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Optimization of Artificial Neural Network in Prediction of Properties of Drying Button Mushrooms

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Abstract: The purpose of this study was to predict the parameters of drying thin layer of button mushroom using artificial neural network. Drying process in three different microwave power (150, 250 and 500 W) and two thickness cases (3 and 6 mm) was performed. The results showed that the lowest mean square error is obtained when the number of neurons in the hidden layer, the factor of momentum and Training epoch 29, 0/43 and 6999, were obtained respectively. The utility and the mean square error of the result in this case were 0/979 and 0/01. The model was able to predict humidity, moisture content and drying rate button mushroom, respectively, with coefficients 0/9861, 0/9826 and 0/8414.

Key words: drying, optimization, button mushroom, artificial neural network.

1. INTRODUCTION

Button mushroom among edible mushrooms has the largest producers in the world, a product with high humidity and low maintenance. Drying food, particularly fruits and vegetables a very long time as a way to increase their shelf life has been common and today, have been identified as one of the important processes in the food industry. Unlike fresh vegetables stored only for a short time and under certain conditions, the dried product can be stored in a long time, without loss of nutritional value. Dried vegetables are also low because of the weight are easily transported. In some cases, drying material causes a significant reduction in size, and this reduces the space required for storage (1). Maintaining the nutritional value and ability to quickly absorb water and dry this product has two parameters that are considered as an indicator of product quality; and the purpose of art and food industry professionals is presentation and implementation of methods that produce products with minimal unwanted changes with the best quality in terms of organoleptic and nutritional.

Microwaves are high-frequency waves that the energy in it hits an object and then would be reflected, absorbed or passed. Factors such as the coefficient of dielectric, forming and moisture in drying food with microwave heating have to be considered. During the microwave absorption by a dielectric material, microwaves waves give energy to the material, and as a result the temperature increases. Two important mechanisms that generate heat in the material that is placed in a microwave field explain, they are ionic polarization and two-pole rotation.

In general, in order to model physical phenomena such as the ratio of moisture of agricultural products, there are two approaches, one way is deductive, I.e. using theories and mathematical formulas such as

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Fick's Second Law or its simplified variant, called Newton's law of cooling, the moisture of products gets model, in other words, indirectly, using relationships and constant coefficients he modeling is done (3). For example, using the drying models of agricultural products like the model of Newton, Page, binomial approximation player, etc. and each has its own constants and coefficients. This approach is relatively simple, but always is associated with approximation with a low precision. The second approach is to model physical phenomena using inductive methods. In this way, modeling can be directly used without any equation or formula in modeling. Modeling of moisture by artificial neural network is of the inductive methods (direct) because we have no relationship or a formula to modeling the process. The advantages of this method are detecting hidden and often non-linear relationships between dependent and independent variables of the studied process and its generalization capability. So far, researchers have used artificial neural networks to predict the parameters in driers that we refer to some of them. In a research, feasibility of Monitoring the process of drying winter squash was studied. The results show that the neural network model can accurately predict the relative humidity of winter squash (R2) (1=0/ 9991).

Also in a research, Green pumpkin drying process was studied by artificial neural network models and fuzzy logic techniques. The results showed that the neural network model was more accurate in predicting the relative humidity of green squash (4). In another study, drying button mushrooms, Brussels sprouts and cauliflower were accelerated through the use of ultrasound and the results showed that ultrasonic pretreatment reduces drying time in all samples. Also features of a second dewatering for samples treated with ultrasound were higher than samples without treatment (5). Artificial neural network modeling was examined to predict moisture content and temperature of the tomato slices with the help of microwave-vacuum drying. The results showed that neural network with two hidden layers and each layer of 25 neurons was determined as the best network. Average values of relative error and average absolute error for temperature are 1/53% and 0/77, respectively (6).

The purpose of this study was to predict the parameters of drying thin layer button mushroom with response surface simultaneous optimization techniques and artificial neural network methodology and determining the optimal points of artificial neural network to estimate the parameters of relative humidity, moisture content and the drying rate. Using a combination of techniques of artificial neural network and response surface methodology is used today as a new tool for forecasting and this research has been used for the first time to predict the drying parameters for thin layer button mushroom.

