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Application of Radial Basis Function Network with a Gaussian Function of Artificial Neural Networks in Osmo-dehydration of Plant Materials

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ABSTRACT

The study presents a critical evaluation of Artificial Neural Networks (ANNs) in food processing by successfully predicting the mass transfer in three plant materials. The used of ANNs in osmo-dehydration was evaluated using two varieties of apple (*Malus domestica* Borkh) of Golden Delicious and Cox, banana cultivar Cavendish and potato (*Solanum tuberosum* L.) variety *Estima*. In the ANNs, the radial basis function (RBF) network with a Gaussian function employing the orthogonal least square (OLS) learning method was used. A single hidden layer of few neurones (NHL = 20) resulted in the neural network being limited in its ability to model the process efficiently and the coefficient of determination (R^2) was 0.76 for water loss. Increased neurones (NHL = 100) the network was improved significantly (R^2 = 0.84) for water loss. Subsequent increase of the neurones to 120 (NHL = 120) showed a significant improvement of the network (R^2 = 0.91) for sucrose gain. The mass transfer in the three plant materials were successfully predicted by the ANN models indicating the ability of ANN to model both linear and non-linear models as an advantage over empirical equations for quality predictions in food processing.

Key words: Artificial neural networks, mass transfer, osmotic dehydration, multilinear regression, apple, banana

INTRODUCTION

The increased demand for healthy, natural and tasty processed foods by consumers in the last few decades has seen much research work to improve the quality of food products. In addressing consumer demands many technologies are now employed into food processing. One of such technology is Artificial Neural Networks (ANNs), which are computer programmes that are designed to emulate human information processing capabilities such as knowledge processing, speech, prediction and control (Basheer and Hajmeer, 2000). Artificial Neural Networks are recognised as good tools for dynamic modelling and consist of an association of elementary cells or neurones grouped into distinct layers and interconnected according to a given architecture

(Bishop, 1994). According the author, there are different forms of ANN's and all ANN networks have inputs that are connected by weights to a transfer function, also called the hidden layer(s), which is the most important part of the network since it is where all non-linear calculation is performed. The output from the transfer function are connected by weights which transforms the values from the transfer function into the output values which are located in the output layer(s). ANN's flexibly to adjust the number of neurones in the hidden layer and also incorporate various mathematical transformations in the hidden layer to operate on the incoming signals is their major strength.

ANN's can accommodate both linear and highly non-linear systems and model very complex relationships as a dynamic response to external inputs. ANN models can further accommodate multiple-input and multiple-output systems (Hertz *et al*., 1991; Jansson, 1991). Therefore, variability of multiple parameters in the development of an ANN model is possible. Another advantage of the ANN over conventional programs is their ability to learn from the system to be modelled without any prior knowledge on the relationships of the variables to be modelled (Chen *et al*., 1991).

