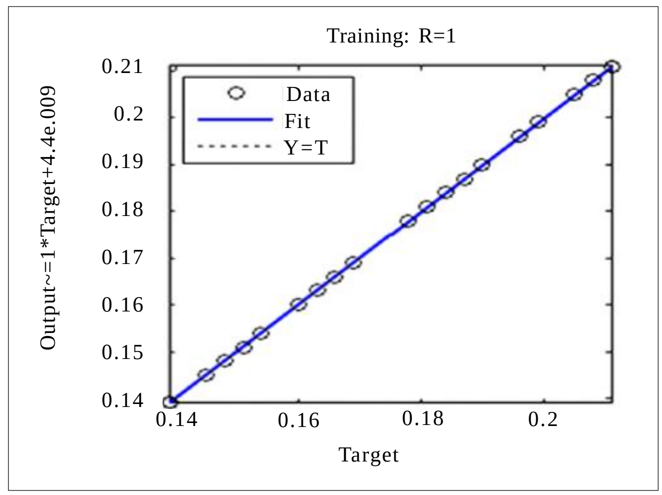

Fig. 2 : Training performance graph for ann analysis of sorghum

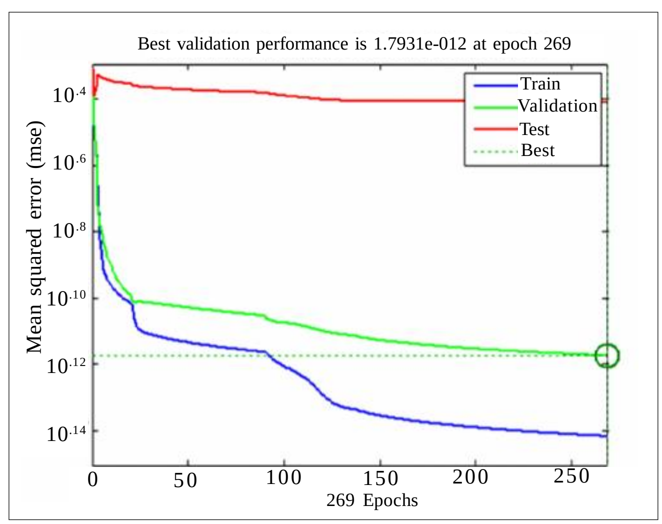

Fig. 3 : Best validation performance for ANN analysis of sorghum

Table 1: Performance of ANN during training, validation and testing

	Sorghum		Wheat		Rice	
	M.S.E	R^2	M.S.E	R^2	M.S.E	R^2
Training	6.703×10^{-15}	0.999	8.8375×10^{-4}	0.996	5.8193×10^{-8}	0.999
Validation	1.791×10^{-12}	0.999	3.3064×10^{-5}	0.999	2.0929×10^{-7}	0.999
Testing	7.9632×10^{-5}	0.943	5.0979×10^{-1}	0.960	4.434×10^{-5}	0.986

ANN, predicted values of thermal conductivity are plotted against the desired/targeted values of thermal conductivity as shown in Fig. 2. Figures showed straight line curves, demonstrating correlation between the predicted and targeted thermal conductivities when the points are joined together (best fit points). Fig. 3 shows the best validation performance for ANN analysis of sorghum grain only. For other grains the same can be performed. The results demonstrate a very good agreement between the predicted and the desired values of thermal conductivity. The MSE versus Epochs graph was generated. It combined the data of all four graphs; training, validation, testing and best. From the graph, the conclusion can be made that with the increase in epochs, mean square error decreases and the best validation performance was at 269^{th} epochs and it was 1.7931e-012. Similar work related to the present investigation was aslo carried out by Fang *et al*. (1998); Hussain and Rahman (1999); Keppeler and Boose (1970) and Vagenas *et al.* (1990).

Conclusion :

In this study three different grain samples named Wheat, Sorghum and Rice grains were selected to predict the thermal conductivity. Thermal conductivity of wheat, sorghum and rice was found in the range of 0.199-0.115W/mK, 0.202-0.139 W/m K and 0.53-0.48 W/m K, respectively at the temperature range from 40 to 60^0C. It is seen from the observation values that the thermal conductivity of grains decreases with increase in temperature because increase in temperature leads to the evaporation of moisture due to which air gets trapped inside the void. As air is bad conductor of heat thermal conductivity decreases with increase in temperature. In this paper, an ANN model was developed for calculating the thermal conductivity of a variety of grains under a wide range of temperature, which show that an artificial neural network model can predict the thermal conductivity of grains with high degree of accuracy. The Input values that used in this model were temperature and time. The optimal model consisted of with 15 hidden layers and 20 neurons in each hiiden layer was done by using a different data set. It was found that the sorghum garin gives the minimum M.S.E 1.791×10^{-12} with R^2 value is 0.999.