2. MATERIALS AND METHODS

2.1. Sample Preparation

The button mushroom samples were bought from the local market. During testing, the samples were stored at proper refrigeration. At the beginning of each button mushroom samples were washed followed by cutting by a sharp polyethylene knife at different thicknesses (3 and 6 mm) and was controlled by a caliper (model Vertex, M502, with a rating of 0/01 mm). The used Button mushrooms were with initial moisture of 91%. Initial moisture of samples was measured by placing the samples at atmospheric oven and at temperature 105°C for 48 hours to achieve constant weight (7).

2.2. Drying Equipment

For testing microwave oven drying of a planned home (Panasonic, NN-S651 WF, Germany) with a volume of 32 liters and a maximum power output of 1000 watts at 2450 MHz was used. To adjust the output power, the oven is equipped with control panel with a digital display, and also the on time of the oven may also be planned. This device is also equipped with air fan. In the process of drying, the said sample was cut at said sizes, and was placed inside revolving tray in the microwave chamber.

2.3. Mathematical modeling of drying curves

In this study, humidity rate and the drying rate of button mushroom were calculated by the following equations:

$$MR = \frac{(m_t - m_e)}{(m_o - m_e)} \tag{1}$$

$$R = \frac{(M_{t+dt} - m_t)}{dt} \tag{2}$$

In this equation, mt is the humidity rate at time (t), m0 is the initial humidity, me is the balance humidity rate, Mt+dt the humidity rate at time t+dt. The humidity rate me is very trivial in comparison with humidity mt and m0 and this issue causes easier diagnosis of these two cases from each other. Samples were dried at 150, 250 and 500 watts and two thicknesses 3 and 6 mm in the microwave oven. The behavior of moisture loss was examined over time.

2.4. Artificial Neural Network Modeling

2.4.1. Perceptron Neural Network

Artificial neural network consists of a set of neurons with internal communication between each other, which can estimate output response based on the data input. Neural networks are usually layered and disciplined. The first layer that the input data comes into it is called input layer. Intermediate layers of hidden layers and the last layer that provides output model provides is called output layer (8). The simplest and most common type of neural network used in many engineering disciplines including applied studies is Multilayer Perceptron Neural Network with observer that uses the method of propagation for training. In this network the number of neurons of the input layer with the number of vector elements and number of output layer neurons output is equal to the number of output vector elements. Precise analysis and real to find the number of neurons in the middle layer is very complex. But can he said that the number of neurons in the middle layer is a function of the input vector elements, as well as the maximum number of areas of the input space which are separated from each other linearly. The number of hidden layer neurons is experimentally obtained. Each neuron is connected by its output to the neurons of next layer, but do not connect with the neurons of its own layer. The output of each neuron is defined by Equation 3:

$$a = f\,(\Sigma_{i=1}^{n} p_i w_{j,i} + b_j) \tag{3}$$

In this equation wj, I is the weight of connection between neuron j of said layer with i neuron of previous layer that indicates the importance of relation between two neurons at two sequential layers, bj is the bias weight for neuron j, pi is the output value from neuron i of previous layer, a is the output value from j neuron, and f is pan of threshold neurons of j.

A large number of functions can be used in the transfer of numbers from previous layer to the next layer; including functions of Sigmoid, Gauss, hyperbolic tangent and hyperbolic secan but Sigmoid function is mostly used in engineering problems. This function is as follows:

$$f(z) = \frac{1}{1 + \exp(-z)} \tag{4}$$

Neural network array used in this study consists of three inputs and three output (about 5). Inputs include drying time, the microwave and the thickness of the sample and output includes button mushroom humidity rate, moisture content and drying rate. The network layout is shown in Figure 1.

