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MODELING ISOSTERIC HEAT OF BANANA FOAM MAT USING NEURAL NETWORK APPROACH

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ABSTRACT

Information on the adsorption isotherm and the thermodynamic properties can assist in optimizing food processing operations such as drying, packaging and storage in the assessment of the quality of food. In this study, an Artificial Neural Network (ANN) was used for modelling the water activity/Equilibrium Relative Humidity (ERH) of banana foam mat under a range of values of the Experimental Equilibrium Moisture Content (EMC) to calculate the isosteric heat of sorption (q_{st}) by applying the Clausius-Clapeyron equation. The EMC of three dry banana foam samples at different densities of 0.21, 0.26 and 0.30 g/cm^3 was determined by a standard gravimetric method over a temperature range of 35-45°C and a relative humidity range of 32-83%. The modified-GAB model best fitted the EMC data. However, the modified-GAB model was not acceptable for predicting the heat sorption behaviour. A negative value of q_{st} estimated using the modified-GAB equation was found at a moisture content above 0.24 kg/kg d.b., showing the poor fit of the model. A multilayer feed-forward ANN trained by back-propagation algorithms was developed to correlate the output ERH to three exogenous inputs (foam density, EMC and temperature). The developed ANN models could predict the ERH more accurately than the modified-GAB model. The predictions from the ANN models produced R^2 values higher than 0.97. No negative q_{st} values were found using the ANN method.

Keywords: ANN, Adsorption Isotherm, Banana Foam, Back-Propagation, Isosteric Heat

1. INTRODUCTION

Net isosteric heat of sorption (q_{st}) is necessary for the modelling and simulation of the dehydration process and provides important information in respect of the sorption mechanisms. Two methods are available for the measurement of the differential heat of sorption. The first is the direct calorimetric measurement of the heat evolved; the second is the application of the Clausius-Clayperon equation on the isosteric equilibrium pressures at different temperatures. The isosteric heat of sorption is proportional to the number of available sorption sites at a specific energy level and provides the theoretical minimum amount of energy required to remove a given amount of water from the food. Conventionally, q_{st} is a positive quantity when heat is released during adsorption and negative when heat is absorbed during desorption. The heat of adsorption is a measure of the energy released on sorption and presents the energy required to break the intermolecular forces between the molecules of water vapour and the surface of the adsorbent.

The value of q_{st} can be calculated through water sorption isotherms. Water sorption isotherms can be expressed mathematically and there are currently more than 200 equations for representing the Equilibrium

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Moisture Content (EMC) of agricultural products and biological materials (Mulet *et al*., 2002). These models, which have different numbers of parameters, are either theoretically based or are empirical. Although several mathematical models can describe the water sorption isotherms of food materials very well, no single equation gives accurate results throughout the whole range of water activities and for all types of foods (Al-Muhtaseb *et al*., 2002). Chowdhury *et al*. (2006) fitted sorption isotherms data of mungbean to isothermal equations in both $M = f(RH,T)$ and $RH = f(M,T)$ forms. They found that the modified Chung-Pfost equation is the most suitable in the $M = f(RH,T)$ form while the modified Oswin equation is the most suitable in the $RH = f(M,T)$ form. In the present study, the sorption isotherm equations needed to be written explicitly in $RH = f(M,T)$ forms to calculate the net heat of sorption by applying the Clausius-Clapeyron equation. If the sorption isotherm model is an implicit equation, then mathematical techniques are required to solve the equation.

Artificial Neural Network (ANN) is an effective tool for modeling complex and non-linear problems in various scientific and technological fields (Shilbayeh *et al*., 2013; Al-Marghilani, 2013; Bhoyar and Kakde, 2010; Omaima, 2010). ANN has been successfully used to predict property and quality changes of a wide array of food products during processing and storage. These include the predictions of fruit maturity and grade the fruit into relevant quality category (Effendi *et al*., 2010), size and shape measurements of fish images (Alsmadi and Omar, 2010; 2011). This methodology does not need the explicit expressions of the physical meaning of the system under study and is considered to belong to the group of “black-box” models. The ANN models permit the study of the relationship between the input variables and the target(s) or output(s) of the process using a limited number of experimental runs (Khayet and Cojocaru, 2012). There are several types of ANNs such as feed-forward networks (perceptron network) and feedback networks (recurrent network). The feed-forward network is commonly used with an error correction algorithm such as back-propagation. The standard Back-Propagation Neural Network (BPNN) algorithm relies on a search technique (e.g., gradient descent), in which the network weights are changed along the negative of the gradient of the performance function. The BPNN procedure compares output and target values and modifies the weight values according to a specific learning algorithm to reduce the overall error. The modified weights are then propagated backwards into the system. This process is carried out for each set of training patterns to compute the global error and is repeated until the difference between the predicted output and target values reaches an accepted range (Tabach *et al*., 2007). The drying or sorption processes involve complex and highly nonlinear phenomena. Recently, ANNs have gained much popularity for simulating nonlinear relationships in drying and sorption processes (Aghbashlo *et al*., 2011; Broyart and Trystram, 2003; Fathi *et al*., 2011; Menlik *et al*., 2010; Mihajlovic *et al*., 2011; Momenzadeh *et al*., 2011). A study on neural network modelling of the isosteric heat of food has been reported by Chayjan and Esna-Ashari (2010). They found that the ANN model could predict soya bean EMC more accurately than sorption isotherm equations. Moreover, the ANN models provide an accurate and rapid way to determine the energy requirements for the dehydration process of soya bean. Once the ANN model has been trained with a set of EMC data covering the range for the parameter of interest, interpolation with the ranges employed is dependable and fast.

In the present study, a banana foam mat product was used that is very hygroscopic and whose crispness is sensitive to moisture migration. Information on the adsorption isotherm and isosteric heat of sorption could provide a better understanding of the equilibrium state of water under certain temperature and RH conditions and assist in the assessment of the quality of dried banana foam mats. However, to date, no study has been found related to banana foam mats that was based on the ANN approach and no information on the isosteric heat of sorption of this product is available. Therefore, the objective of present study was to develop an ANN model to predict ERH. The developed ANN model was then used to calculate the isosteric heat of sorption of the banana foam mats.

