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OPTIMIZED NEURAL NETWORK MODEL FOR A POTATO STORAGE SYSTEM

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ABSTRACT

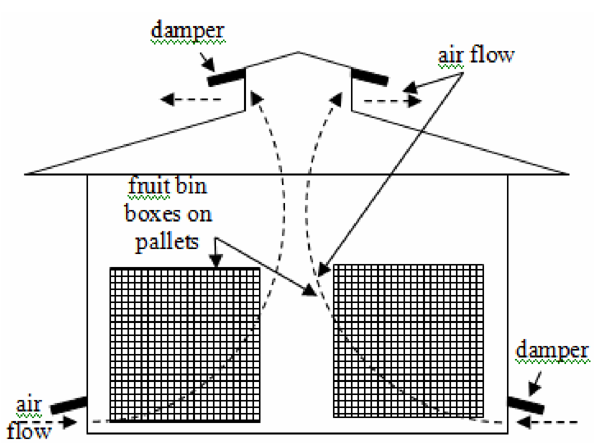
The postharvest storage process is a highly nonlinear one involving heat and mass transfer. The need to capture these nonlinearities demands the use of intelligent models. In this study a neural network model (for a potato storage process) was normalized using the standard deviation technique and optimized through different combinations of network configurations. The optimum model had a mean squared error (MSE) value of 0.8314 and a coefficient of determination (R^2) value of 0.7347. In comparison to a previous study, where the network was based on the min-max method of normalization, the network provided a better representation of the storage process. The proposed model would be useful in simulation processes involving intelligent controllers.

Keywords: potato tubers, optimization, artificial neural networks, modeling, post harvest storage.

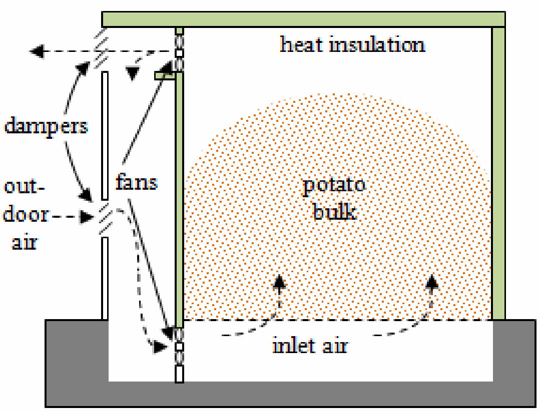
1. INTRODUCTION

Postharvest storage is one of the numerous processes that follow after the harvesting period in an agricultural food production process. One way of ensuring food security is through the improvement of postharvest storage techniques. In recent times it has become an issue as noted in the Food and Agricultural Organization (FAO) Corporate Document Repository (2010) which concludes that there is a need for improved storage techniques. This conclusion was borne out of the fact that after so much production of food quite some large amounts go to waste because of poor storage facilities.

Under storage, postharvest products emit heat, moisture, carbon dioxide and ethylene gases. The storage process involves passing conditioned air through the product pile such as to convey away the byproducts of the physiological processes. This is illustrated in Figures-1(a) and (b).



a. A fruit storage facility [natural convection].



b. Potato storage process with fans and dampers.

Figure-1. Different types of postharvest storage systems. a) Natural convection fruit storage system employing pallet mode of food containment. b) A forced-convection potato storage system with the products heaped in the storage volume.

Interaction between the conditioned air and the stored products result in a temperature and moisture gradient within the storage volume. This makes the storage process a very complex one requiring some form of control. The control process aims to optimally maintain certain air conditions within the storage system. Modern techniques employing automated control have improved on the storage efficiency. With respect to nonlinear processes, fuzzy logic control (based on computational intelligence platform) has been found to perform well in comparison to model-based control.

