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Modelling and optimization of ohmic heating using artificial neural network (ANN)

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■ **ABSTRACT :** In this study the tomato juice was heated in a laboratory scale ohmic heater. This tomato juice passed through applying voltage gradient in the range of 100-200V and their properties were compared with the untreated raw tomato juice. The linear temperature dependent electrical conductivity relationship was obtained. System performance co-efficient was in the range of 0.9057 to 0.9887. Temperature, time, voltage, current and electrical conductivity data were generated by conducting the experiments and these data were used to develop artificial neural network (ANN) models. Optimized ANN models were developed for rapid and more accurate prediction of electrical conductivity. The MSE for training, testing and validation were 1.114e-17, 2.218e-5 and 4.057e-8. The correlation co-efficient for all data set was > 0.982.

■ **KEY WORDS :** Ohmic heating, Tomato juice, Modelling, Optimization, Artificial neural network

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Ohmic heating is not a new concept of heating at lab scale, but at industrial level it is little difficult due to some of its disadvantages. There are many applications of ohmic heating for horticultural products for blanching, peeling, sterilization, etc. Conventional heating methods are heat transfer by conduction, convection and sometimes by radiation. Conventional heating has a major disadvantage of non-uniform heating Castro *et al*. (2004) and Darvishi *et al*. (2011). Ohmic heating is directly proportional to the electric conductivity of the food material under electric field Palanippan and Sastry (1991) and Zhu *et al*. (2010). Hence, uniform heating can be easily achieved. Ohmic heating is time and energy saving method of heating as heating efficiency is high. Such heating efficiency is dependent on the system's performance hence, it is also known as system performance co-efficient (SPC).

Tomato is major horticultural produce used as canning product worldwide. There are different products of tomato available in the market such as tomato paste, tomato puree, tomato soup, tomato ketchup and many more. Tomato has large nutritional benefits. It is a low calorie fruit. It is rich in lycopene and zeaxanthin, flavonoid antioxidants and good source of vitamin A, vitamin C, potassium, moderate source of vitamin B complex Santos-Sánchez *et al*. (2012). The objective of this study is to get the electrical conductivity of tomato juice in ohmic heating and study it under different voltage gradients. System performance and physico-chemical properties of after ohmically heated tomatoes is studied. To achieve these objectives, on-line control techniques are required. Food processes are highly nonlinear which complicates food process automation. However, 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 worked on ANN as a modelling tool in food technology. 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 Duan *et al.* (2011); Assiry *et al.* (2010); Icier and Ilicali (2005b) ; Zhu *et al.* (2010); Darvishi *et al.* (2011) and Sarang *et al.* (2008). This study has been undertaken to develop ANN model for prediction of electrical conductivity for process optimization during ohmic heating.

METHODOLOGY

Experimental setup :

A picture of experimental setup is shown in Fig. A. Ohmic heater of a lab scale assembly consists of a 3 phase AC power supply with voltage regulator. Two electrodes of stainless steel 316 (16% chromium, 10% nickel, 2% molybdenum) at both the sides are fitted in a glass chamber. Teflon caps were used to close both the ends of chamber. The distance between the electrodes is about 20cm and diameter of electrode is 6.5 cm. There was a provision of holes for thermal sensors, inlet, outlet of products and removal of vapours during boiling at different location. Chromel-Alumel (K type) thermocouple was installed at the geometric centre of the glass chamber for continuous temperature measurement. Ohmic heater was operated at six different voltages gradient like 100, 120, 140, 160, 180, and 200V at 50Hz frequency.

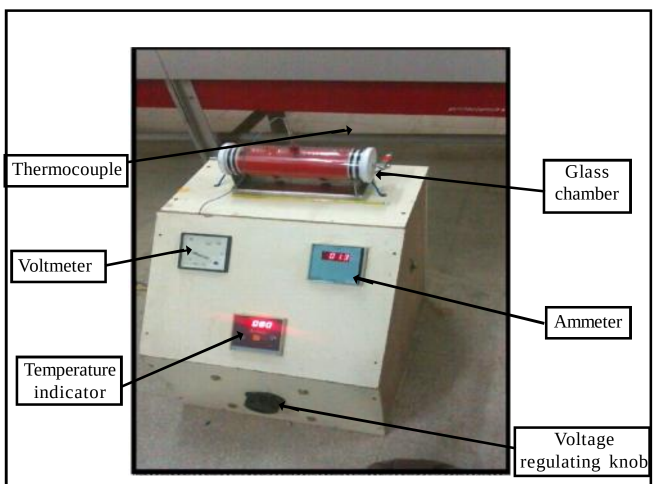

Fig. A : Ohmic heating assembly

Sample preparation :

Tomatoes were procured form the local market in Anand, Gujarat, India. The sample tomatoes were washed, crushed and the filtered with muslin cloths. The viscous tomato juice was obtained with high moisture content. The clarified tomato juice was poured through the port at the top of the glass chamber. Different voltages were applied to the electrodes to heat the tomato juice. Each experiment was replicated three times.