Further advantage of ANN is the ability to model without any assumptions about the nature of the underlying mechanisms and their ability to take into account non-linearities and interactions between variables (Bishop, 1994; Yu *et al*., 2007; Qasem and Shamsuddin, 2010). Most importantly of ANN is the unique capability of learning from exemplar training data sets and consequently, an ability to adapt to the changing environment (Jansson, 1991; Linko and Zhu, 1991). ANN is also able to deal with uncertainties and with noisy and approximate data (Linko and Zhu, 1991). Artificial neural networks (ANN) have been the focus of interest in many diverse fields of science and technology. They have been used as a modelling tool in several foods processing applications and have been demonstrated to perform better than conventional tools which were based on regression, statistical or parametric models. ANN's are rapidly becoming an interesting, novel method in the estimation, prediction and control of dynamic bioprocesses (Linko and Zhu, 1991, 1992a-c; Linko *et al*., 1992). The application of the ANN models to food processing systems is very novel (Trelea *et al*., 1997). In the field of food process engineering, it is a good alternative to the conventional empirical modelling based on polynomial and linear regressions (Baughman and Liu, 1995; Eerikainen *et al*., 1993). ANN modelling performances to the conventional empirical modelling have been recognized and confirmed by many research reports (Hertz *et al*., 1991; Eerikainen *et al*., 1993). Neural (1996) provides a wide overview of potential applications of the neural network as classification, prediction, data association and optimisation. ANN applications in food and agriculture included fermentation (Latrille *et al*., 1993), extrusion (Linko *et al*., 1992), filtration (Dornier *et al*., 1995), drying (Huang and Mujumdar, 1993), psychrometry (Sreekanth *et al*., 1998), thermal processing (Sablani *et al*., 1995), rheology (Ruan *et al*., 1995) and sensory science (Park *et al*., 1995). ANNs had been applied in modelling for estimation of aflatoxin contamination in peanuts and it performed better (R^2 = 0.925) than traditional linear regression techniques (R^2 = 0.822) (Parmer *et al*., 1997). It has been shown that artificial neural networks (ANNs) have the capability of integrating large numbers of independent variables (e.g. fruit sample physical state, initial moisture content of the sample, temperature, concentration of the osmotic solution, time of immersion in osmotic solution) in such a way that the value of the dependent variable(s) (e.g. final target moisture content of the semi-dried product) can be predicted with a high degree of accuracy (Trelea *et al*., 1997). This paper evaluated the used of ANNs in osmo-dehydration of apple, banana and potato.

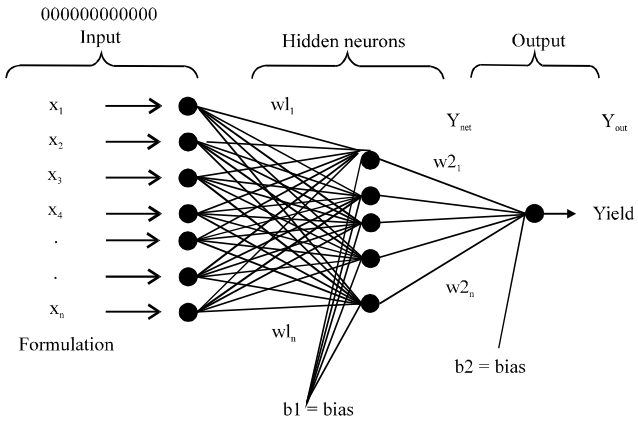

Fig. 1: Generalized Artificial Neural Network architecture for radial basis function networks depicting input, one hidden and one output layer and neurons with feedback link

MATERIALS AND METHODS

Principles of ANN models: Artificial neural networks (ANN) have inputs that are connected by weights to a transfer function, also called the hidden layer(s). This is the most important part of the network since it is where all non-linear calculation is performed. The output from the transfer function are connected by weights which transforms the valves from the transfer function into the output valves, which are located in the output layer(s). Each element of the input, hidden and output layers are generally referred to as neurons.

The multilayer feed forward neural networks are often used in studies (Basheer and Hajmeer, 2000). In these networks, signals are propagated from the input layer through the hidden layer to the output layer. Thus a node receives signals via connections from other nodes, or from the outside world in the case of input layer. The schematics description of Fig. 1 illustrates n neuron with various signals of intensity x as input with *y* output and hidden layer neurons generalized. The network is connected with w 1 weights between the input and the hidden layer and w 2 between the hidden layer and the output layer with a threshold (bias) of b.

The principle of using ANN in modelling is aim at obtaining the parameter W in Eq: 1.:

$$Y = WX+E \quad (1)$$

The main purpose is to establish a relationship between X and Y the input and output, respectively, which minimizes E (bias) by generating the coefficients W (weights) in the hidden layer and outer layer.

The experimental data are repeatedly passed through the network. The repeated submission of data to the network is called training and learning. During each pass, the weights w 1 and w 2 are adjusted according to the error minimization criterion between the calculated output and the known target outputs until an acceptable error differences is obtained after submitting the data to the network several times. When satisfactory results are obtained, the weights in the input and output are stored and used to perform predictions on future data.