Several attempts have been made to apply intelligent control to nonlinear processes. Takagi *et al.* (1990) developed a method for tuning the fuzzy control rules automatically, using neural networks. In this method two networks were used where one of the networks classified the present control performance while the other simulated control performances against combinations of fuzzy labels in the control rules. However the determined fuzzy control rules did not provide optimal solutions. Karr and Gentry (1993) developed an adaptive fuzzy controller that altered membership functions optimally using genetic algorithms (GAs). It was applied to the PH control of a solution. However, the control objects they treated were well understood and the problem was modeled using a deterministic model. Morimoto *et al*. (1997) Combined 3 intelligent methods to optimize the storage process. ANN was used to identify the relationship between the relative humidity and ventilation while GA was used to determine the membership functions and control rules efficiently during storage. GA due to its iterative nature affects the controller response. Morimoto *et al*. (1999) used two decision systems consisting of both ANN and GA to identify and optimize the storage process. The neural network identified the fruit responses as affected by the relative humidity while the GA selected the optimal values of the membership functions and control rules. In both the cases the controller adjusted only the storage relative humidity using on-off control of the dampers and temperature was not controlled. Gottschalk *et al*. in 2003 improved the climate control for stored potato using a fuzzy controller supported by genetic algorithm (GA). Here the GA was used to fit some parameters to the criteria to minimize the total storing cost. However, the storage humidity was not controlled optimally. In 2005, Kiralakis and Tsourveloudis compared a fuzzy controller and a neur-fuzzy controller on drying of olive stones. They concluded that in terms of stability and set point tracking the Neuro fuzzy performed better than the fuzzy logic controller, but the fuzzy did better at higher initial moisture content. Congda *et al*. (2006) applied a fuzzy logic controller in a microwave based Chinese herbs drying equipment. Good results were obtained from matlab simulations in the fuzzy logic Toolbox. Zazilah *et al*., in 2006 developed 2 fuzzy logic controllers to reduce the operational times and cooling energy generation for air-conditioning purposes of some buildings. Simulation results showed promising results in achieving optimal operations of the chilling system. Wali *et al*., in 2009 developed a fuzzy logic controller in Labview environment to automatically and continuously adjust the applied power of a microwave reactor system. The fuzzy logic controller tracked the reactor desired temperature precisely with minimal overshoot and a fast warm-up phase. Disturbance in the form of varying flow rate in the process input was well rejected by the controller. In 2010, Mansor *et al*., designed and applied fuzzy logic control technique to grain drying. Simulation results obtained, proved to be good in comparison with those obtained in literature in the areas of settling time and steady state error. Melendez *et al*., in 2011 developed a fuzzy greenhouse fertigation control system based on a field programmable gate array. Results were confirmed good experimentally and the controller found to be extendable to control greenhouses of other crops that have different nutritional needs. Areed *et al*. (2012) developed a dynamic model for the rotary drying plant and a neuro-fuzzy controller for the drying process and compared it with a fuzzy logic and PID controllers. Simulations results proved that the neuro-fuzzy controller yielded the best dynamic performance followed by the fuzzy logic controller, in terms of rising time, settling time, maximum overshoot and steady-state error.

A neural network model developed to mimic a potato storage process considered 2 normalization techniques involving the min-max and standard deviation methods. The ANN plant model will be simulated against a developed neuro-fuzzy controller. Figure-2 provides the schematic for the controlled storage process. The network data used is taken from literature. The rest of the paper is presented as follows: Section 2 deliberates on the back ground of artificial neural networks (ANNs). The 3rd section describes the method used. Results and discussions are presented in section 4. Section 5 and 6 concludes the study and lists the references, respectively.

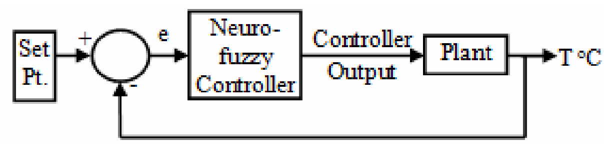


Figure-2. Schematic for the controlled storage process.

2. BACKGROUND

Artificial neural networks possess learning abilities thus making them applicable to the following areas: pattern classification, clustering/categorization, function approximation, prediction/forecasting, optimization and control just to mention a few. They were designed following the biological neural network. In its simplest form it consists of a cell capable of receiving, processing and transmitting signals.

A neural network structure consists of an input, hidden and output layer consisting of nodes that can process signals. Figure-3 illustrates a typical feed forward neural network structure. Setting up a neural network model entails a training and validation process. The data to be modeled is divided into two parts. One part is used for training while the other is used for validation. For a feed forward neural network, a supervised learning process consists of a one-directional forward pass where the signals move from the left to the right followed by an error back propagation where the error (desired output - actual output) is distributed backwards amongst the various nodes making up the network structure. The various weights linking the nodes are then updated thus minimizing the objective function. Factors affecting the network performance include the training scheme employed, transfer/activation functions used, learning rate specified, number of iterations (epoch number) allowed, number of hidden layers employed and the number of nodes in the hidden layer just to mention a few.

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3. MATERIALS AND METHOD

A desktop with the configurations listed in Table-1 was employed as the hardware. Matlab (2007) Neural Network Toolbox was used with instructions written in a Matlab m-file.