2. MATERIALS AND METHODS

2.1. Dried Banana Foam Preparation

Gros Michel bananas (*Musa sapientum* L.) with a maturity stage of 5 (corresponding to a yellow peel and green tip) were purchased from a local market. The total soluble solids of the banana were measured using an ATC-1E hand-held refractometer (ATAGO, Japan) at a temperature of 23°C. The bananas used in the experiments contained a total soluble solids content of 23-25°Brix. To prepare the banana foam, the bananas were sliced and pretreated by immersing them in 1 g/100 g sodium metabisulphite solution for 2 min and rinsing them with distilled water for 30 s, in order to prevent discoloration during the foaming process. Then, 100 g banana puree with 5 g fresh egg albumen used as a foaming agent, was whipped with a kitchen aid mixer (model no. 5K5SS, Strombeek-Bever, Belgium) at the maximum speed to produce foam densities of 0.3, 0.5 and 0.7 g/cm^3. The banana foam density was determined by measuring the mass of a fixed volume of the foam. The banana foam was poured slowly into a steel block with dimensions of 45×45×42 mm (W×L×H) and then placed on a mesh tray, which was covered with aluminium foil. After that, it was dried to about 0.03 kg/kg d.b. using a tray dryer which was operated at 80^{o}C and an air velocity of 0.5 m/s. The banana foam prepared from the initial foam densities of 0.3, 0.5 and 0.7 g/cm^3 could produce dried banana foam densities of 0.21±0.02, 0.26±0.02 and 0.30±0.02 g/cm^3, respectively. The product thicknesses after drying were 2.8±0.15, 3.2±0.1 and 3.4±0.1 mm for the banana foam densities of 0.21, 0.26 and 0.30 g/cm^3, respectively. Three replications were performed for each banana foam density.

2.2 Adsorption Experiment

Moisture adsorption experiments were carried out using the static method. Samples were placed into glass jars containing saturated salt solutions ($MgCl_2 .6H_2O$, $Mg(NO_3)_2 .6H_2O$, KI, NaCl and KCl) which provided a Relative Humidity (RH) in the range 32-82% at corresponding temperatures of 35, 40 and 45°C. All the jars were placed in a temperature-controlled oven with a precision of ±1°C (UFE500, Memmert, Germany). Samples were weighed at different exposure times ranging from 1 to 120 h. At RH values of more than 74%, 1 mL of toluene was held in a vial and fixed in each glass jar in order to prevent sample spoilage by microbial activity. The moisture content of each sample after reaching equilibrium conditions was determined by drying the sample in the hot air oven at a temperature of 103°C for 3 h (AOAC, 1995). At this temperature, the percentage error of moisture content determination was approximately 0.4% when compared to the result obtained by the standard vacuum method (Thuwapanichayanan *et al*., 2008). The experiment under each adsorption condition was repeated three times and the mean value was reported.

2.3. Isotherm Equation and Fitting Method

The criteria used to select the most appropriate sorption model were the degree of fit to the experimental data and the simplicity of the model. Therefore, five widely used empirical equations were chosen to fit the experiment data. A non-linear multiple regression analysis was used to fit the experimental data using the models shown in **Table 1**.

The Root Mean Square Error (RMSE) was used to measure the accuracy of the model and the coefficient of determination (R^2) was used to show the variability between the predicted and measured data.

Equation 5 in **Table 1** was modified in a GAB empirical way by adding a term (Viollaz and Rovedo, 1999). The second term of the equation allows the necessary flexibility to obtain a good fit for high RH values. This term has a very low value compared to the first term for a low value of RH, so that the values of *A*, *B* and *C* are not severely affected by the addition of this new term. It can be observed that if the value of *D* is equal to zero, the GAB isotherm can be obtained. The constant parameter of Equations 1-5 were obtained by non-linear regression, using as the objective function the minimization of the relative deviations:

$$RMSE(\%) = \sqrt{\frac{\sum_{i=1}^{N}\left(M_i^{\exp} - M_i\right)^2}{N}} \times 100 \quad (1)$$

where, M^{exp} and M are the experimental and predicted values, respectively and N is the number of data points.

2.4. Artificial Neural Networks

A Back-Propagation Artificial Neural Network (BPNN) is a non-linear processing system operating in parallel that is composed of neurons which between them can be used for mapping input and output data (Khayet and Cojocaru, 2012). The BPNN is a single computational processor, which has four steps: (1) Assembly of the dataset, defining the input and output data, (2) deciding the network architecture, (3) training (network learning) and (4) simulating the network response to new inputs. The schematic structure of the BPNN used in the present study for predicting the moisture ratio is shown in **Fig. 1**.

Figure 1 shows a 3-layer BPNN with n,m and p as the number of input, hidden and output layers respectively. Scalar input X_i is transmitted via a connection that multiplies its strength by the scalar weight W_{ij} to form the product $W_{ij}×X_i$. The bias W_j is much like a weight, except that it has a constant input of unity and it is simply added to the product $W_{ij}×X_i$ by summing junction. The summing junction operator of a single neuron summarizes the weights and bias into a net input A_j known as the argument to be processed:

$$A_j = W_j + \sum_{i=1}^{n} W_{ij} \times X_i \quad (2)$$

Where:

W_j = Called the bias value
W_{ij} = The connection weights between the input layer and the hidden layer
X_i = The input variable
n = The number of input variables and
i = the integer index. The transfer function takes the argument
A_j = Produces the scalar output of the neurons

The most widely used transfer functions to solve linear and non-linear regression problems are the linear transfer function (purelin), log-sigmoid transfer function (logsig) and tan-sigmoid (tansig) transfer function (Hagan *et al*., 1996). The outputs of neurons computed by these transfer functions can be written as:

$$S(x) = \frac{1}{1+exp(-x)} \quad (LOGSIG) \tag{3}$$

$$S(x) = \frac{2}{(1+exp(-2x))-1} \quad (TANSIG) \tag{4}$$

$$S(x) = x(PURELIN) \tag{5}$$

The BPNN used in this study is based on the following Equation 6:

$$O_k = S\left(\sum_{j=1}^{m} W_{jk} \times S\left(\sum_{i=1}^{n} W_{ij} X_i\right)\right) \tag{6}$$

Where:

O_k = The output values
W_{jk} = The connection weights between the hidden layer and the output layer and
S = The transfer function. At each node, the weighted input signals are summed and the bias value
W_j = added. The combined input
A_j = Then passed through the transfer function
S = Produce the output node
O_j = Illustrated in **Fig. 1**. The output of one node contributes as input to the nodes in the next layer

The schematic structure of the ANNs used in present study for predicting the ERH is shown in **Fig. 2**. The foam density, equilibrium moisture content and temperature were the parameters chosen as the input layer and ERH was the output layer. Two training algorithms (the Levenberg-Marquardt (Trainlm) and Bayesian regulation (Trainbr) back-propagation algorithms) were used for updating the network weights.