LITERATURE CITED

Cuevas, R. and Cheryan, M. (1978). Thermal conductivity of liquid foods-A review. *J. Food Process. Engg.*, **2** : 283.

Denys, S. and Hendrickx, M. E. (1999). Thermal conductivity of foods at high pressure. *J. Food Sci.*, **64** : 709-713.

Fang, Q., Bilby, G., Haque, E., Hanna, M.A. and Spillman, C.K. (1998). Neural network modeling of physical properties of ground wheat. *Cereal Chem.*, **75** : 251-253.

Hussain, M.A. and Rahman, M. S. (1999). Thermal conductivity prediction of fruits and vegetables using neural networks. *Internat. J. Food Propert.*, **2** : 121-138.

Keppeler, R.A. and Boose, J. R. (1970). Thermal properties of frozen sucrose solutions. *Trans. ASAE*, **13** : 335-339.

Kerdpiboon, S. Kerr, S. L. and Devahastin, S. (2006). Neural network prediction of physical property changes of dried carrot as a function of fractal dimension and moisture content. *Food Res. Internat.*, **39** : 1110-1118.

Luo, X., Jayas, D. S. and Symons, S.J. (1999). Comparison of statistical and neural network methods for classifying cereal grains using machine vision. *Trans. ASAE*, **42**:413-419.

Maroulis, Z. B. Saravacos, G. D. Krokida, M. K. and Panagiotou, N.M. (2002). Thermal conductivity prediction for foodstuffs: Effect of moisture content and temperature. *Internat. J. Food Properti.*, **5** : 231-245.

Mittal, G. S. and Bhang, J. (2003). Artificial neural networks-based psychrometric prediction. *Biosystem Engg.*, **85**:283-289.

Nahor, H. B., Scheerlinck, N., Verniest, R., Baerdemaeker, J. D. and Nicolaï, B. M. (2001). Optimal experimental design for the parameter estimation of conduction heated foods. *J. Food Engg.*, **48** : 109-119.

Popescu, O. Popescu, C. and Wilder, J. (2001). A new approach to modeling and control of a food extrusion process using

ANN and an expert system. *J. Food Process Engg.,* **24**:17-36.

Rahman, M. S. (1992). Thermal conductivity of four food materials as a single function of porosity and water content. *J. Food Engg.,* **15**: 261–268.

Rahman, M. S. Chen, X. D. and Perera, C. O. (1997). An improved thermal conductivity prediction model for fruits and vegetables as a function of temperature, water content and porosity. *J. Food Engg.,* **31**:163-170.

Ramesh, M. N. (2000). Effect of cooking and drying on the thermal conductivity of rice. *Internat. J. Food Propert.,* **3** : 77-92.

Ruan, R. Alamer, S. and Zhang, J. (1995). Prediction of dough rheological properties using neural networks. *Cereal Chem.,* **72** : 308-311.

Sablani, S.S., Baik, O.D. and Marcotte, M. (2002a). Neural networks for predicting thermal conductivity of bakery products. *J. Food Engg.,* **52**:299-304.

Sablani, S.S. Baik, O. D. and Marcotte, M. (2002b). Neural networks to predict thermal conductivity of food as a function of moisture content, temperature and apparent porosity. *Food Res. Internat.,***36** : 617-623.

Shihani, N. Khumbhar, B.K. and Kulshreshthra, M. (2004). Modeling of extrusion process using response surface methodology artificial neural network. *J. Engg. Sci.& Technol.,* **1** : 31-40.

Singh, R. P. (1982). Thermal diffusivity in food processing. *Food Technol.,* **36** (2) : 87-89.

Srivastav, S. and Kumbhar, B.K. (2009). Modeling and optimization for prediction of moisture content, drying rates and moisture ratio. *Internat. J. Agric. & Biological Engg.,* **2** : 58-65.

Srivastava, S. and Kumbhar, B. K. (2011). Drying kinetics and ANN modeling of paneer at low pressure superheated steam. *J. Food Sci. &Technol.,* **48** : 577-583.

Srivastava, S. and Kumbhar, B.K. (2014). Modeling drying kinetics of paneer using artificial neural networks (ANN). *J. Food Res. Technol.,* **2** : 39-45.

Vagenas, G. K. Marinos, K. and Saravacos, G. D. (1990). Thermal properties of raisins. *J. Food Engg.,* **11**:147-158.

8th Year
★★★★★ of Excellence ★★★★★