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The Application of Neural Network Method for the Prediction of the Osmotic Factors of Crookneck Squash

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ABSTRACT: In this study the reliability of using response surface-neural network method to predict the osmotic dehydration properties of crookneck squash has been investigated. In order to carry out this project, the osmotic solution concentration, the osmotic solution temperature and immersion time were chosen as inputs and solid gain and water loss were selected as outputs of the designed network. The results showed that the optimal points for the artificial neural network parameters such as the number of neurons, momentum coefficient, learning epoch and the rate to predict water loss and solid gain were 15.75, 0.90, 4999.98 and 0.55, respectively. The results also demonstrated that the model was able to forecast water loss and solid gain with R^2 values equal to 0.967 and 0.890 where relative error values corresponding to each of these factors were estimated at 0.0205 and 0.0872, respectively.

Keywords: *Artificial Neural Network, Crookneck Squash, Modeling, Osmotic Dehydration.*

Introduction

Dehydration is one of the most commonly used techniques for creating new food products. Osmotic dehydration is a process for partial removal of the water from plant tissue by direct contact with a hypertonic solution (i.e. sugar, salt or mixtures of salt and sugar) (Singh *et al.*, 2007). In the process of placing the food such as fruits or vegetables, either chopped or whole in an osmotic solution, the food cell wall acts as semi permeable membrane due to the concentration gradient between the osmotic solution (containing the higher osmotic pressure and the lower water activity) and intracellular fluid driving force (Singh *et al.*, 2007; Jayaraman, 1990). Several factors, such as the concentration of osmotic solution, processing temperature and time, agitation, material to solution ratio and raw material characteristics have impacts on the osmotic dehydration process (Uddin *et al.*, 2004; Lazarides, 2001). Several studies on the osmotic dehydration process and processing of food products have been conducted. An *et al.* (2013) worked on the osmotic dehydration of Chinese ginger (Zingiber officinale Roscoe) slices by response surface methodology. The results indicated that the optimum operating conditions were found to be the process duration of 102 min, solution temperature of 30°C, solution concentration of 50 Brix sucrose and 7.31% sodium chloride with the solution to food ratio of 8:1 (w/w). Fernandes *et al.* (2009) studied the effect of osmosis and ultrasound on pineapple cell tissue structure during dehydration. The results showed that the use of ultrasound osmosis due to the changes in the cellular structure of the pores has increased solid gain and water diffusion. Nawirska *et al.*

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(2009) investigated the drying kinetics and quality parameters of pumpkin slices in different ways and expressed that drying rate in a vacuum-microwave dryer is higher than convection, vacuum and freeze drier. Kowalska *et al*. (2008) examined the effect of blanching and freezing on the osmotic dehydration of pumpkin. They stated that both pretreatments increased water loss and especially solid gain, in comparison with the controlled samples. Rodrigues *et al*. (2009) evaluated the effect of osmo-ultrasound process on the cell structure of papaya during dehydration. The results indicated that water loss and solid gain were increased because of the cellular damage by ultrasound.

Nowadays, artificial neural networks play an important role as a powerful tool in predicting the process parameters. Many studies have been undertaken in the field of artificial neural networks to predict the parameter of various processes. For example, Tavakolipour & Mokhtarian (2012) used an ANN approach for the prediction of moisture ratio of pistachio. Koc *et al*. (2007) applied the artificial neural network and genetic algorithm to predict the free fat content, lactose crystallinity and average particle size of spray-dried whole milk powder. Goni *et al*. (2008) used an artificial neural approach to predict the freezing and thawing times on foods. Momenzadeh *et al*. (2011) investigated shelled corn drying in a microwave-assisted fluidized bed dryer using artificial neural network and predicted the drying time during dehydration. Menlik *et al*. (2010) investigated freeze-drying behaviors of apples by means of ANN and anticipation of moisture content, moisture ratio and drying rate. Madadlou *et al*. (2009) predicted the size of re-assembled casein micelles using response surface methodology coupled with artificial neural network (RSM-ANN) method. Mateo *et al*. (2011) used two different networks called MLP and RBF to forecast accumulation of deoxynivalenol in barley seeds contaminated with Fusarium culmorum. Fernandes *et al*. (2011) determined anthocyanin concentration in whole grape skins using hyperspectral imaging and adaptive boosting neural networks. Lertworasirikul & Saetan (2010) used artificial neural network modeling to predict mass transfer parameters of kaffir lime peel (i.e. water loss and solid gain).