The main strength of ANN is the ability to flexibly adjust the number of neurons in the hidden layer and also incorporate various mathematical transformations in the hidden layer to operate on the incoming signals.

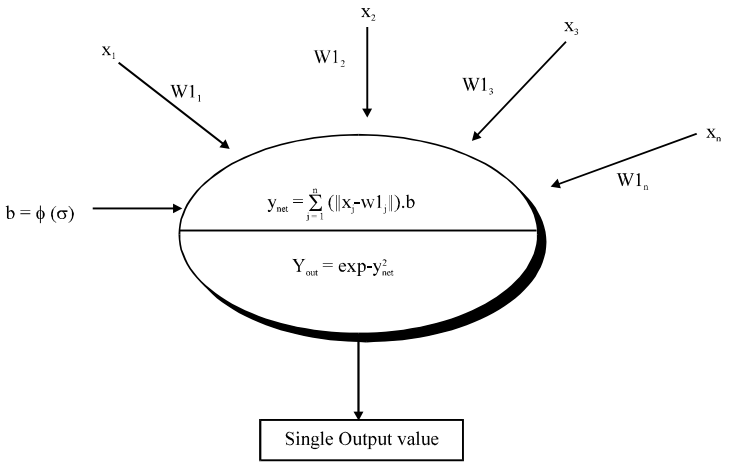

Fig. 2: The schematics of a single radial basis Gaussian neuron in hidden layer

Radial Basis Gaussian Function (RBF) Networks: Radial Basis Gaussian Function (RBF) networks are a special case of multilayer feedforward error-back propagation network with three layers (Schalkoff, 1997). This type of network generally has one hidden layer and the output is generally a linear function. Radial basis function networks are powerful in function optimisation modelling and they train rapidly compared to a back propagation (BP) network (Bishop, 1995; Haykin, 1994; Morris and Boddy, 1996; Wilkins *et al.*, 1999). The hidden layer is used to cluster the inputs of the network. They can be trained by a number of learning algorithms. The network employs a radial basis function such as the Gaussian function (Haykin, 1994; Yen and Lu, 2003; Yu *et al.*, 2007; Qasem and Shamsuddin, 2010), which is the most popular hidden layer function. Figure 2 shows the radial basis Gaussian function overview with schematic data flow. The others are thin-plate-spline, multiquadric and inverse multiquadric function. The mathematical relationships are simplified below:

$$\text{Gaussian function: } f(x) = \exp(-x^2/2\sigma^2) \quad (2)$$

$$\text{Thin-plate-spline function: } f(x) = x^2 . \log x \quad (3)$$

$$\text{Multiquadric: } f(x) = (x^2+\sigma^2)^{1/2} \quad (4)$$

$$\text{Inverse multiquadric: } f(x) = (x^2+\sigma^2)^{-1/2} \quad (5)$$

where, f(x) is the function of an input x and σ is the spread of the function.

Single output value: Figure 2 shows a single output value radial basis Gaussian neuron.

In the hidden and output layers, the net input to unit j is of the form:

$$Y_{net} = \Sigma (||x_j - w1_j||).b \quad (6)$$

where, x_j are the inputs, $w1_j$ are the weights associated with each input connection and b is the bias associated with the node j (j = 1,... , n).

This sum is used in a Gaussian function to give an output of the node as follows:

$$Y_{out} = \exp(-Y_{net})^2 \quad (7)$$

The hidden neuron function as a radial basis Gaussian function (RBF) is given as:

$$f(x) = \exp\{-(|x_j - w_j|)^2/\sigma^2\} \quad (8)$$

where, $0<f(x)<1$; $b1 = f(\sigma)$ and σ = spread (width, scaling) of the function:

$$Y_{net} = \Sigma(|x_j - w1_j|) \,.\, b1 \quad (9)$$

$$Yield = \Sigma(Y_{out} \,.\, w2j+b2) \quad (10)$$

Training of the neural network is by modification of connection weights (w) given as:

$$M_w = Y_{out} - Y_{known} \quad (11)$$

where, $x1_j$, x_n = input variables, $w1_j$, w_n = connection weights of respective input variables, Y_{net} = network input, Y_{out} = the output of the network processes, Y_{known} = target value, M_w = modification of the connection weights and b1, b2 = bias associated with the neurons.