$$\text{Output} = f(T, t, v) \tag{5}$$

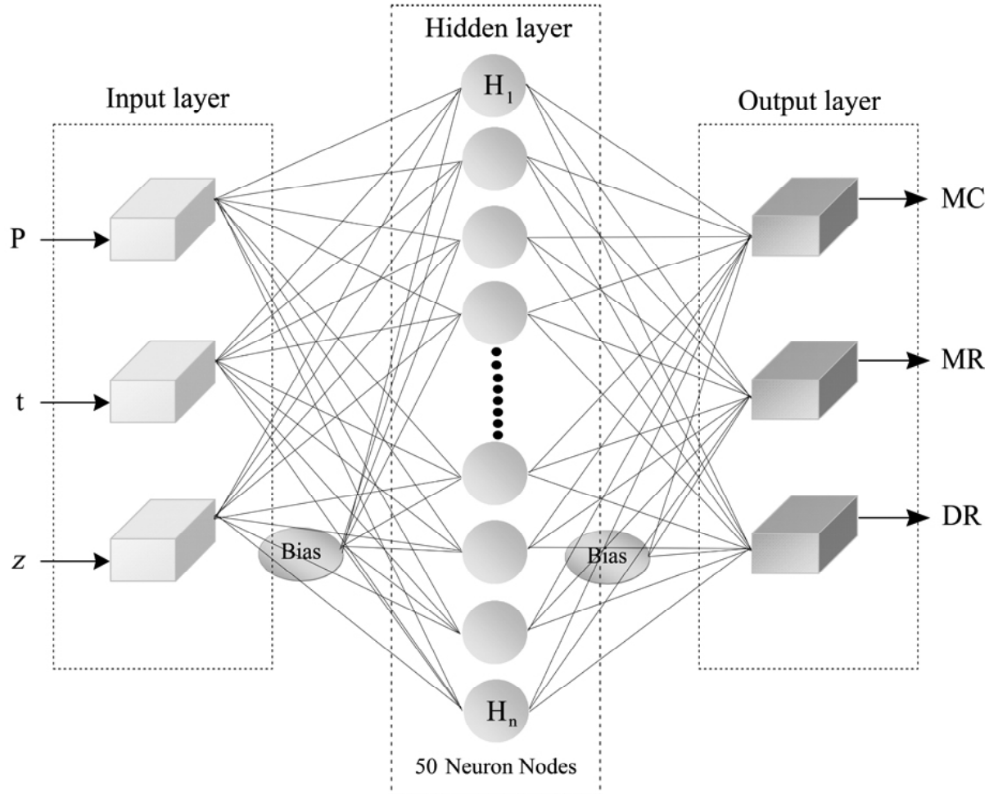

Figure 1: The structure of the neural network, t drying time, P is power microwave, z sample thickness, MR humidity rate, MC moisture content and DR drying rate.

The learning process and choosing the best network performance function

In order to optimize model, first data was divided into two subsets: 70 percent of data was allocated for training and 30% for testing network. The data was modeled using SPSS version 17. To determine the best network layout, the two coefficient criteria and Mean relative error (MRE) are used that the purpose is respectively the minimizing and maximizing the above parameters. These measures are calculated by equations 6 and 7.

$$MRE = \left(\frac{1}{N} \Sigma_{i=1}^{N} \frac{|P_{ANN,i} - P_{\exp,i}|}{P_{\exp,i}} \right) \times 100 \tag{6}$$

$$R^2 = 1 - \left[\frac{\Sigma_{i=1}^{N} (P_{ANN,i} - P_{\exp,i})^z}{\Sigma_{i=1}^{N} (\bar{P}_{ANN,i} - MR_{ANN,i})^z} \right] \tag{7}$$

In these equations, PANN is the predicted value for output parameters of network, PE is the experimental data values of test and N is the number of observations.

Design of experiments and modeling of optimization process

In this study, Response surface optimization techniques was used to determine the neural network. At optimization process Momentum coefficient (M), Training epoch (Te) and Number of neuron (NN) were elected as the independent variables. The mean relative error was evaluated as the response variable in this study. For statistical analysis, the Face-Centered Central Composite Design (CCF) including 20 tests with 6 replicates was used in central locations. Coded and actual values of independent variables used in optimization process of neural network are shown in Table 1.