Few works have been carried out on the application of RSM-ANN approach. Therefore, the aim of this study is the reliability of using response surface-neural network to predict mass transfer factors of crookneck squash during osmotic dehydration and reduced modeling time.

Materials and Methods

- *Preparation of raw material*

Fresh crookneck squash was purchased from a local market in Sabzevar, Iran and were kept in the refrigerator at 5^oC. The initial moisture content of fresh crookneck squash was determined according to AOAC method (1990) at 105^oC using an oven (Memmert, model UNE 400 PA, Scheabach, Germany). Each sample was cut as cube in 10×10×5 mm length, width and height, respectively and the dimensions were controlled by caliper (Vertex, M502, with a sensitivity of 0.01 mm).

- *Preparation of osmotic solution and dehydration process*

Different concentrations of osmotic solution [(5% NaCl+50% sucrose w/v), (10% NaCl +50% sucrose) and (15% NaCl +50% sucrose)] and different temperatures (5^oC, 25^oC and 50^oC) were employed. The cubed samples were submerged in osmotic solution at time interval of 0, 30, 60, 90, 120 and 180 minutes. After the end of osmotic process, the cubes were removed from osmotic solution and the surface was washed with water and placed on the tissue paper to remove excess water and finally weighted. Water loss and solid gain in different stages (before osmotic dehydration, after osmotic dehydration and after drying in the oven) were computed using the following equations (Eqs. 1 and 2).

$$WL = \frac{(1-S_0)m_0 - (1-S_t)m_t}{S_0 m_0} \quad (1)$$

$$SG = \frac{S_t m_t - S_0 m_0}{S_0 m_0} \quad (2)$$

Where, m_0 is the initial mass of the sample, m_t is the sample mass at time t_0, S_0 and S_t are the solid content in the osmotic solution prior to osmotic dehydration and the solid content in osmotic solution during osmotic dehydration, respectively (An *et al.*, 2013).

- *Artificial neural network (ANN)*

ANN consists of a set of neurons with internal communication between each other, which it is able to predict the output basis on input data. In this study, response surface methodology was used for ANN optimization which this model design was based on three inputs and two outputs. Osmotic solution temperature (x_1), immersion time (x_2) and osmotic solution concentration (x_3) were selected as inputs and water loss (y_1) and solid gain (y_2) for the chosen outputs (Figure 1).

In the optimization process, number of neuron (T_1), momentum coefficient (T_2), learning epoch (T_3) and learning rate (T_4) were the independent variables and Mean Relative Error (MRE) was as response variable. The logarithm sigmoid ($\log sig = (1+e^{-z})^{-1}$) was chosen as threshold function for optimization process. The Central Composite Design (CCD) including 30 experiments with 6 replications in the central points were used for the statistical analysis (Table 1).

In order to optimize and model the artificial neural network, the Design Expert (Version 6.01) and SPSS (Version 19) software were employed. The experimental data were fitted by a third-order polynomial model as the following:

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

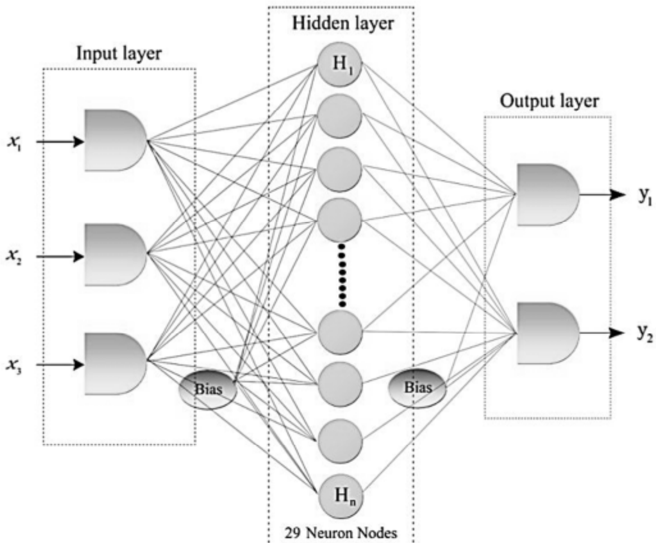

Fig. 1. ANN architecture; x_1: osmotic solution temperature, x_2: immersion time, x_3: osmotic solution concentration, y_1: water loss and y_2: solid gain

Where, β_{kn} and X_i are the constant regression coefficients and independent variables, respectively. Evaluation of the best model was carried out via lack of fit test therefore, the model with non-significant lack of fit (LOF) was selected as the best model.