The 180 data patterns, obtained from different experimental conditions, were randomly divided into 108 (60%), 36 (20%) and 36 (20%) data sets for good representation of the situation diversity; these data sets were used for training, Cross-Validation (CV) and testing the neural networks, respectively. The neural network toolbox of the Matlab software (MathWorks, Natick, Massachusetts, USA) was used in this study.

When using a back-propagation algorithm, a number of control parameters need to be set. The number of hidden layers and neurons within each hidden layer can be varied with the complexity of the problem and data set. In this study, the control parameters chosen were the number of neurons in the hidden layer (2-10), momentum coefficient (0.01-0.1), step size (0.01-0.05) in the hidden layer, epoch number (50-1000) and training runs (1-5). The prediction performance of the developed BPNN model can be evaluated by using different error analysis methods. In general, these methods are the Root Mean Square Error (RMSE), coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE). A higher value of R^2 and lower values of both the RMSE and MAPE are indications of better performance of the developed BPNN model. These parameters can be calculated as follows Equaton 7 and 8:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N}\left(D_{exp,i} - D_{ANN,i}\right)^2}{\sum_{i=1}^{N}\left(D_{ANN} - \overline{D}\right)^2}\right] \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{D_{ANN} - D_{exp}}{D_{ANN}}\right| \times 100 \tag{8}$$

Where:

D_{eap} = The experimental data
D_{ANN} = Predicted data
$\overline{D}$ = The average value of experimental data and *N* the number of observations

To increase the accuracy and processing velocity of network, input and output layers are normalized in the [-1, 1] or [0, 1] range Equation 9:

$$G_N = \frac{G_R - G_{min}}{G_{max} - G_{min}} \tag{9}$$

where, G_R is the actual value, G_{min} and G_{max} are minimum and maximum values in the data set, respectively.

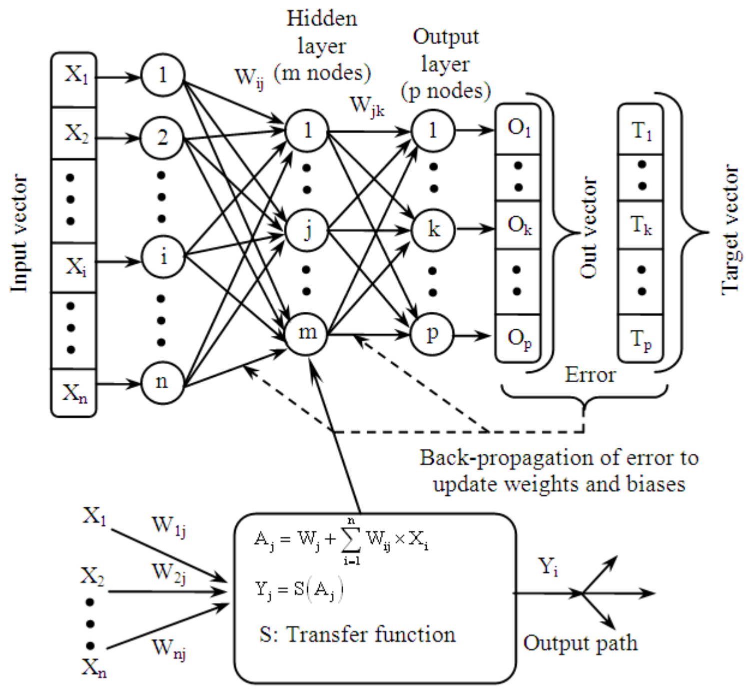


Fig. 1. Architecture of a typical BPNN

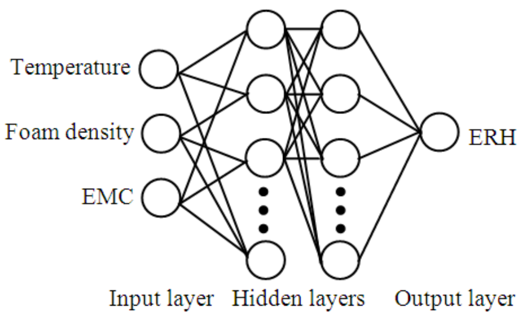


Fig. 2. Schematic of multilayer neural network

2.5. Thermodynamic Properties of Sorption

The isosteric heat at each level of moisture equilibrium can be used to estimate the energy requirements for the dehydration process. The isosteric heat of adsorption was calculated by applying the Clausius-Clapeyron equation to the experimental equilibrium isotherm data and it can be determined by the following equation:

$$\left.\frac{\partial \ln RH}{\partial(1/T)}\right|_{EMC} = -\frac{q_{st}}{R} \quad (10)$$

where, q_{st} is the net isosteric heat of sorption (kJ/mol), R is the universal gas constant, EMC is the equilibrium moisture content (kg/kg d.b.) and T is the absolute temperature (K). The net isosteric heat of sorption is calculated from the slope of the plot of ln RH versus 1/T at a constant equilibrium moisture content. This approach assumes that the isosteric heat of adsorption does not change with temperature. The isosteric heat of sorption, Q_{st}, was calculated using Equation 11:

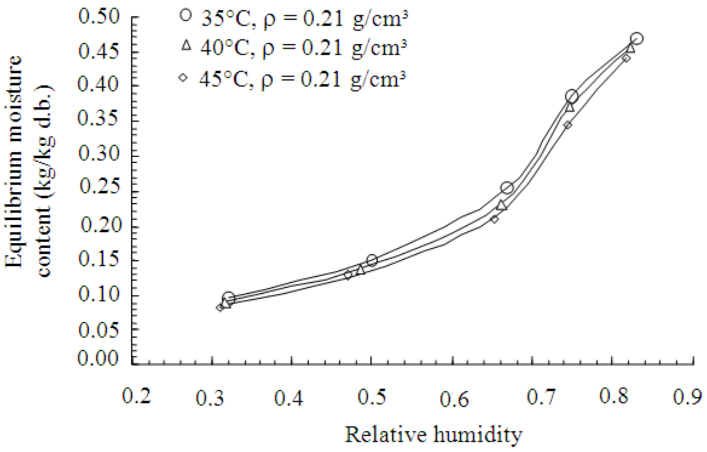
$$Q_{st} = q_{st} + \lambda \quad (11)$$

where, λ is the latent heat of pure water (kJ/mol).