Table 1
Coded and actual values of optimization process of network

Coded and actual values of process variables		*Variables*
Low	*High*	
2	50	Neuron number (X1)
0/1	0/7	Momentum factor (X2)
50	7000	Training epoch (X3)

For statistic analysis of data, software Design Expert version 6/01 was used. Experimental data with a quadratic polynomial model was fitted. This model is as follows:

$$Y_k = \beta_{k0} + \Sigma_{i=1}^{3}\beta_{ki}x_i + \Sigma_{i=1}^{3}\beta_{kii}x_i^2 + \Sigma_{i=1}^{2}\Sigma_{j=i}^{3}\beta_{kij}x_ix_j + \varepsilon_k \quad (9)$$

In this equation âkn is model constant factors and Xi is independent variables used in neural network optimization process.

Assessing the best model for network optimization was done by techniques of level of response by examining the fit-free test of said model. So the model that made the fit-free test insignificant was chosen as the best model. Independent and non-independent variables of ANN optimization is shown in Table 2.

Table 2
Independent and non-independent variables of ANN optimization

Responses	*Studied variables*			
sum of error squares (Y)	*Training epoch (X3)*	*Momentum factor (X2)*	*Neuron number (X1)*	*Test No.*
0/06467	3525	0/4	26	1
0/03715	7000	0/7	50	2
0/09745	50	0/7	2	3
0/04820	3525	0/7	26	4
0/04771	3525	0/4	2	5
0/01740	3525	0/4	26	6
0/06316	50	0/1	2	7
0/03026	50	0/1	50	8
0/01916	3525	0/4	26	9
0/01976	3525	0/4	26	10
0/02750	7000	0/1	50	11
0/04101	3525	0/4	50	12
0/09328	7000	0/1	2	13
0/06733	3525	0/4	26	14
0/10069	7000	0/7	2	15
0/02598	50	0/7	50	16
0/03130	3525	0/4	26	17
0/04490	50	0/4	26	18
0/05011	3525	0/1	26	19
0/01207	7000	0/4	26	20

3. RESULTS AND DISCUSSION

In this study, a combination of different layers and neurons with log sigmoid activation function (in hidden and output layers) was used to optimize the Perceptron network. Neural network with a hidden layer, 2 to 50 randomly selected neurons and network power in anticipation of a thin layer button mushroom drying parameters were evaluated. For training perceptron network with error back-propagation learning algorithm was used with momentum in which the momentum factor in the range of 0/1 -0/7 and learning rate was 0/4. Table 3 shows change range of input and output variables of artificial neural networks.

Table 3
Change range of input and output parameters of Network

change range	*Parameter*
220-0	Drying time(min)
6-3	Sample thickness (mm)
500-150	Microwave power (W)
10/11-0/3583	Moisture content (dry basis)
1-0	Humidity rate (dimensionless)
0/1975-0/00416	Drying rate (kg water / kg of solid per minute)

Hybrid models of level of response of artificial neural network was used to determine the optimum conditions of artificial neural network parameters in order to minimize the relative error maximize the correlation coefficient. Artificial neural network optimization variables include the number of neurons, Training epoch and the momentum factor. Statistical analysis results of ANN layout optimization showed that fourth-level model due to making Non-significant lack of fit test (F-value equal to 0/091 and P equal to 0/7751), was selected as the best model in the optimization process optimization factors in artificial neural network. In addition, the results showed that the coefficient of determination and adjusted determination coefficient for above model is 0/89 and 0/78 respectively. Response equation for the impact of the optimization parameters of ANN was obtained on the average value of the relative error for the coded data.

MRE = 0.035 - 3.353E-003 X1 - 9.56E-004 X2 - 0.016 X3 + 0.012 X12 + 0.016 X22 - 4.249E-003 X32 - 4.541E-003 X1X2 - 3.12E-003 X1X3 - 1.618E-003 X2X3 + 6.839E-003 X12X2 + 0.022 X12X3 - 0.026 X1X22 + 5.102E-003 X1X2X3, (R2 = 0.89)

Figure 2 shows three-dimensional diagram of response surface, the average relative error to the number of neurons and the momentum factor. As can be seen with the increase in the number of neurons from 2 to 50, the mean of relative error is decreased and the three-dimensional curve shows the response level of minimum response curve. On the other hand, increase in the amount of momentum factor shows also the same trend and increase in momentum factor from 0/1 to 0/7 spends declined trend relative error. Here the results were observed by researchers (9).