Two criteria such as coefficient of determined (R^2) and mean relative error were used to compare the neural network performance according to the following equations;

$$MRE = \left(\frac{1}{N} \sum_{i=1}^{N} \frac{|U_{p,i} - U_{e,i}|}{U_{e,i}} \right) \times 100 \quad (4)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N} (U_{p,i} - U_{e,i})^2}{\sum_{i=1}^{N} (\overline{U}_{p,i} - U_{p,i})^2} \right] \quad (5)$$

Where $U_{p,i}$ is the predicted data, $U_{e,i}$ is the experimental data, $\overline{U}_{p,i}$ is the average of experimental data and N is the number of observations (Tavakolipour & Mokhtarian, 2012).

Results and Discussion

In this research, the possibility of using response surface-neural network to predict the mass transfer factors (i.e. water loss and solid gain) of crookneck squash during osmotic dehydration was studied. Optimization variables of ANN consist of neuron number, momentum coefficient, learning epoch and learning rate. ANOVA results of response surface indicated that, cubic model due to the non-significant of LOF test was selected as goodness model to optimize the process. The results also demonstrated that, linear (T_1, T_2, T_3 and T_4), interaction (T_1T_2, T_1T_3, T_1T_4, T_2T_3, T_2T_4, T_3T_4, $T_1^2T_2$, $T_1^2T_3$, $T_1^2T_4$, $T_1T_2T_3$ and $T_1T_3T_4$) and quadratic (T_1^2 and T_4^2) terms have significant effects on optimization variables (i.e. neuron number, momentum coefficient, learning epoch and learning rate) (Table 2). The F-values indicated that (i.e. F_{WL} and F_{SG}), among the linear terms, the effects of learning epoch and neuron number had the greatest impact on the model (Table 2). A similar result was stated by Nazghelichi *et al.* (2011). They have

Table 1. The central composite design (CCD) consisting of 30 experiments with 6 replications for neural network optimization

Run	variables				Response (MRE)		Run	variables				Response (MRE)	
	T_1[a]	T_2[b]	T_3[c]	T_4[d]	WL	SG		T_1[a]	T_2[b]	T_3[c]	T_4[d]	WL	SG
1	+1	-1	-1	+1	0.0563	0.2014	16	0	0	0	+1	0.0262	0.0717
2	+1	0	0	0	0.0311	0.0757	17	+1	-1	-1	-1	0.0346	0.0715
3	-1	-1	+1	+1	0.0327	0.1139	18	+1	+1	-1	+1	0.0420	0.1603
4	0	0	0	-1	0.0345	0.1390	19	-1	-1	+1	-1	0.0147	0.1160
5	-1	+1	-1	+1	0.0405	0.0811	20	0	0	0	0	0.304	0.0720
6	-1	0	0	0	0.0435	0.0785	21	0	+1	0	0	0.0269	0.0855
7	+1	+1	-1	-1	0.0232	0.0881	22	0	0	0	0	0.0306	0.0709
8	0	-1	0	0	0.0368	0.0959	23	+1	-1	+1	+1	0.0290	0.1241
9	-1	+1	+1	+1	0.0378	0.0809	24	+1	+1	+1	-1	0.0325	0.1137
10	-1	-1	-1	+1	0.0330	0.1104	25	-1	+1	+1	-1	0.0371	0.1031
11	+1	+1	+1	+1	0.0495	0.0936	26	0	0	0	0	0.0291	0.0934
12	0	0	+1	0	0.0180	0.0943	27	0	0	-1	0	0.0362	0.0925
13	+1	-1	+1	-1	0.0293	0.1101	28	0	0	0	0	0.0313	0.0545
14	0	0	0	0	0.0281	0.0837	29	-1	-1	-1	-1	0.0487	0.1038
15	-1	+1	-1	-1	0.0533	0.1606	30	0	0	0	0	0.0294	0.0781