Training, learning and testing RBF network: The RBF network employed the orthogonal least squares (OLS) learning method. The OLS method is one of the most efficient learning methods reported for RBF neural modelling. During learning the OLS receives a net input vector distance $||x-w||$ between its weight vector w and the input vector x, multiplied by the bias b. The bias is a direct function of the spread parameter σ which determines the proportion of the input space where the jth RBF neuron has sufficient non-zero response. Thus the valve of the spread should be such that it results in neurons responding strongly to overlapping regions of the input space. Neurons are created one at a time during the training cycle. At each iteration, the input vector, which will result in lowering the network error the most, is used to create a RBF neuron. The error of the network is checked and if lower than the set of error, training is terminated otherwise the next neuron is added. This procedure is repeated until the error level set is met or the set maximum number of neurons is exhausted. A mathematical summary of OLS is presented below. The desired response d(n) is represented in a linear regression equation as:

$$d(n) = \Sigma x_i(n)a_i + e(n) \quad (12)$$

where, $n = 1, 2, \ldots, N$; i ($i = 1, \ldots, m$); a_i are the model parameters, the $x_i(n)$ are the regressors and e(n) is model error. In matrix notation, the above equation becomes:

$$d = Xa + e \quad (13)$$

Where:

$$d = [d(1), d(2), \ldots, d(N)]^T \quad (14)$$

$$a = [a_1, a_2, \ldots, a_M]^T \quad (15)$$

$$x = [x_1, x_2, \ldots, x_M]^T \tag{16}$$

$$x_i = [x_i(1), x_i(2), \ldots, x_i(N)]^T (1 = i = M) \tag{17}$$

$$e = [e(1), e(2), \ldots, e(N)]^T \tag{18}$$

The regressor vectors x_i form a set of the basis vectors and the least-squares solution of the matrix equation satisfies the condition that the matrix product Xa be the projection of the desired response vector d onto the space spanned by the basis vectors. The OLS method involves the transformation of the regressor vector $x_1, x_2, \ldots, x_M$ into a corresponding set of orthogonal basis vectors denoted by $u_1, u_2, \ldots, u_M$. For example, the standard Gram-Schmidt orthogonalization procedure (Marcus, 1993) may be used to perform the transformation, as shown by:

$$u_1 = x_1 \tag{19}$$

$$\alpha_{ik} = (u_i^T x_k)/(u_i^T u_k), (1 = i = k) \tag{20}$$

$$u_k = x_k - \Sigma \alpha_{ik} x_i (i = 1 \text{ and } k-1) \tag{21}$$

where, k = 2, ..., M.

The OLS learning procedure choose the radial basis function centres $t_1, t_2, \ldots, t_M$ as a subset of the training data vectors $x_1, x_2, \ldots, x_N$t, where M<N. The centres (neurons) are determined one by one in a well defined manner following the Gram-Schmidt orthogonalization procedure until a network of adequate performance is constructed. At each step of the procedure the increment to the explained variance of the desired output is maximized. This resulted in the OLS learning procedure generally producing an RBF network whose hidden layer is smaller than that of a RBF network with randomly selected centres, for a specific level of unexplained variance of the desired response. Generally the correct choice of the optimum neurons for the RBF networks depends on the spread σ. The problem at hand determines the correct choice of the spread. Therefore a systemic approach to finding the optimum network configuration is important.

The selection of the optimum neurons for the RBF network depends on the spread, σ. The spread is however a function of the final bias used in the Gaussian networks.