Table-1. Desktop configuration used for the study.

Hardware component	Description
Processor type	Core 2 Duo
Processor speed	2.4 GHz
Ram	6 GBytes
Hard disk	300 GBytes

Data from literature (Gottschalk *et al*., 2003) was used to develop the neural network. As seen from Table-2, the training data consisted of 3 input parameters namely: ambient air temperature and relative humidity; and inlet air temperature. The temperature of the air within the potato storage unit (potato temperature) formed the only output parameter. In all for training 6786 sets of data was used. 8952 sets of data consisting of the same 4 parameters were used to validate the network.

Table-2. Distribution of data used in developing the ANN.

Data	Units	Quantity
Training data		
Input data		
Ambient air temperature	^{0}C	6786
Inlet air temperature	^{0}C	6786
Ambient rel. hum.	%	6786
Output data		
Potato temperature	^{0}C	6786
Validation data		
Input data		
Ambient air temperature	^{0}C	8952
Inlet air temperature	^{0}C	8952
Ambient rel. hum.	%	8952
Output data		
Potato temperature	^{0}C	8952

In trying to build a robust model of the storage process the training and validation data were collated in such a way as to have a wide coverage area (spread) within the range of operation of the storage process. This was achieved by first plotting a graph of the parameters against time, and then a visual inspection of the variation in the parameters over time enabled sectioning of the data which led to allocation of portions for either training or validation purposes.

Since the objective was to develop a neural network model which would capture to a large extent the dynamics of the storage process, factors affecting network performance were all combined variously in the optimization process. That which had the least mean squared error (MSE) was thus selected as the optimal model for the potato storage process.

Table-3 provides a list of factors that influence the performance of a neural network. Two most popular types of normalization techniques namely the minimum-maximum and the standard deviation methods were tested. The effects of the transfer functions used in the hidden and output layers were also investigated. The transfer functions considered were log sigmoid and hyperbolic tangent sigmoid transfer functions. The 3 learning functions considered were conscience bias, gradient descent with weights/bias and gradient descent with momentum weight/bias learning functions. Eight training functions as listed in the Table were considered. A rule of thumb suggests choosing for the hidden layer number of neurons, a value between the number of input units (3 in this case) and the number of output units (1 in this case). 1 to 5 neurons in the hidden layer was considered to sort of compensate for the oneness of the hidden layer. The effect of iterations (epoch number) was investigated employing values between 100 and 500 iterations. The learning rate and the momentum constant were varied between 0.02 to 0.1 and 0.25 to 1.0, respectively.

The neural network tool box was driven by a program developed in an m-file. The program consisted of about 7 nested loops. Data was first imported from an Excel file and normalized using one of the specified techniques. The program then allocates a transfer function for the hidden and output layers, as well as training and learning functions for the network. Also allocated are values for number of neurons in the hidden layer, epoch number, learning rate and momentum constant. The inner-most loop is then cycled thru all the values allocated to it. The loops are updated by cycling thru the values allocated to the parameter until the end of the outermost loop is reached. Figure-4 summarizes the m-file codes in the form of a flow chart.

4. RESULTS AND DISCUSSIONS

A cursory glance through the results, Figures 5(a) – 5(h) shows that the standard deviation (Std) normalization technique generally yielded lower mean squared errors (MSE) than the Minimum-maximum normalization technique. Thus, the following analysis is based on the more successful STD-normalized neural network results in Figures 5(a) – 5(h). Figure-5(a) shows that the neural network hidden layer with a Logsig transfer function performs better than that with Tansig transfer function. However, as

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Table-3. Factors considered as affecting the network performance.

Factor	Parameter type	Matlab syntax
Normalization Technique (NT)	Min-max method	-
	Std. Dev. method	-
Transfer Function (Tff)	Log-sigmoid Tff.	logsig
	Hyperbolic tangent sigmoid Tff.	tansig
Learning Function (Lf)	Conscience bias Lf.	learncon
	Gradient descent weight/bias Lf.	learngd
	Gradient descent with momentum weight/bias Lf.	learngdm
Training Function (Tf)	Gradient descent Bp.	traingd
	Gradient descent with adaptive learning rule Bp.	Traingda
	Gradient descent with momentum Bp.	traingdm
	Gradient descent with momentum and adaptive learning rule Bp.	traingdx
	Levenberg-Marquardt Bp.	trainlm
	One step secant Bp.	trainoss
	Resilient Bp.	trainrp
	Scaled conjugate gradient Bp.	trainscg
Hidden Neuron Number (HNN)	1, 2, 3, 4 and 5	-
Epoch Number(EN)	100, 200, 300, 400 and 500	-
Learning Rate (LR)	0.02, 0.04, 0.06, 0.08 and 0.1	-
Momentum Constant (MC)	0.25, 0.50, 0.75 and 1.0	-