[a] Number of neuron, [b] Momentum coefficient, [c] learning epoch, [d] Learning rate.

determined the optimum neural network architecture for carrot drying by GA-RSM method. They stated that, the increase in the neuron number from 20 to 30 and learning epoch from 100 to 3000, caused the value of ln (MSE) to be decreased to minimum. Effects of neuron number and learning epoch on the MRE_{WL} are shown in Figure (2a). According to the contour plot, increased learning epoch decrease the amount of MRE_{WL}. Also, according to Figure (2b), it is clear that by increasing the training epoch from 1000 to 5000 and neurons number from 3 to about 15, the MRE_{SG} decreased to a minimum value. A similar result was stated by Nazghelichi *et al*. (2011). They stated that, the increase in the neuron number from 20 to 30 and learning epoch from 100 to 3000, caused a decrease in the value of ln (MSE) to the minimum.

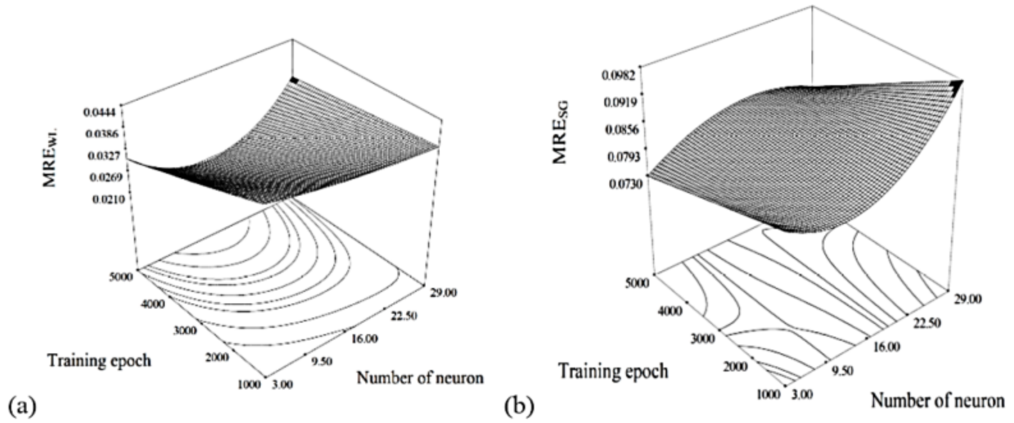

Fig. 2. Three-dimensional plot of interaction of the neurons number and the training epoch versus (a) MRE_{WL} (b) MRE_{SG}.

Table 2. ANOVA results of cubic model in the optimization of ANN

Source	F Value		Regression coefficient (β_n)	
	F_{WL}	F_{SG}	MRE_{WL}	MRE_{SG}
Model	8.43	5.42	+0.0565	+0.1785
T_1 [a]	0.53	**1.28**	$+1.2\times10^{-3}$	-6.5×10^{-3}
T_2 [b]	2.48	1.01	+0.0178	+0.0300
T_3 [c]	**21.70**	4.2×10^{-3}	-9.3×10^{-6}	-1.1×10^{-5}
T_4 [d]	1.75	0.16	-0.0297	-0.3386
T_1^2	20.14	0.053	-6.6×10^{-5}	$+8.9\times10^{-5}$
T_4^2	-	9.14	-	+0.3399
T_1T_2	5.54	-	-4.5×10^{-3}	-
T_1T_3	4.55	0.25	$+2.1\times10^{-7}$	$+1.5\times10^{-6}$
T_1T_4	14.43	15.22	-1.6×10^{-3}	+0.0108
T_2T_3	13.48	-	$+1.7\times10^{-6}$	-
T_2T_4	-	6.93		-0.1030
T_3T_4	1.75	4.51	$+1.1\times10^{-5}$	$+1.6\times10^{-5}$
$T_1^2T_2$	4.83	-	$+1.07\times10^{-4}$	-
$T_1^2T_3$	-	0.36		-2.5×10^{-8}
$T_1^2T_4$	4.59	-	$+1.3\times10^{-4}$	-
$T_1T_2T_3$	3.70	-	$+2.03\times10^{-7}$	-
$T_1T_3T_4$	16.18	11.68	-5.6×10^{-7}	-2.05×10^{-6}
Lack of Fit	19.58	$2.45^{n.s}$	-	-
R^2	0.8872	0.7927	-	-
C.V.	12.87	18.66	-	-
PRESS	0.0024	0.020	-	-

[a] Number of neuron, [b] Momentum coefficient, [c] learning epoch, [d] Learning rate.