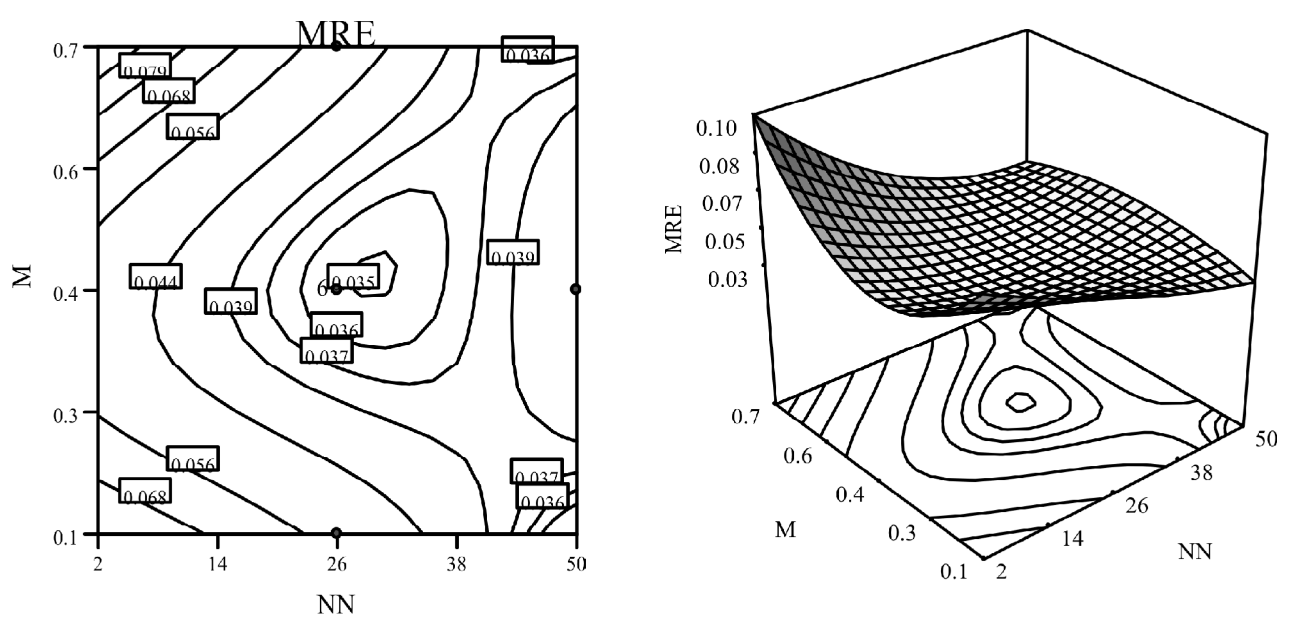

Figure 2: Three-dimensional curve of effect of the number of neurons (NN) and the coefficient of momentum (M) on the mean relative error (MRE).

The following figure (Figure 3) shows Response surface diagram and contour of Training epoch and number of neurons to optimize the ANN. The results showed that the increase in the number of neurons has a negligible impact on the value of the average relative error and on the other hand increased Training epoch from 50 to 7,000 reduces the average value of the relative error. So that the average value of the relative error in Training epoch 1000, 0/04 and in 5500, is 0/02.