ANN performance validation: The validation of the neural network configurations performance is decided by using the absolute error of prediction (AE) and the standard error of prediction (SE). In addition, the correlation coefficient (R) value of the regression between the predicted values and the experimental values was also used for comparison. The formulae of the paramters are presented below:

$$AE = \Sigma[(X-Y)^2/n] \tag{22}$$

$$SE = \{\Sigma[(X-Y)^2/n\}^2 \tag{23}$$

where, X = experimental data, Y = predicted data and n = number of samples.

Plant materials: Three plant materials were used in this study. They were banana (*Musa* spp.) cultivar Cavendish, potato (*Solanum tuberosum* L.) variety *Estima* and apple (*Malus domestica* Borkh) varieties Golden Delicious and Cox of 150 days after full bloom (DAFB) maturity levels were obtained from Horticultural Research International, East-Malling, Kent, England. Banana and potato were purchased from a local supermarket in Chatham, Kent, England and used immediately after purchase for each experiment. Banana fruits from a single bunch were used for each experiment ensuring that fruits selected were at stage four of ripeness, more yellow than green (UFSC, 1964).

Experimental design: Two gravimetric data sets on water loss and sucrose gain were used for training, testing and validating of the ANNs models. Set (1) data of osmo-dehydration at short sampling period of 0-50 min with sampling intervals of 5 min and a longer sampling period of 0-10 h with 1 h sampling intervals conducted at three levels for temperature (32.2, 40 and 55°C) and one level of osmotic solution of sucrose concentration (70%) for the three plant materials. Set (2) data is a factorial design at three levels for temperature (32.2, 40 and 55°C) and three levels of sucrose concentration solution (40, 50 and 60%) conducted at a sampling period of 0-3 h with 30 min sampling intervals for osmo-dehydration of apple, banana and potato. Experiments were conducted in triplicate.

Preparing ANN Data: Experimental data sets were divided into three groups. The first (Group A) cases were for training. The second (Group B) cases were for testing and the third (Group C) cases were for validation of the model. Groups were formed by employing a systematic approach of numbering all the original data points by 1, 2 and 3. To obtain three equal groups of data, every data row assigned 1 was selected and removed from the original set. These formed the first (Group A) data set for training. The same procedure was repeated for the remaining two data sets each forming groups B and C. In this study, gravimetric experimental data set of 1,026 was used to obtain three group data sets of 33.3% for training, testing and validation of ANNs models. The RBF network algorithm using Orthogonal Least Squares (OLS) was employed. It consisted of a network of 20-100 neurones in the hidden layer (NHL) for the model generation as schematised in Fig. 1 (where: n = neuron; x = input; y = output; w1 = weights between input and hidden layer; w2 = weight between hidden layer and output; b = bias). The diameter or spread of the function was 0.5-1.4.

Development of ANN models: The Matlab Neural Net Tool Box version 1.0 (The Matlab Inc., Mass., USA) was used for evaluating ANNs modelling.

Radial Basis Function (RBF) networks: Radial basis function network with a Gaussian function was used in this study (Bishop, 1995; Haykin, 1994; Morris and Boddy, 1996; Wilkins *et al*., 1999; Yen, 2006; Yu *et al*., 2007). The simplified mathematical relationships of the Gaussian function and mass transfer during osmo-dehydration are given as:

$$f(x) = \exp(-x^2/2\sigma^2) \quad (24)$$

$$WL = \exp-(T.\ C.\ t.\ Ss.\ St)^2/2\sigma^2 \quad (25)$$

$$SG = \exp-(T.\ C.\ t.\ Ss.\ St)^2/2\sigma^2 \quad (26)$$

where, T = temperature, C = concentration of osmotic solution (sucrose), t = immersion time, Ss = sample size, St = sample type and σ = spread of the function.