Electrical conductivity :

Electrical conductivity of the tomato juice was estimated by measuring the electrical resistance offered by it and the chamber parameter (Icier and Ilicali, 2004 and Icier and Ilicali, 2005).

$$\sigma = \frac{L \times I}{A \times V} \quad ....(1)$$

where, σ is electrical conductivity in s/m, I is the current in ampere (A), V is voltage gradient in volt (V), L is the distance between two electrodes in meter (m) and A is the cross-section area of sample in heating (m^2). L/A is the chamber or cell constant of the heating unit *viz.*, 69.3 m^{-1}.

System performance :

System performance was measured by the system performance co-efficient (SPC). It is numerically:

$$SPC = \frac{E_{utilised}}{E_{supply}} = \frac{mc_p (T_f - T_i)}{\sum VIt} \quad ....(2)$$

where, E_{supply} is the electrical energy supplied to the heating system in joule (J), $E_{utilised}$ is the heat energy taken by the tomato juice to increase its temperature in joule (J), c_p is the specific heat of tomato juice (3980J/kgk), t is heating time in second(s), T_f and T_i are the final and initial temperature of the tomato juice, respectively.

For ideal system, energy utilised is equal to energy supplied. But it is not possible as such, there are some heat losses. Hence,

$$E_{supply} = E_{utilised} + \text{energy losses}$$

The possible energy loss can be heat energy utilised to heatup the glass chamber, electrodes and some may be escaped to surrounding Amiali *et al.* (2006).

ANN description of the process :

Neural network model will be consisted of an input, a hidden and an output layer. The input layer has four nodes which correspond with processing conditions or independent variables: temperature, time, voltage and current of sample. The output layer consists of dependent variable as electrical conductivity.

Training and testing algorithms :

MATLAB-10 software was used for artificial neural networks (ANN) modelling. The networks were simulated based on a multilayer feed forward neural network. This type of network is very powerful in function optimization modelling Kerdpiboon *et al*. (2006). The input layer, hidden layers, and output layer structures are arranged in such a way to give best optimization. ANN modelling was performed with back propagation, algorithm for minimization of error - Levenberg-Marquardt, the network training - Different size of epochs, goal - Minimum error and the transfer functions - Hyperbolic tangent, sigmoid transfer function and linear transfer function.

A back-propagation algorithm was used to implement supervised training of the network. During training, weighting functions for the inputs to each ANN were automatically adjusted such that the predicted output best matched with the actual output from the data set. Weights were randomly assigned at the beginning of the training phase according to the back-propagation algorithm. A hyperbolic tangent was selected as the transfer function in each hidden layer and a linear transfer function for the output layer. Minimization of error was accomplished using the Levenberg – Marquardt (LM) algorithm. This algorithm trains a neural network 10 to 100 times faster than the usual gradient descent back propagation method. It will always compute the approximate Hessian matrix which had dimensions n-by-n. Training was finished when the mean square error (MSE) converged and was less than 0.001. If the MSE did not go below 0.001, training was completed after 10000 epochs, where an epoch represents one complete sweep through all the data in the training set Ruan *et al*. (1995). The networks were simulated with the learning rate equal to 0.05. For training, testing and validation of ANN configuration different ratio of data sets were examined. It was found that 70 per cent of data set was used for training, 15 per cent for testing and other 15 per cent for validation to predict the best output.

Optimization of ANN configuration :

The optimal configurations from training, testing and validation for each neuron were selected based on neural network predictive performance which gave the minimum error from training process. Mean squared error (MSE) is the average squared difference between outputs and targets, lower values are better and zero means no error. Regression (R) values measure the correlation between outputs and targets.

RESULTS AND DISCUSSION

The changes in electrical conductivity of tomato juice with temperature during ohmic heating at six different voltage gradients are given in Fig. 1, which shows the linear relationship of electrical conductivity with temperature. Electrical conductivity increased as the temperature increased during ohmic heating. The linear relation is due to presence of high amount of water in the tomato juice and also when biological tissue is heated, its electrical conductivity increases due to increase in the ionic mobility Assiry *et al*. (2010) and Chen *et al*. (2010). This phenomenon occurs because of structural changes in the tissue like cell wall protopectin breakdown, expulsion of non-conductive gas bubbles and softening. Bubbling of juice is observed at temperatures above 80°C at lower voltages but as voltages increases the bubbling temperature raises to above 85°C. There was a separation phenomenon observed. The separation of phases starts at the temperature of 72°C at lower voltages but as voltage increases the separation temperature rises to 85°C. The suspected reason for this phenomenon is, on applying the juice to the voltages, the pH decreases. This brings the ionic compounds to its isoelectric point.