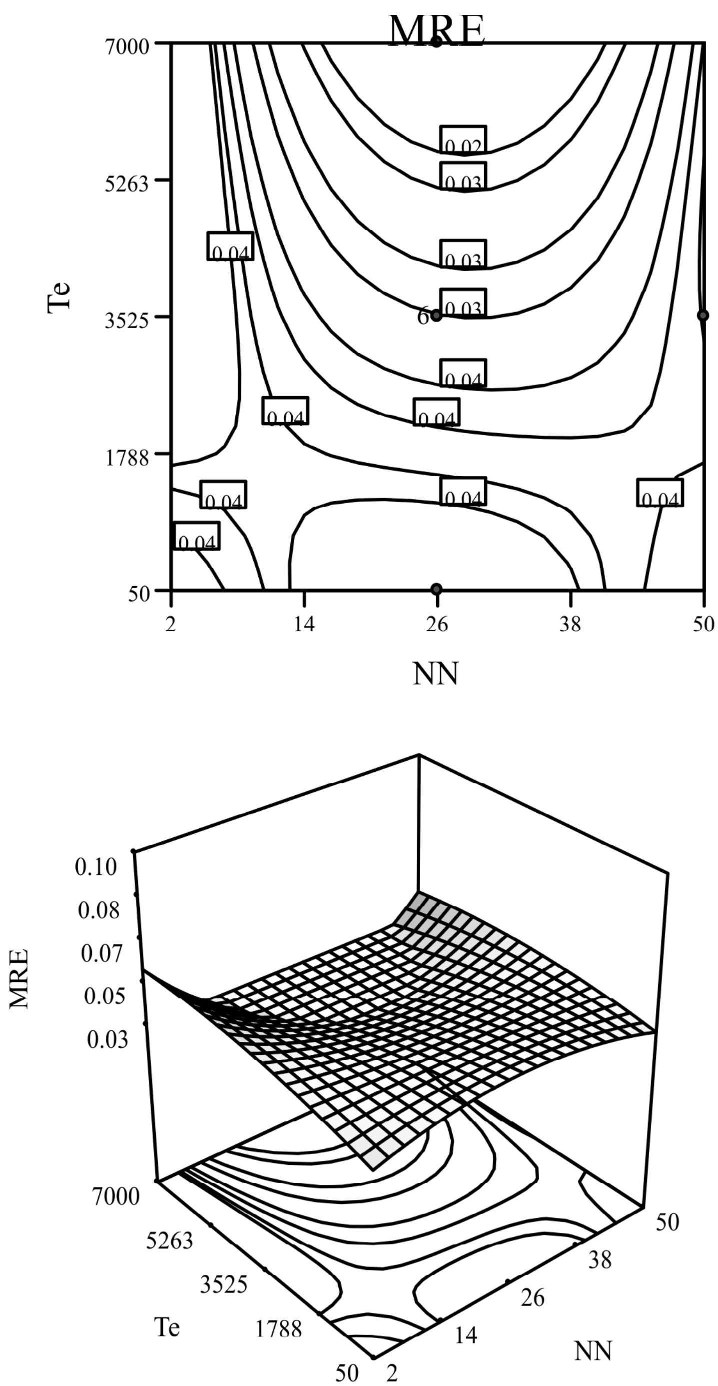

Figure 3: Three-dimensional curve of effect of the number of neurons (NN) and Training epoch (Te) on the mean relative error (MRE)

Figure 4 shows response level of training epoch and the momentum factor to optimize the artificial neural network. The results showed that the increase of Momentum factor from 0/1 to 0/4 reduces the mean relative error and increase in the amount of Momentum factor from 0/4 to 0/7 increases the mean relative error. Similarly, as can be seen increase in training epoch from 50 to 7000 reduces the average value of the relative error. So that the average value of the relative error in training epoch 1000, 0/05 and in 7000, is 0/02.