RESULTS AND DISCUSSION

Model development and optimisation: In order to achieve the best ANNs, several networks were trained on a grid of 64 networks of various combination of σ and added-on number of neurons. The error of each network was evaluated and the one with the minimum error on the test data set was selected and finally evaluated on further validation data sets. This is in conformance with reported studies in literature indicating one hidden layer was sufficient to approximate any and continues non-linear function, although more complex neural networks are used in special applications (Linko and Zhu, 1991; Chen *et al*., 1991; Hertz *et al*., 1991; Jansson, 1991; Haykin, 1994; Baughman and Liu, 1995; Bishop, 1995; Morris and Boddy, 1996; Wilkins *et al*., 1999; Basheer and Hajmeer, 2000; Poligne *et al*., 2002). Therefore, RBF that can model non-linear function using single hidden layer was used. To achieve this, several networks were trained on a grid of 64 networks of various combination of σ and added-on number of neurones. Each network's error was evaluated and the one with the minimum error on the test data set was selected. This selected network was finally evaluated on further validation data sets. Notably, using a single hidden layer of few neurones (NHL = 20) resulted in the neural network being limited in its ability to model the process efficiently and the coefficient of determination (R^2) was 0.76 for water loss. Increasing the neurones (NHL = 100) the network was improved significantly (R^2 = 0.84) for water loss. Subsequent increase of the neurones to 120 (NHL = 120) showed a significant improvement of the network (R^2 = 0.91) for sucrose gain. Figure 3-6 shows ANNs plots of optimisation of training and testing for water loss and sucrose gain during osmo-dehydration of apple, banana and potato. Comparing the experimental water loss and the predicted water loss (Fig. 3, 4) for both training and testing shows inadequate fit compared to sucrose gain (Fig. 5, 6). The near perfect fit of the sucrose gain is an indication of the ANNs to model the solids gain.

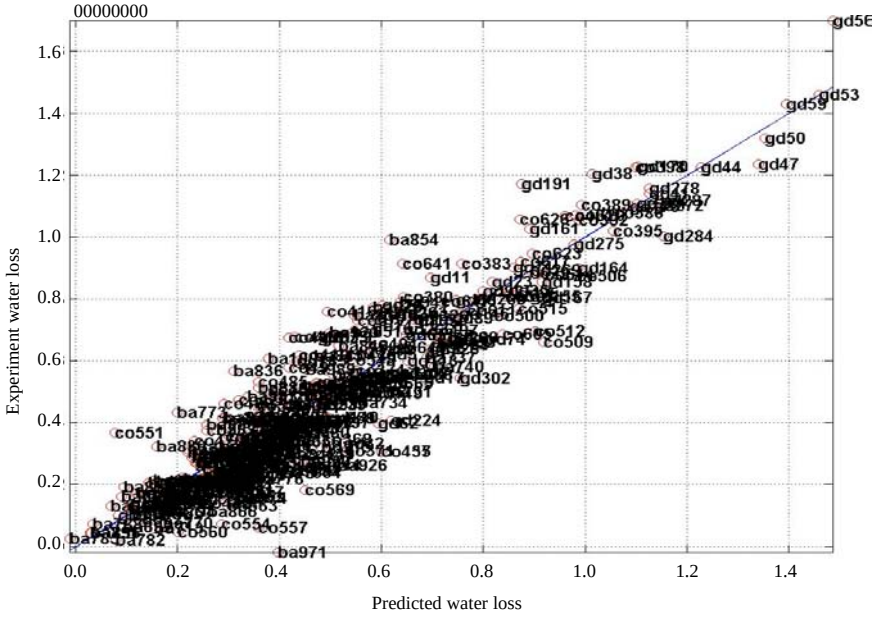

Fig. 3: Process optimal training of neural network experimental verse predicted water loss