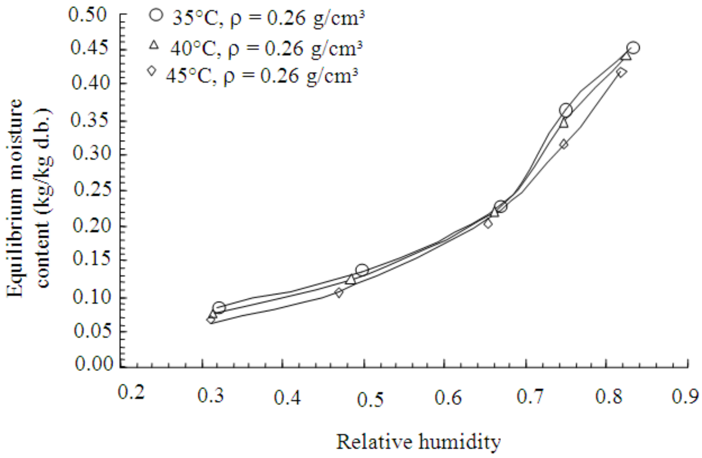
3. RESULTS AND DISCUSSION

3.1. Adsorption Isotherm of Banana Foam Mat

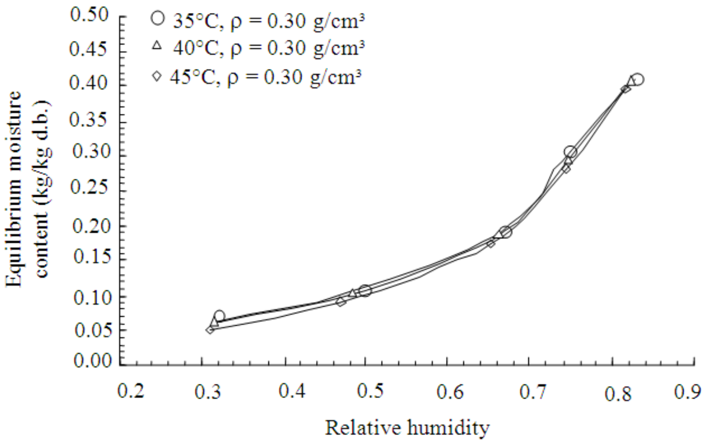
Figure 3a-c shows the experimental adsorption isotherms at 35, 40 and 45°C. The isotherms of banana foam exhibited the sigmoid (Type II) shape common to most food materials. The curves showed no intersection or crossover points with an increase in the temperature. At a constant relative humidity, the equilibrium moisture content decreased as the temperature increased. This trend may be explained by the excitation states of water molecules.



(a)



(b)



(c)

Fig. 3. Adsorption isotherm of banana foam densities at (a) 0.21 g/cm^3, (b) 0.26 g/cm^3 and (c) 0.30 g/cm^3

At an elevated temperature, the water molecules are in higher states of excitation, thus increasing their distance apart and decreasing the attractive forces between them (Kaya *et al*., 2007). Kim and Okos (1999) and Palou *et al*. (1997) found that the sorption capacity or equilibrium moisture content of products such as crackers and cookies decreased with an increase in temperature.

Figure 4 shows the influence of banana foam densities on the adsorption isotherm at 35°C. At a constant relative humidity, an upward shift in the density from 0.21 to 0.30 g/cm^3 led to a shift of isotherms toward a lower value for the equilibrium moisture content. Similar behaviours were observed at 40 and 45°C (graphs not shown).

The behaviour could be explained by the fact that as the foam density decreased, the porosity of the banana foam increased and the adsorption capacity of banana foam was higher at lower foam density. ANOVA showed that there was no significant difference among the adsorption isotherms between foam densities of 0.21 and 0.26 g/cm^3, but there was a significant difference when the foam density increased to 0.30 g/cm^3 ($p<0.05$).

3.2. Fitting of Adsorption Models

Experimental data of the banana foam mats were compared with the isotherms predicted by Equation 1-5. The value of the parameters of Equations 1-5 and the values of RMSE (%) and R^2 are shown in **Table 2**.

As seen in **Table 2**, the modified-GAB equation only gives values for RMSE that are lower than 4%. The modified-GAB equation well described the equilibrium moisture data within a wide range of RH values and could predict the experimental data with reasonable agreement (RMSE <2% and R^2>0.99). Viollaz and Rovedo (1999) found that the modified-GAB equation was acceptable for describing the sorption behavior of starch and gluten for relative humidities higher than 90%. From the RMSE and R^2 values, it could be deduced that the modified-GAB equation was reasonable to use in describing the moisture adsorption of banana foam mats.

3.3. Heat of Adsorption Predicted by Sorption Isotherm Models

In this study, Equations 4 and 5 were selected to study the isosteric heat of the banana foam mats. The isosteric heat of adsorption values were calculated from Equation 10 by plotting the natural logarithm of Relative Humidity (ln RH) against $1/T$, for the specific moisture data derived from the adsorption isotherm. Equations 4 and 5, together with the parameters in **Table 2**, were used to calculate the RH values. Equation 4 could be written explicitly in the *RH = f(M)* form as shown in **Table 1**. On the other hand, Equation 5 is an implicit form. A mathematical technique is required to solve the implicit equation. In this study, the *fzero* function in MATLAB was used to determine the RH value.