indicated in Figure-5(b), for the output layer the reverse is the case as the Tansig transfer function yielded the lower MSE. Figures 5(c) and 5(d) showed that the network performed best with gradient descent with momentum learning (learngdm) and training (traingdm) functions, respectively. The network with a hidden layer consisting of 3 neurons and an epoch number of 400 iterations both yielded the lowest MSEs in their respective domains (Figures 5(e) and 5(f)). Figures 5(g) and 5(h) show that a learning rate of 0.04 and momentum constant of 1.0 gave the best results in form of lower MSEs.

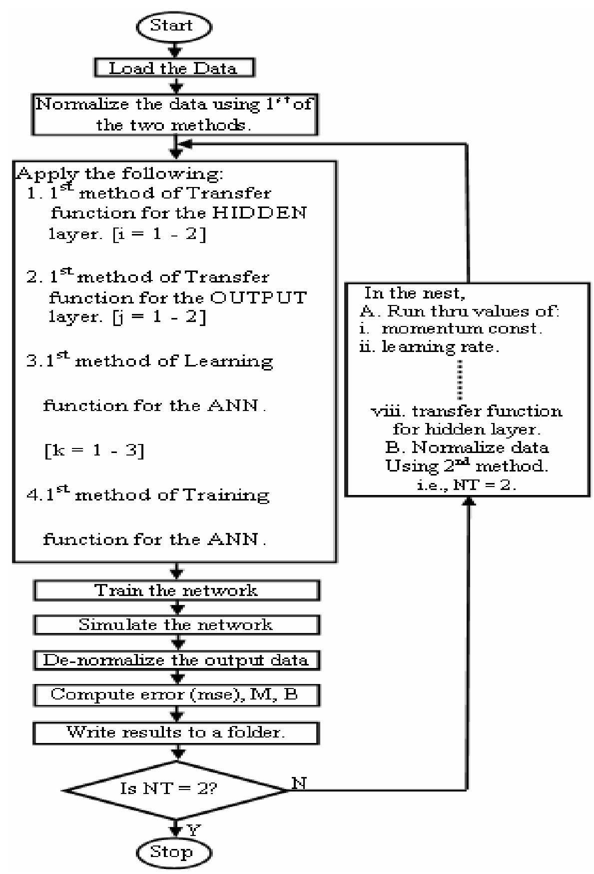

Figure-4. Flow chart of the Matlab m-file that drove the neural network toolbox.

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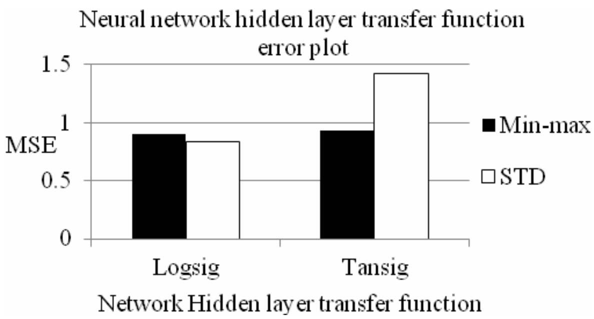
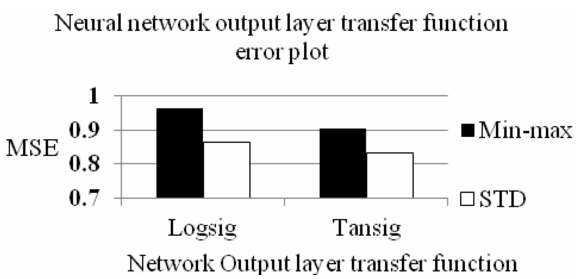
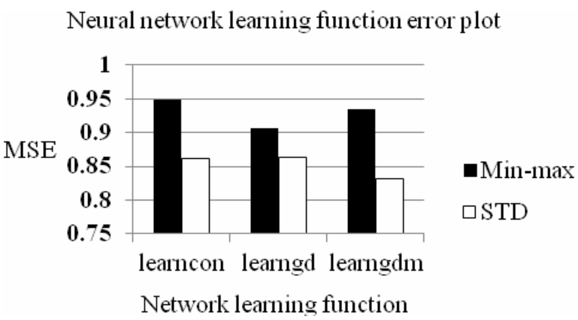