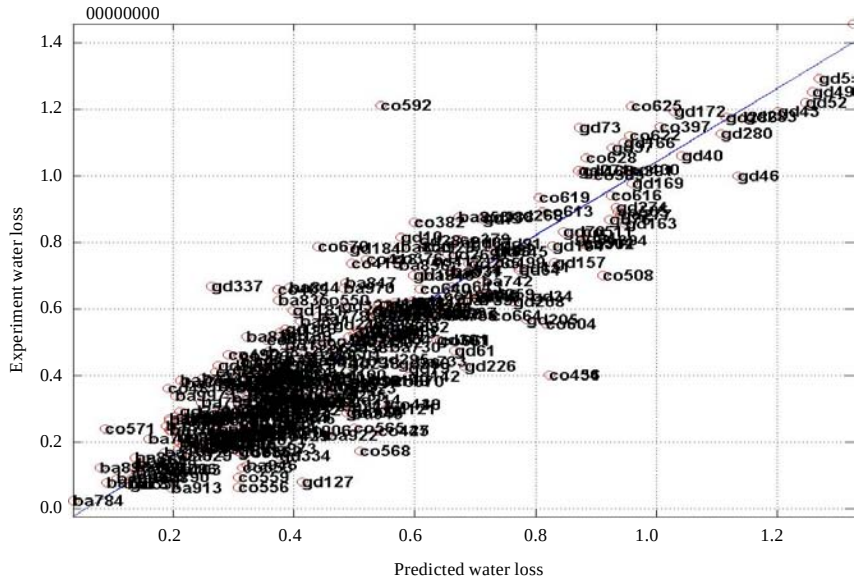

Fig. 4: Testing of neural network showing experimental verse predicted water loss

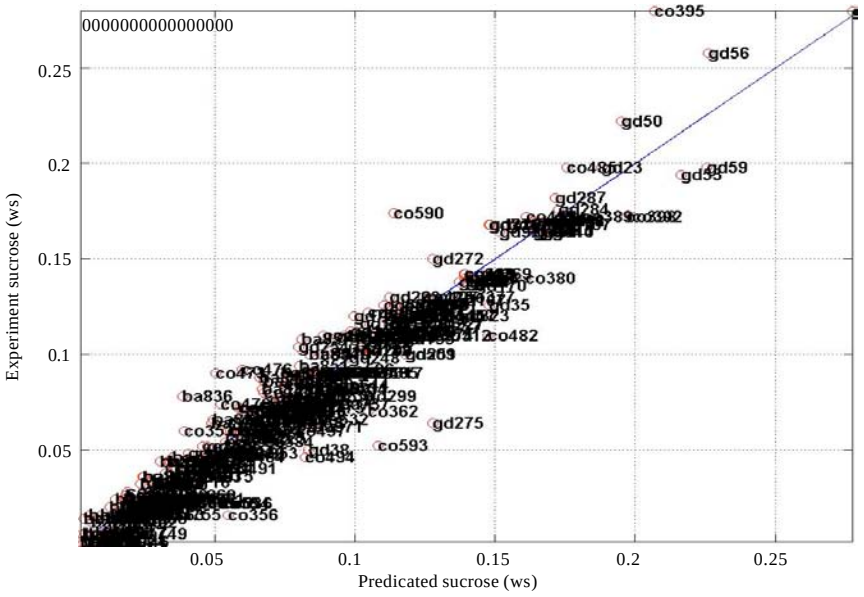

Fig. 5: Process optimal training of neural network experimental verse predicted sucrose gain

Performance of the ANN models: The performance of the ANN models for water loss and solids gain indicated evenly distribution and satisfactorily represent the experimental data at all stages of the experiment. Statistical results show values of the correlation coefficient (R) for water loss was 0.9142 and solid gain was 0.9547, absolute error in the range of 0.1113-0.0089 and standard error 0.1515-0.0125, representing that neural network has good prediction ability for both water loss and solid gain. Authors in the past had compared the performances of the ANN models with regression models, which showed some similarity or differences depending on the materials under study, in the regression coefficients of determination (R^2) and coefficient of regression (R) (Chen *et al.*, 1991;