Figures 5 and 6 show the q_{st} values estimated through the water sorption isotherms of the GAB and modified-GAB models, respectively. Although the modified-GAB model can predict the experimental isotherms of banana foam mats better than the GAB model, when using the modified-GAB to calculate the heat of sorption, it was found that it was not acceptable for describing the heat adsorption behavior. As shown in **Fig. 6**, the negative value of q_{st} estimated using the modified-GAB equation is found in a moisture content range of 0.24-0.44 kg/kg d.b. for the dry banana foam densities of 0.21 and 0.26 g/cm^3, showing the poor fit of this model. A negative q_{st} value as the error of determination has no physical meaning.

3.4. Heat of Adsorption Predicted by ANN Models

In order to achieve the optimal result, several algorithms were tested. The adjustment of the neural network parameters included the number of neurons, the type of transfer function, learning rate, momentum and the number of patterns. The performance of the ANN models was compared using the RMSE, R^2 and MAPE. The training process was run until a minimum value of the RMSE was reached in the validation process. The performance of the trained network was estimated based on the accuracy of the network with the test data. Test data were presented to the network after the training process was completed.

The structures of the model used in this study are shown in **Table 3**. The number of hidden neurons and threshold functions were selected for good performance after several experiments. The best results were produced with the Trainlm algorithm, TANSIG-TANSIG-PURELIN threshold function and 3-4-2-1 topology. This composition produced values of RMSE = 2.12, R^2 = 0.97 and MAPE = 3.44, with convergence after 66 epochs.

A comparison between the experimental and predicted data at ρ = 0.5 g/cm^3 and T = 45°C obtained by the modified-GAB model (implicit equation) and the BPNN model for prediction of outputs is presented in the correlation plots shown in **Fig. 7**.

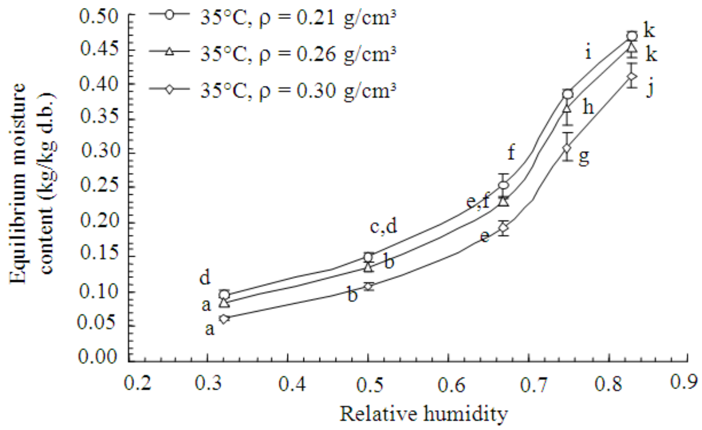


Fig. 4. Influence of foam densities on the adsorption isotherm 35°C

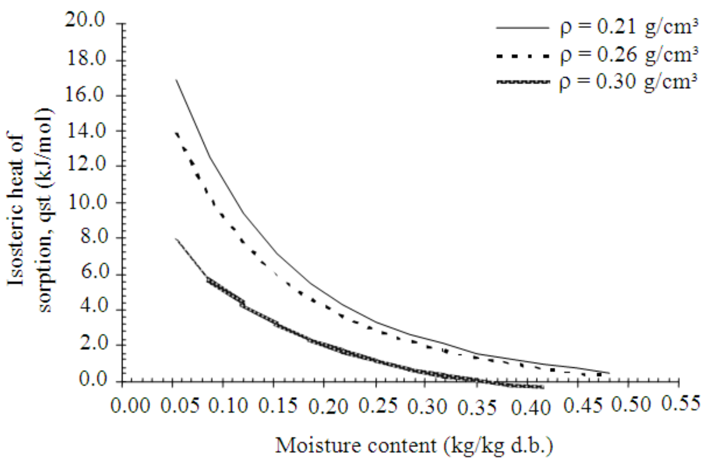


Fig. 5. Isosteric heat of sorption for different foam densities estimated using the GAB model

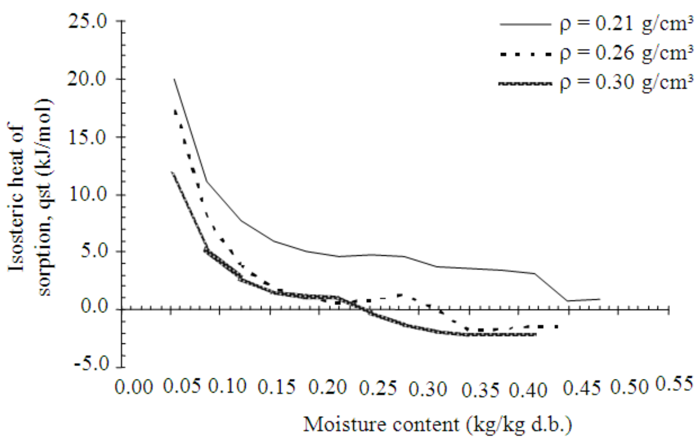


Fig. 6. Isosteric heat of sorption as function of moisture content for different foam densities; data estimated from modified-GAB model

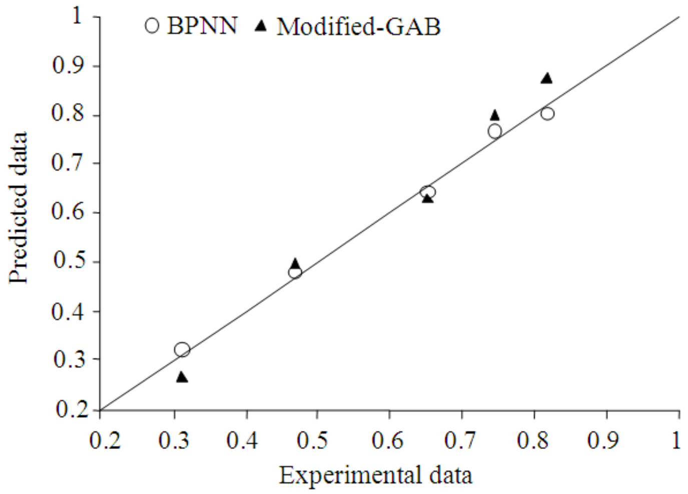


Fig. 7. Relationship between measured and predicted ERH using modified-GAB model and BPNN model for testing data set (ρ = 0.5 g/cm^3 and T = 45°C)