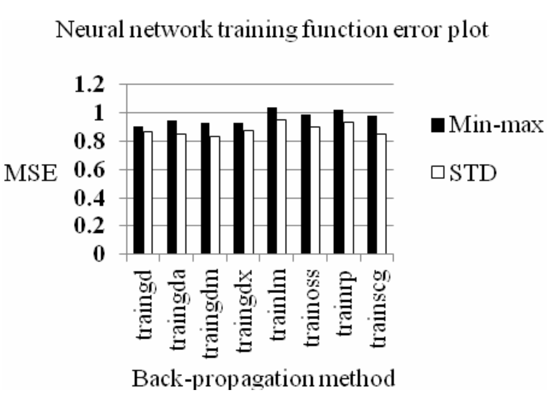
(a)



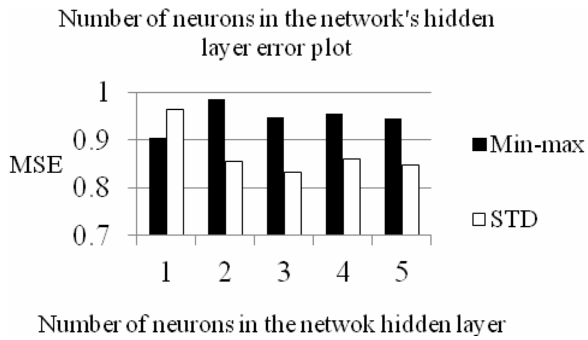
(b)



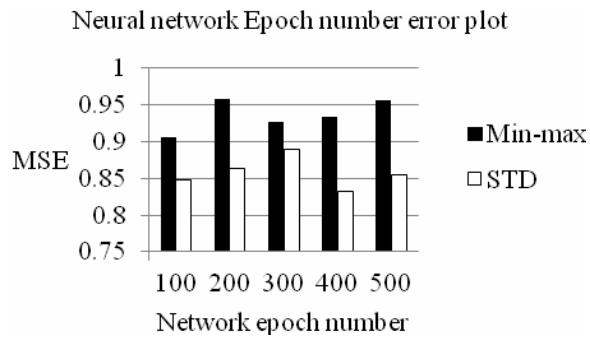
(c)



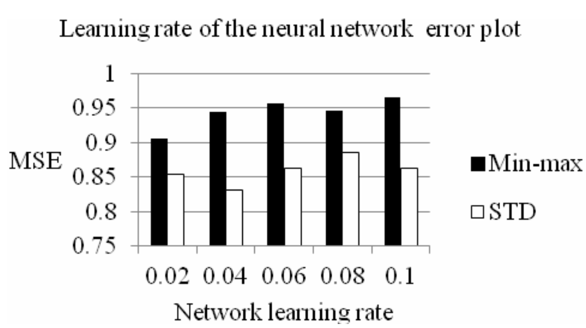
(d)



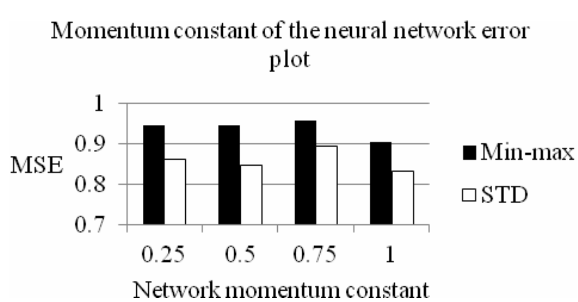
(e)



(f)



(g)



(h)

Figure-5(a)-5(h). Graphical results of the study.

5. CONCLUSIONS

Data from literature was used to develop a neural network model mimicking the potato storage process. Two normalization techniques were used on the data. The network was then optimized using different network configurations known to affect network performance. In comparison to the networks based on the min-max method, the standard deviation method provided better representations of the potato storage process. Table-4 lists the configuration of the optimized neural network model. The optimal network model had a coefficient of determination (R^2) value of 0.7347 while the mean squared error was found to be 0.8314.

Table-4. The optimized neural network model.

S. No.	Factor	Employed value
1	Normalization technique	STD.
2	Hidden layer transfer function	Logsig
3	Output layer transfer function	Tansig
4	Learning function	learngdm
5	Training function	traingdm
6	Hidden layer neuron number	3
7	Epoch number	400
8	Learning rate	0.04
9	Momentum constant	1.0

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