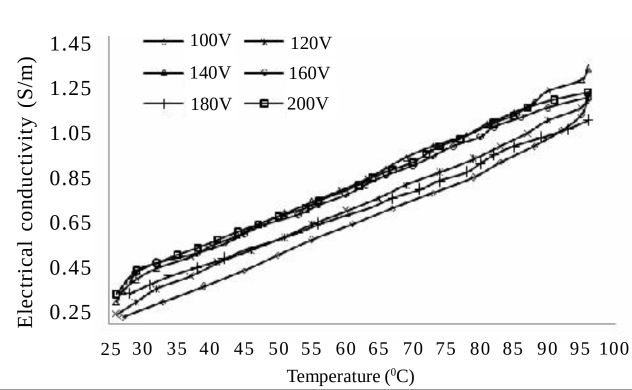

Fig. 1 : Relation of electrical conductivity with temperature at different voltage gradients

With proper homogenization of tomato juice, the separation of layers delays significantly. One way analysis of variance were used for statistical analysis and showed that voltage gradient had a significant effect ($p<0.05$) on the electrical conductivity of tomato juice.

Fig. 2 shows the relation of holding time and voltage gradients. As voltage gradient increases the holding time decreases. This can be explained by joule's law. High voltage leads to high current by ohm's law, therefore, heat generation is high, hence holding time decreases to achieve desired temperature *i.e.* 96°C.

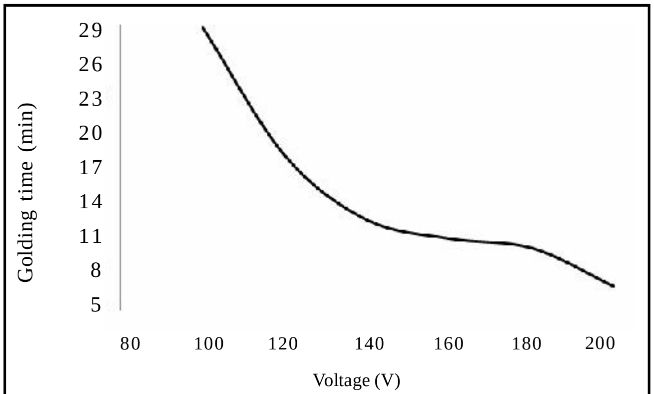

Fig. 2 : Relationship between holding time and voltage gradients

Average electrical conductivities of the tomato juice and SPCs at different voltages are shown in Table 1. SPC is the ratio of E_u and E_s both are strongly voltage dependent. The electrical energy is decreasing with increasing voltage gradient. One reason might be that the heating time is longer under lower voltage gradient and result in the increase of electrical energy. Same results were also achieved by Vikram *et al.* (2005) and Zell *et al.* (2009). For the tomato juice samples the SPCs increased from 0.9057 to 0.9887 as the voltage gradient decreased, which indicated that 1.13 -9.43 per cent of the electrical energy given to the system was not used in heating up the test sample.

Table 1: Electrical conductivity of tomato juice and SPCs at different voltages in ohmic heating

Voltage (V)	Average electrical conductivity (S/m)	SPC
100	0.7394	0.9887
120	0.7707	0.9878
140	0.7876	0.9859
160	0.8759	0.9835
180	0.8801	0.9558
200	0.8912	0.9057

Since the experimental electrical conductivity results for the tomato juice samples given in Fig. 1, showed a linear trend with increasing temperature, a linear equation shown in equation 3 was used to fit the experimental data. The properties of tomato juice are tabulated in Table 2. The constants and the linear regression co-efficients are given in Table 3.