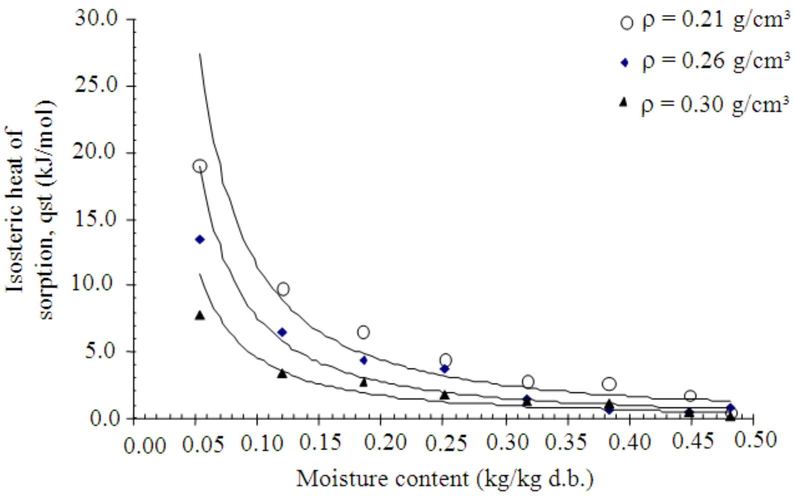


Fig. 8. Isosteric heat of sorption as function of moisture content for different foam densities; data estimated by optimum BPNN model and solid line is trend line

It is clear that the BPNN application exhibits better correlation between the experimentally observed and predicted results compared to the modified-GAB equation with values of R^2 = 0.94 and 0.98, respectively.

The ERH values of the banana foam mats at the three temperature levels and eight moisture content levels were computed using the optimized BPNN model. **Figure 8** shows the isosteric heat of sorption for the different foam densities. As shown in **Fig. 8** at the low moisture content, there are water molecules bound by a high binding strength on the adsorbent surface and high amounts of energy are required to remove the water molecules. On the other hand, when water was adsorbed far from the adsorbent surface, the binding force was low and it required low net isosteric heat. At a moisture content higher than 0.48 kg/kg d.b., the q_{st} value approached zero, implying that the heat of sorption is equal to the heat of vaporization of water. Such similar trends were observed in crackers, cookies and many cereal grains (Tolaba *et al*., 1997; Kim *et al*., 1998).

Table 1. Sorption isotherm models used for fitting the experimental data

Equation	M = f(RH, R) form		RH = f(M, T) form	
MOE	$M = (A+BT)\left(\frac{RH}{1-RH}\right)^{1/C}$	(1)	$RH = \frac{1}{1+\left(\frac{A+BT}{M}\right)^{C}}$	(6)
MCE	$M = -\frac{1}{C}\ln\left[\frac{(T+B)\ln(RH)}{-A}\right]$	(2)	$RH = \exp\left[\frac{-A}{T+B}\exp(-CM)\right]$	(7)
MHE	$M = \left[\frac{-\ln(RH)}{\exp(A+BT)}\right]^{-1/C}$	(3)	$RH = \exp\left[\frac{-\exp(A+BT)}{M^{C}}\right]$	(8)
GAB	$M = \frac{ABC\cdot RH}{(1-C\cdot RH)(1-C\cdot RH+BC\cdot RH)}$ $where\, B = B_o\exp\left(\frac{H_B}{RT}\right)$ $C = C_0\exp\left(\frac{H_C}{RT}\right)$	(4)	$RH = \frac{2+\left(\frac{A}{M}-1\right)B-\left\{\left[2+\left(\frac{A}{M}-1\right)\right]^2-4(1-B)\right\}^{\frac{1}{2}}}{2C(1-B)}$	(9)
MGAB	$M = \frac{ABC\cdot RH}{(1-C\cdot RH)(1-C\cdot RH+BC\cdot RH)}$ $+\frac{ABCD\cdot RH^2}{(1-C\cdot RH)(1-RH)}$ $where, D = D_0\exp\left(\frac{H_D}{RT}\right)$	(5)	-	

M = Equilibrium moisture content (kg/kg d.b.), A, B, B_0, C, C_0 and D = equation constants, RH = Relative Humidity (decimal), MOE = Modified Oswin Equation, MCE = Modified Chung-Pfost Equation, MHE = Modified Hasley equation, GAB = Guggenheim, Anderson and de Boer equation, MGAB = Modified GAB

Table 2. Estimated values of equation coefficients and equation fit errors

				Equation constants								
Model	ρ (g/cm^3)	RMSE	R^2	A	B	C	B_0	C_0	D_0	H_B	H_C	H_D
MOE	0.3	11.620	0.92	-20.010000	0.35500	2.714	-	-	-	-	-	-
	0.5	11.020	0.93	-44.210000	0.44000	2.810	-	-	-	-	-	-
	0.7	11.560	0.92	33.930000	0.20500	2.950	-	-	-	-	-	-
MCE	0.3	10.430	0.93	7.03E10	1.19E10	0.023	-	-	-	-	-	-
	0.5	10.430	0.93	1.26E11	1.75E10	0.024	-	-	-	-	-	-
	0.7	8.870	0.94	4.60E11	7.78E15	0.021	-	-	-	-	-	-
MHE	0.3	14.740	0.89	4.54900	0.00610	1.500	-	-	-	-	-	-
	0.5	14.390	0.89	4.17600	0.00750	1.507	-	-	-	-	-	-
	0.7	15.210	0.87	5.72800	0.00290	1.512	-	-	-	-	-	-
GAB	0.3	8.133	0.96	0.15900	-	-	1.57E-5	1.396	-	29.680	-1.188	-
	0.5	6.026	0.97	0.17300	-	-	2.92E-5	1.377	-	27.150	-1.183	-
	0.7	8.650	0.96	0.10600	-	-	3.04E-5	1.667	-	27.680	-1.453	-
MGAB	0.3	0.029	0.99	0.08900	-	-	0.7221	0.828	-0.083	3.145	-	0.963
	0.5	0.548	0.99	0.06800	-	-	0.6830	0.864	-0.088	4.146	-	1.066
	0.7	1.342	0.99	0.07400	-	-	0.9710	1.06	-0.130	1.250	-	0.329