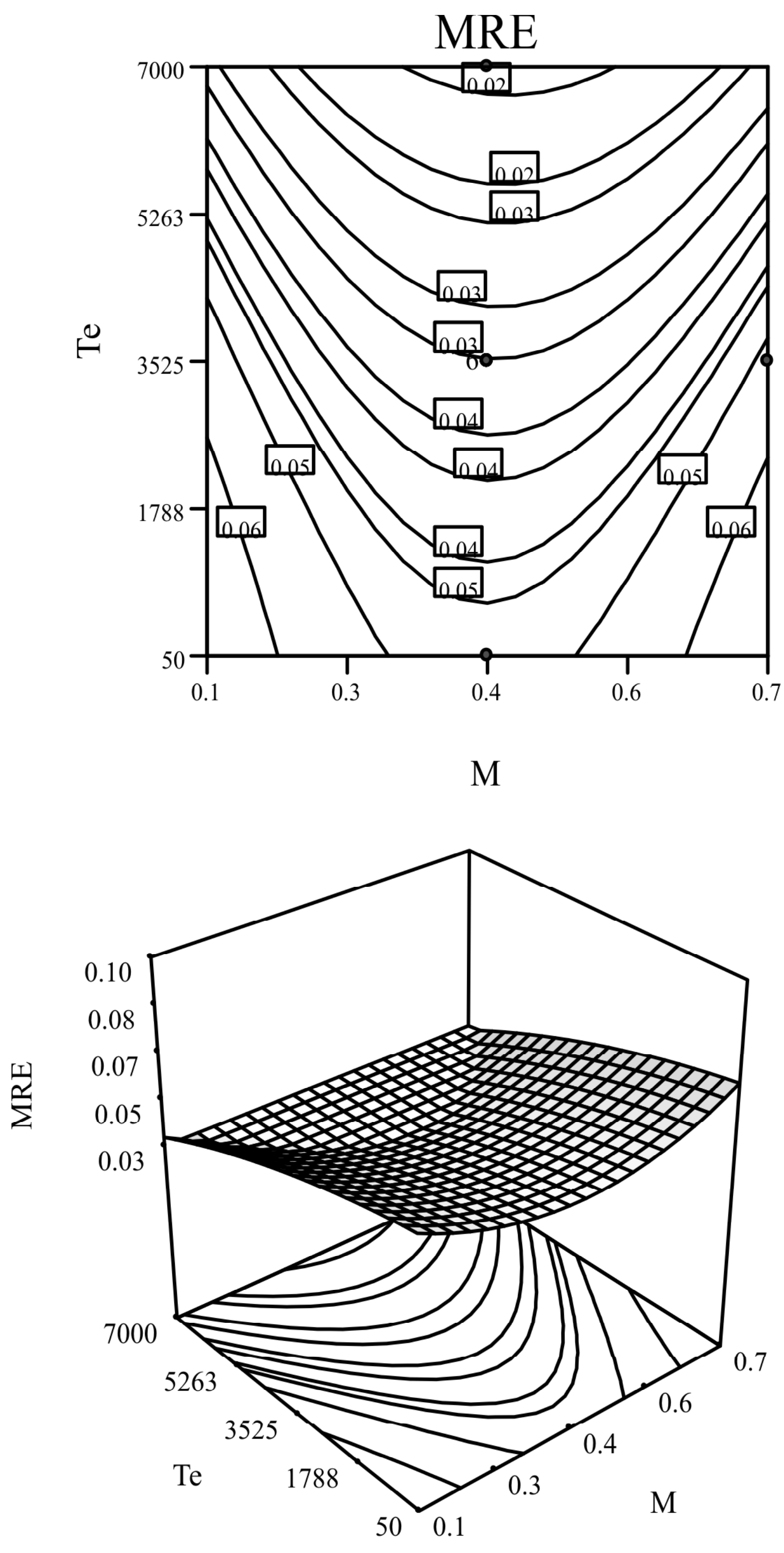

Figure 4: Three-dimensional curve of effect of the momentum factor (M) and Training epoch (Te) on the mean relative error (MRE)

The results showed that at the optimum conditions, ANN optimization variables, the number of neurons, training epoch and the momentum factor, respectively, are 29, 6999 and 0/43. In these conditions, the relative error is minimal and 0/01. Utility obtained in optimum conditions for responses and variables studied were reported 0/979. Sensitivity analysis chart of predicted values by neural network against the experimental values for the best layout (3-29-3 structure or the neural network with 3 inputs and 29 neurons in the hidden layer and 3 outputs) ANN showed that data are randomly around the regression line with determination coefficient higher than 0/8414 that this is proof of the accurate assessment of a neural network in the forecast parameters button mushroom drying thin layer optimization techniques and artificial neural network response surface methodology (Figure 5). As was seen, this method could predict the drying parameters thin layer of Button mushroom I.E humidity rate, moisture content and drying rate with regression coefficients, respectively, 0/9861, 0/9826 and 0/8414.