In optimum conditions of ANN parameters such as neuron number, momentum coefficient, learning epoch and learning rate, water loss and solid gain were 15.75, 0.90, 4999.98 and 0.55 for prediction, respectively. In optimal conditions, desirability value was 0.861. Regarding this point, response value (i.e mean relative error) of water loss and solid gain was determined to be 0.0190 and 0.075, respectively. Comparison of experimental data and predicted data were obtained by RSM-ANN approach as presented in Figure 3. As shown and as can be observed the data were randomly located around the regression line and this could be a reason for carefully evaluating the RSM-ANN model to predict the mass transfer parameters of crookneck squash during osmotic dehydration.

Generally, the results have shown that, RSM-ANN model could predict water loss and solid gain values with high precision. According to Figure 3 it was observed that, this model was able to forecast water loss and solid gain with R^2 values of 0.967 and 0.890 respectively, which the relative error values corresponding to each of these values were estimated at 0.0205 and 0.0872, respectively.

The coupled RSM and ANN is a superior, less expensive and faster optimization technique to find appropriate ANN topology when compared to the traditional trial and error methods. Therefore, the integrated RSM and ANN approach is an appropriate alternative over lone RSM and trail-and-error methods, that can reduce the computational cost and accelerate the ANN development.

Weights matrix obtained in the optimized network is as follows. Where, Q is the weight matrix between the input and the first hidden layer, Z is the weight matrix between the hidden layer and the output layer, Binput is the matrix of input bias and Boutput is the matrix of output bias.

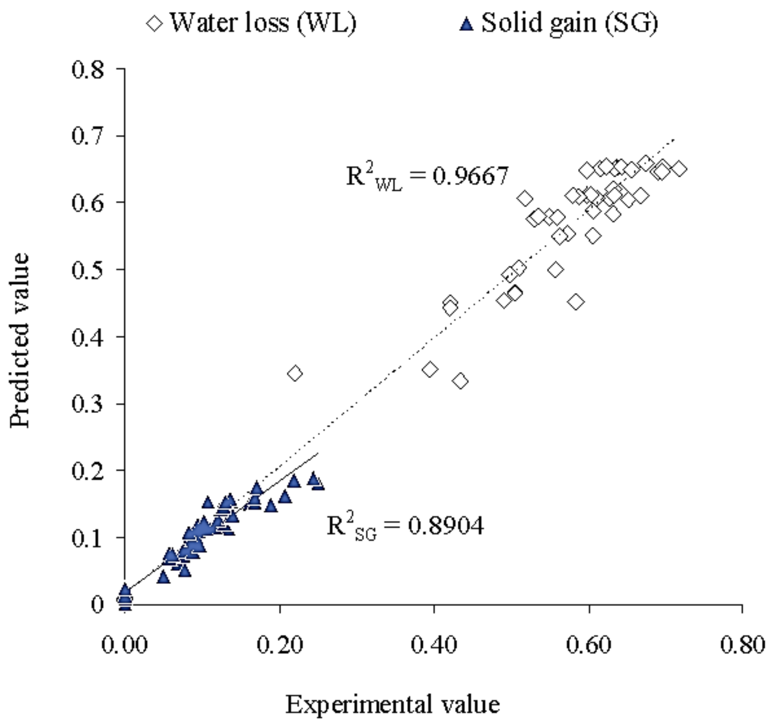

Fig. 3. Comparison of experimental and predicted values obtained by RSM-ANN approach.