Table 2 : Properties of tomato juice used in calculations

Property	Value
Density (kg/m^3)	1079.36
Specific heat (J/kg^{0}C)	3719

$$\sigma = ZT + C \quad \text{....(3)}$$

The ANN optimization process was performed usinga trial and error technique. Temperature, time, voltage and current of sample were used as input in the artificial neural network structure. The data set of inputs and outputs used to train the ANN. Each data set was divided into three groups, consisting 70 per cent for training, 15 per cent for testing and other 15 per cent for validation Shrivastav and Kumbhar (2009); Srivastava and Kumbhar (2011 and 2014). As far as above selection of data is concerned, author tested different combinations of data set like 70%~ 20%~10%, 30%~30%~40%,70%~ 10% ~20% and found that the best result was with

Table 3 : Parameters of linear model of tomato juice during ohmic heating

Voltage gradient (V/cm)	Z	C	R^2
100	0.210	-0.454	0.99
120	0.040	- 1.052	0.98
140	0.053	-1.250	0.99
160	0.061	-1.444	0.98
180	0.075	-1.521	0.98
200	0.082	-1.978	0.98

70%~15%~15% data set. The MSE for training, testing and validation were 1.114e-17, 2.218e-5 and 4.057e-8. The system equations representing the ANN for predicting electrical conductivity are also shown below. The system equations show the input, transfer function and relative weights of each nodes. The equation can be used in computer program to predict the electrical conductivity for any given set of conditions Srivastava and Kumbhar (2011).

System equations :

X = Voltage

W = Current

$X_1 = \tanh[(-0.0233)*X + (-0.1041)*W + (10.2816)]$

$X_2 = \tanh[(-0.3271)*X + (1.2529)*W + (-0.0695)]$

$X_3 = \tanh[(0.0124)*X + (-0.2476)*W + (7.8621)]$

$X_4 = \tanh[(-0.0182)*X + (-0.1961)*W + (8.4308)]$

$X_5 = \tanh[(0.005)*X + (-0.2789)*W + (13.1905)]$

$X_6 = \tanh[(0.0716)*X_1 + (0.1841)*X_2 + (0.7023)*X_3 + (1.1286)*X_4 + (0.9809)*X_5 + [(0.8936)*X_6 + (-0.2146)*X_7 + (-0.096)*X_8 + (-0.3852)*X_9 + (-1.7976)]$

$X_7 = \tanh[(-0.4246)*X_1 + (-2.1702)*X_2 + (0.3959)*X_3 + (0.7386)*X_4 + (-0.7758)*X_5 + [(-0.0696)*X_6 + (-0.8621)*X_7 + (0.9432)*X_8 + (0.0476)*X_9 + (1.4224)]$

$X_8 = \tanh[(-0.669)*X_1 + (1.8015)*X_2 + (0.2982)*X_3 + (-0.2019)*X_4 + (-0.6159)*X_5 + [(-0.8185)*X_6 + (0.7864)*X_7 + (-0.311)*X_8 + (0.5863)*X_9 + (0.6479)]$

$X_9 = \mathrm{purelin}[(1.027)*X_1 + (-0.5584)*X_2 + (-1.2743)*X_3 + (-1.0635)*X_4 0.3642)*X_5 + (0.4652)]\ \sigma = ((0.51)*X_9 + (0.12))$

Plots of experimentally determined electrical conductivity versus ANN predicted values for all combined data are shown in Fig. 3. The correlation co-efficient was greater than 0.98 in all the cases. This shows that the ability of ANN to predict electrical conductivity was very good.

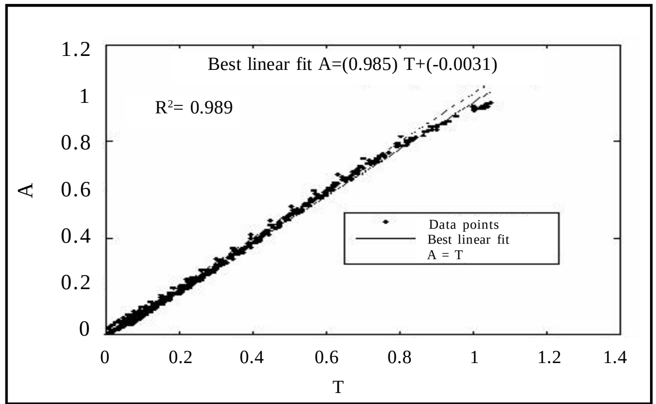

Fig. 3 : Correlation between predicted and experimental values of electrical conductivity

Conclusion :

The product was heated upto 96°C. Electrical conductivity of tomato juice varied from 0.27 S/m to 1.28 S/m. It increased as the voltage increased. System performance co-efficient was in the range of 0.9057 to 0.9887. System performance co-efficient decreased with an increase in voltage. Bubbling temperature of the tomato juice was above 80°C at lower voltages and 85°C at higher voltages. Separation of layers of tomato juice occurs at temperatures about 72°C if the juice is raw and unhomogenized and if not, the separation temperature increases. The results showed that the linear model was found to be the most suitable model for describing the electrical conductivity curve of the ohmic heating process of tomato juice. ANN can be used to predict the electrical conductivity of tomato juice. The optimal models for combined data can predict the electrical conductivity with R^2 value greater than 0.98.

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