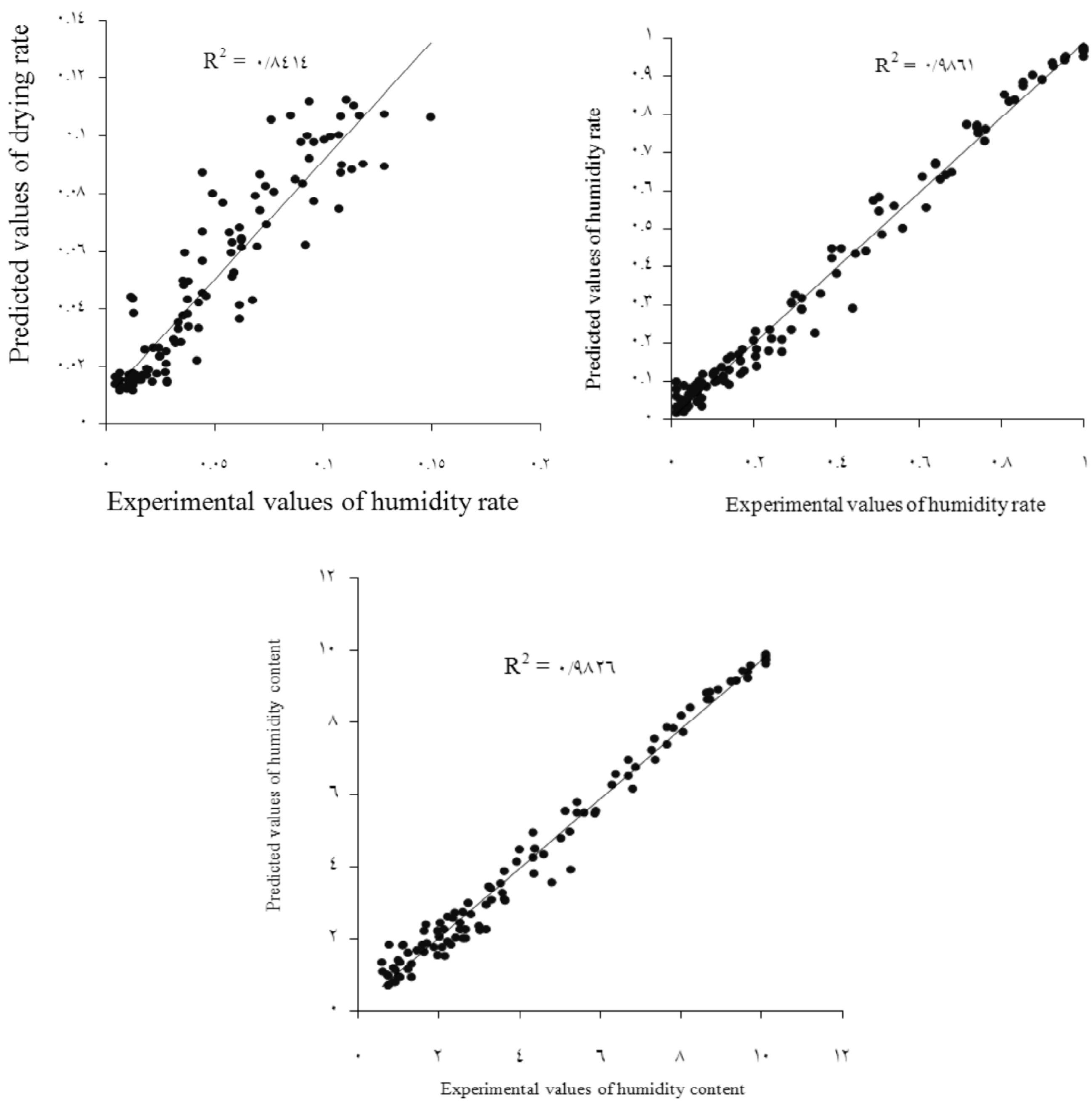

Figure 5: Predicted and experimental values parameters of button mushroom drying thin layer by optimization techniques and methodology of response surface and artificial neural network

4. CONCLUSION

In this study, factors affecting drying button mushroom by hybrid model of methodology of response surface and artificial neural network were predicted. The results showed that the hybrid model of response surface methodology and artificial neural network could predict the amount of humidity, moisture content and drying rate with regression coefficients, respectively, 0/9861, 0/9826 and 0/8414, that these coefficients indicate high accuracy of model in estimating parameters of drying button mushroom. In general, it is suggested that at further research we should use other estimator tools, such as neuro-fuzzy systems as well as other models of artificial neural networks and various activation functions for comparison with experimental models and the power of these tools to estimate the button mushroom drying parameters, should be evaluated.

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