MOE = modified Oswin equation, MCE = modified Chung-Pfost equation, MHE = modified Hasley equation, GAB = Guggenheim, An-derson and de Boer equation, MGAB = modified GAB

Table 3. Training algorithms for different neurons and hidden layers of networks for prediction of ERH

Training algorithm	Threshold function	Numbers of hidden layers and neurons	RMSE	R^2	MAPE	Epoch
Trainlm	TANSIG-TANSIG-LOGSIG	3-4-3-1	5.58	0.95	8.56	37
Trainlm	TANSIG-TANSIG-PURELIN	3-4-2-1	2.12	0.98	3.44	66
Trainlm	TANSIG-LOGSIG-PURELIN	3-5-2-1	7.74	0.93	10.22	29
Trainbr	TANSIG-LOGSIG-PURELIN	3-4-3-1	10.02	0.92	12.13	38
Trainbr	TANSIG-TANSIG-PURELIN	3-3-2-1	5.97	0.95	8.66	47
Trainbr	TANSIG-TANSIG-TANSIG	3-4-2-1	9.87	0.92	12.18	88

Trainlm = Levenberg-Marquardt back-propagation, Trainbr = Bayesian Regulation back-propagation

Figure 8 also reveals that lower values of q_{st} were found at higher banana foam densities. The surface area may be affected in determining the water binding properties of particulate materials (Toğrul and Arslan, 2006). The void area fractions for the banana foam densities of 0.21, 0.26 and 0.30 g/cm^3 obtained by counting the pore area of binary images, were 31, 26 and 23%, respectively (Prakotmak *et al*., 2011). The lower surface area of the solid matrix present in samples with a low banana foam density may reduce the material's ability to interact with water molecules, thereby reducing the energy required to remove them from the porous matrix.

The evaporation of water from banana foam requires energy to overcome the heat of evaporation of pure water. The maximum q_{st} value of banana foam at a density of 0.3 g/cm^3 (about 8-12 kJ/mol at 0.05 kg/kg d.b.) was close to that of cookies and corn snacks (6.7-10.1 kJ/mol and 7.5 kJ/mol, respectively) and in a moisture content range 0.05-0.07 kg/kg d.b., as reported by Palou *et al*. (1997). Arogba (2001) reported higher values of isosteric heat of sorption for mango flour with a maximum value of 18.2±1.6 kJ/mol, in a moisture content range of 0.10-0.12 kg/kg d.b. McMinn *et al*. (2007) also reported higher values of isosteric heat of sorption for microwave-baked oatmeal biscuits with a maximum value of 16.1 kJ/mol at a moisture content of 0.01 kg/kg d.b. As shown in **Fig. 8**, at 0.20 kg/kg d.b., the q_{st} value of banana foam did not exceed 6.0 kJ/mol. Yan *et al*. (2008) found that the value of q_{st} of dried banana was 8.91 kJ/mol at 0.20 kg/kg d.b. The results of the present study indicated that drying of the banana foam mats requires a lower energy level to remove water than is required with fresh banana (without a foaming technique).

4. CONCLUSION

The information of adsorption isotherm and isosteric heat of sorption could provide a better understanding of the equilibrium state of water under certain temperature and the Equilibrium Relative Humidity (ERH) conditions and in assessing quality of dried banana foam mats. Artificial neural networks have proved to be an effective tool to predict the ERH of banana foam mat as a function of input parameters, namely, banana foam density, equilibrium moisture content and temperature. The optimized model structure for prediction of ERH consists of two hidden layers with three and two neurons per layer, respectively. The ANNs could predict ERH values more accurately than the modified-GAB model with R^2 value higher than 0.97. However, one of the main problems with ANNs for modeling is that they cannot be applied to similar but different materials.

From the results obtained, it was found that the isosteric heat decreased exponentially with an increase in the moisture content. In addition, the isosteric heat for a low foam density was greater than those at higher foam densities at any moisture content level. The high isosteric heat value indicates the covering of the strongest binding sites and the greatest water-solid interaction. This implies that banana foam mats needs more energy at a lower moisture content for dehydration and storage, but require a low energy at higher moisture contents.

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6. REFERENCES

Aghbashlo, M., M.H. Kianmehr, T. Nazghelichi and S. Rafiee, 2011. Optimization of an artificial neural network topology for predicting drying kinetics of carrot cubes using combined response surface and genetic algorithm. Dry. Technol., 29: 770-779. DOI: 10.1080/07373937.2010.538819

Al-Muhtaseb, A.H., W.A.M. McMinn and T.R.A. Magee, 2002. Moisture sorption isotherm characteristics of food products: A review. Food Bioproducts Process., 80: 118-128. DOI: 10.1205/09603080252938753

Al-Marghilani, A., 2013. Artificial neural network in face detection human on digital image. Am. J. Applied Sci., 10: 1234-1239. DOI: 10.3844/ajassp.2013.1234.1239

Alsmadi, M.K., K.B. Omar, S.A. Noah and I. Almarashdeh, 2010. Fish recognition based on robust features extraction from size and shape measurements using neural network. J. Comput. Sci., 6: 1088-1094. DOI: 10.3844/jcssp.2010.1088.1094

Alsmadi, M.K., K.B. Omar and S.A.M. Noah, 2011. Fish classification based on robust features extraction from color signature using back-propagation classifier. J. Comput. Sci., 7: 52-58. DOI: 10.3844/jcssp.2011.52.58

AOAC, 1995. Official Methods of Analysis. 16th Edn., Association of Official Analytical Chemists, Washington, D.C. ISBN-10: 9780935584240

Arogba, S.S., 2001. Effect of temperature on the moisture sorption isotherm of a biscuit containing processed mango (*Mangifera indica*) kernel flour. J. Food Eng., 48: 121-125. DOI: 10.1016/S0260-8774(00)00144-8

Bhoyar, K.K. and O.G. Kakde, 2010. skin color detection model using neural networks and its performance evaluation. J. Comput. Sci., 6: 963-968. DOI: 10.3844/jcssp.2010.963.968