$$Q = \begin{bmatrix} 0.814 & 0.310 & -0.182 & 1.511 & -0.738 & -0.362 & 1.468 & 0.760 & 0.315 & 1.182 & 0.302 & -1.326 & -2.436 & 0.672 & -0.522 & -1.250 \\ -0.022 & 0.580 & -0.275 & -0.228 & -0.311 & 0.033 & 0.495 & 0.189 & -0.064 & -0.068 & 0.257 & 0.141 & -0.010 & 0.372 & -0.032 & -0.193 \\ -0.224 & -0.305 & 0.411 & -0.572 & 0.055 & -0.255 & 0.087 & -0.035 & -0.459 & 0.094 & 0.356 & 0.120 & 0.233 & 0.057 & -0.075 & 0.304 \\ 0.058 & -0.229 & 0.623 & -0.646 & 0.184 & 0.207 & -0.640 & 0.039 & 0.179 & -0.302 & -0.439 & 0.083 & 0.748 & 0.301 & -0.321 & -0.195 \\ 0.237 & -0.355 & 0.221 & -0.782 & 0.410 & -0.163 & -0.039 & -0.205 & -0.227 & -0.310 & -0.008 & 0.144 & 1.051 & -0.643 & 0.082 & 0.611 \\ -0.184 & 0.101 & 0.126 & -0.664 & -0.002 & -0.141 & -0.365 & 0.316 & -0.115 & -0.701 & -0.164 & 0.590 & 0.732 & 0.188 & 0.080 & 0.715 \\ 0.160 & -0.358 & -0.053 & 0.143 & -0.469 & 0.252 & 0.713 & 0.012 & 0.056 & -0.741 & -0.385 & 0.626 & -0.005 & -0.113 & -0.567 & 0.169 \\ -0.153 & -0.021 & -0.324 & -0.320 & -0.032 & -0.221 & 0.135 & -0.402 & 0.082 & 0.253 & -0.227 & 0.338 & -0.040 & 0.295 & -0.288 & 0.113 \\ -0.468 & 0.806 & -0.140 & -0.329 & 0.028 & -0.242 & -0.110 & -0.755 & -0.186 & 0.059 & -0.107 & 0.157 & 0.193 & 0.257 & 0.184 & -0.427 \\ 0.145 & -0.549 & -0.428 & 0.313 & 0.263 & 0.085 & -0.387 & 0.080 & 0.131 & -0.122 & -0.533 & 0.374 & 0.066 & -0.151 & -0.107 & 0.397 \\ -0.458 & -0.139 & 0.343 & -0.335 & -0.196 & -0.252 & -0.290 & 0.102 & 0.094 & 0.078 & -0.187 & 0.351 & -0.003 & -0.302 & -0.002 & 0.339 \\ 0.120 & -0.373 & -0.308 & 0.099 & 0.029 & 0.384 & 0.312 & -0.216 & 0.256 & -0.078 & -0.115 & -0.108 & -0.258 & -0.037 & -0.418 & 0.387 \end{bmatrix}$$

$$Z = \begin{bmatrix} -0.475 & -0.919 \\ -0.551 & 0.712 \\ 0.180 & 0.156 \\ -1.766 & -1.429 \\ 0.832 & 0.372 \\ 0.076 & -0.336 \\ -1.276 & -1.024 \\ -0.438 & -0.683 \\ -0.529 & -0.450 \\ -1.414 & 0.009 \\ -0.367 & 0.153 \\ 1.242 & 0.259 \\ 2.749 & 1.442 \\ -0.672 & 0.093 \\ 0.246 & 0.532 \\ 1.687 & 0.043 \end{bmatrix}$$

$$Bias_{input} = [0.395 \;\; 0.094 \; -0.028 \; 0.173 \; -0.364 \; -0.378 \; -0.270 \;\; 0.355 \;\; 0.170 \; 0.312 \; -0.325 \;\; -0.284 \; 0.739 \; 0.537 \; 0.389 \; -0.289]$$

$$Bias_{output} = [0.541 \; -0.101]$$

Conclusion

In this research, the application of response surface methodology conjugated with artificial neural network to predict osmotic dehydration properties of crookneck squash was investigated. The result indicated that, this model was able to predict water loss and solid gain with R^2 values equal to 0.967 and 0.890, respectively. The optimal points in this state include values of 15.75 for neuron, 0.90 for momentum coefficient, 4999.98 for learning epoch and 0.55 for learning rate. Thus, according to the researchers' hypothesis, RSM-ANN model provides the opportunity to determine the best arrangement of neural network in a short time. Generally, the response surface methodology hydride with artificial neural network can be utilized in order to optimize the best arrangement of neural network to predict industrial processes.

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