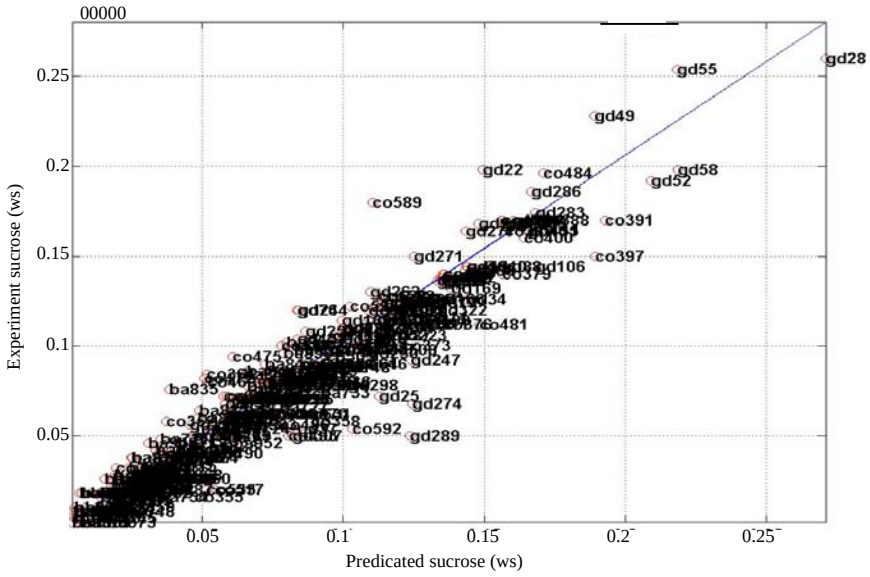

Fig. 6: Testing of neural network showing experimental verse predicted sucrose gain

Linko *et al.*, 1992; Eerikainen *et al.*, 1993; Latrille *et al.*, 1993; Huang and Mujumdar, 1993; Haykin, 1994; Baughman and Liu, 1995; Bishop, 1995; Dornier *et al.*, 1995; Sablani *et al.*, 1995; Ruan *et al.*, 1995; Park *et al.*, 1995; Trelea *et al.*, 1997; Parmer *et al.*, 1997; Sreekanth *et al.*, 1998; Basheer and Hajmeer, 2000; Poligne *et al.*, 2002; Tortoe *et al.*, 2008). In such situations it indicates some degree of similarity and differences in terms of water loss and solid gain prediction when the correlation coefficient (R) for ANN and the MLR models are compared. ANN ability to model the solid gain excellently is due to its flexibility to model both linear and nonlinear models (Park *et al.*, 1995; Parmer *et al.*, 1997; Tortoe *et al.*, 2008; Basheer and Hajmeer, 2000; Schalkoff, 1997; Bishop, 1995; Haykin, 1994; Chen *et al.*, 1991; Poligne *et al.*, 2002). Generally the ANN models showed an improvement on the MLR models. Poligne *et al.* (2002) employing ANN showed good performance valves of 0.9851 for water loss, 0.9855 for salt gain and 0.8811 for sugar gain. The authors applied ANN to pork curing at 10 - 70°C in DE21 glucose syrup (0-1.362 kg kg^{-1} water) and liquid smoke flavouring (7.5-42.5 mL kg^{-1} water). Tortoe *et al.* (2008) predicted regression coefficient for determination (R^2) in MLR for water loss of 0.8861 whereas ANN was 0.8358. However, a major difference was observed for solid gain prediction by the two methods. The R^2 for solid gain in MLR models was 0.3054 and for ANN was 0.9115. This indicates a very significant improvement by ANN models for solid gain compared to the MLR. The lower R^2 value of the MLR model for solid gain shows that there is insignificant correlation between the experimental data and the predicted data.

CONCLUSION

The ability of ANN to model both linear and non-linear models is an advantage over empirical equations for quality predictions in food processing. The mass transfer in plant materials was successfully predicted by ANN models. However, further ANN modelling needs to be carried out on other plant and animal materials and for variable operating conditions.

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