Broyart, B. and G. Trystram, 2003. Modelling of heat and mass transfer phenomena and quality changes during continuous biscuit baking using both deductive and inductive (neural network) modeling principles. Food Bioproducts Proc., Trans IChemE, 81: 316-326. DOI: 10.1205/096030803322756402

Chayjan, R.A. and M. Esna-Ashari, 2010. Modeling isosteric heat of soya bean for desorption energy estimation using neural network approach. Chilean J. Agric. Res., 70: 616-625. DOI: 10.4067/S0718-58392010000400012

Chowdhury, M.M.I., M.D. Huda, M.A. Hossain and M.S. Hassan, 2006. Moisture sorption isotherms for mungbean (*Vigna radiate* L). J. Food Eng., 74: 462-467. DOI: 10.1016/j.jfoodeng.2005.03.036

Effendi, Z., R. Ramli and J.A. Ghani, 2010. A back propagation neural networks for grading *Jatropha curcas* fruits maturity. Am. J. Applied Sci., 7: 390-394. DOI: 10.3844/ajassp.2010.390.394

Fathi, M., M. Mohebbi and S.M.A. Razavi, 2011. Application of fractal theory for prediction of shrinkage of dried kiwifruit using artificial neural network and genetic algorithm. Dry. Technol., 29: 918-925. DOI: 10.1080/07373937.2011.553755

Hagan, M.I., H.B. Demuth and M. Beale, 1996. Neural Network Design, PWS Publishing Co., Boston, ISBN-10: 0-53494332-2, pp: 730.

Kaya, A., O. Aydin and C. Demirtas, 2007. Drying kinetics of red delicious apple. Biosyst. Eng., 96: 517-524. DOI: 10.1016/j.biosystemseng.2006.12.009

Khayet, M. and C. Cojocaru, 2012. Artificial neural network modelling and optimization of desalination by air gap membrane distillation. Separat. Purificat. Technol., 86: 171-182. DOI: 10.1016/j.seppur.2011.11.001

Kim, M.K. and M.R. Okos, 1999. Some physical, mechanical and transport properties of crackers related to checking phenomenon. J. Food Eng., 40: 189-198. DOI: 10.1016/S0260-8774(99)00055-2

Kim, S.S., S.Y. Kim, D.W. Kim, S.G. Shin and K.S. Chang, 1998. Moisture sorption characteristics of composite foods filled with strawberry jam. Lebensmittel-Wissenschaft und-Technol., 31: 397-401. DOI: 10.1006/fstl.1998.0368

McMinn, W.A.M., D.J. McKee and T.R.A. Magee, 2007. Moisture adsorption behavior of oatmeal biscuit and oat flakes. J. Food Eng., 79: 481-493. DOI: 10.1016/j.jfoodeng.2006.02.009

Menlik, T., M.B. Ozdemir and V. Kirmaci, 2010. Determination of freeze-drying behaviors of apples by artificial neural network. Expert Syst. Applic., 37: 7669-7677. DOI: 10.1016/j.eswa.2010.04.075

Mihajlovic, T., S. Ibric and A. Mladenovic, 2011. Application of design of experiments and multilayer perceptron neural network in optimization of the spray-drying process. Drying Technol., 29: 1638-1647. DOI: 10.1080/07373937.2011.592960

Momenzadeh, L., A. Zomorodian and D. Mowla, 2011. Experimental and theoretical investigation of shelled corn drying in a microwave-assisted fluidized bed dryer using Artificial Neural Network. Food Bioproducts Proc., 89: 15-12. DOI: 10.1016/j.fbp.2010.03.007

Mulet, A., P. Garcya-Pascural, N. SanjＵun and J. Garcia-Reverter, 2002. Equilibrium isotherms and isosteric heats of model (*Morchella esculenta*). J. Food Eng., 53: 75-81. DOI: 10.1016/S0260-8774(01)00142-X

Omaima, N.A., 2010. Improving the performance of backpropagation neural network algorithm for image compression/decompression system. J. Comput. Sci., 6: 1347-1354. DOI: 10.3844/jcssp.2010.1347.1354

Palou, E., A. Lopez-Malo and A. Argaiz, 1997. Effect of temperature on the moisture sorption isotherms of some cookies and corn snacks. J. Food Eng., 31: 85-93. DOI: 10.1016/S0260-8774(96)00019-2

Prakotmak, P., S. Soponronnarit and S. Prachayawarakorn, 2011. Effect of adsorption conditions on effective diffusivity and textural property of dry banana foam mat. Dry. Technol., 29: 1090-1100. DOI: 10.1080/07373937.2011.569044

Shilbayeh, N.F., M.M. Alwakeel and M.M. Naser, 2013. An efficient neural network for recognizing gestural Hindi digits. Am. J. Applied Sci., 10: 938-951. DOI: 10.3844/ajassp.2013.938.951

Tabach, E.E., L. Lancelot, I. Shahrour and Y. Najjar, 2007. Use of artificial neural network simulation meta modeling to assess groundwater contamination in a road project. Math. Comput. Modell., 45: 766-776. DOI: 10.1016/j.mcm.2006.07.020

Thuwapanichayanan, R., S. Prachayawarakorn and S. Sopornronnarit, 2008. Modeling of diffusion with shrinkage and quality investigation of banana foam mat drying. Dry. Technol., 26: 1326-1333. DOI: 10.1080/07373930802330979

Tolaba, M.P., C. Suarez and P. Viollaz, 1997. Heats and entropies of sorption of cereal grain: A comparison between internal and differential quantities. Dry. Technol., 15: 137-150. DOI: 10.1080/07373939708917222

Toğrul, H. and N. Arslan, 2006. Moisture sorption behaviour and thermodynamic characteristics of rice stored in a chamber under controlled humidity. Biosyst. Eng., 95: 181-195. DOI: 10.1016/j.biosystemseng.2006.06.011

Viollaz, P.E. and C.O. Rovedo, 1999. Equilibrium sorption isotherms and thermodynamic properties of starch and gluten. J. Food Eng., 40: 287-292. DOI: 10.1016/S0260-8774(99)00066-7

Yan, Z., M.J. Sousa-Gallagher and F.A.R. Oliveira, 2008. Sorption isotherms and moisture sorption hysteresis of intermediate moisture content banana. J. Food Eng., 86: 342-348. DOI: 10.1016/j.jfoodeng.2007.10.009