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Moisture Estimation in Cabinet Dryer with Thin-Layer Relationships Using Genetic Algorithm and Neural Network

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Abstract

Nowadays, industrial dryers are used instead of traditional methods for drying. In designing dryers suitable for controlling the process of drying and reaching a high-quality product, it is necessary to predict the instantaneous moisture loss during drying. For this purpose, ten mathematical-experimental models with a neural network model based on the kinetic data of pistachio drying are studied. The data obtained from the cabinet dryer evaluated at four temperatures of inlet air and different air velocities. The pistachio seeds will be placed in a thin layer on an aluminum sheet on a drying tray and weighed by a scale attached to the computer at different times. In the neural network, data divided into three parts: educational (60%), validation (20%) and test (20%). Finally, the best mathematical-experimental model using a genetic algorithm and the best neural network structure for predicting instantaneous moisture are selected based on the least squared error and the highest correlation coefficient.

Keywords: cabinet dryer; genetic algorithm; neural network; temperature; air velocity; moisture

Introduction

During the past few years, some studies have focused on applying neural network models for different engineering applications [1,2]. As an example, Baghban et al. [3] used ANN approach for predicting heat transfer of coiled tube heat exchanger. Additionally, pulsating heat pipes' thermal resistance has been estimated by Ahmadi et al. [4] with the help of using ANN. In addition

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to these, some investigations have been done on evaluating the thermal performance of various applications with the help of neural networks [5–7]. Among these applications, artificial neural networks have been widely used in drying processes and other processes [8–15]. Farkas [16] focused on ANN modeling of heat and mass transfer in drying technology. As mentioned in the results, neural networks can be properly utilized in order to detect the moisture distribution in a fixed-bed dryer. Also, a hybrid neuro-fuzzy model named ANFIS has been utilized by Jumah et al. [17] for the aim of modeling intermittent drying of grains. Furthermore, Koni et al. [18] proposed a controller based on ANFIS model for baker's yeast drying. The efficiency of the introduced ANFIS was identified by using this controller.

On the other hand, limited investigations have been carried out regarding the pistachio drying. In 2008, Mohammadpour et al. [19] examined pistachio drying in a fluid bed dryer. They conclude that changes in moisture content over time are strongly influenced by the temperature and speed of the air. They also stated that the effect of temperature on kinetic drying is higher than air velocity. The researchers also used thin-layer models to predict pistachio drying data and concluded that the binary model in all conditions and the Henderson and Pabis model at higher temperatures and velocities would be the best predictor of experimental data. Zang et al. [20] used the neural network for the prediction of the final moisture content of the product, the drying rate, and the energy consumption indices in the process of drying. The input vector consisted of four parameters of layer thickness, hot air flow, drying air temperature and drying time. Islam et al. [21] predicted the rate of drying of thin potatoes in dryers by the neural network. The purpose of this study was to develop a neural network model for drying thin potato plates under conditions of different speeds of hot air, different temperatures and moisture content in a one-dimensional liquid diffusion model.

The liquid diffusion model was used to produce data in different thicknesses of thin potato plates under different conditions of air velocity, temperature and mositure. Data were used to predict the rapid drying rate in the neural network. The proposed model of the neural network had the proper accuracy in determining the rate of drying in the range of the studied parameters. Arenturk et al. [22] compared the genetic algorithm and neural network in the process of drying thin carrots.

The carrots at different temperatures and velocities and three thicknesses (5.7, 5 and 10 mm) in a thin layer were dried. Then the data was called in the neural network. In this research, carrot thin

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layer drying in an experimental scale was investigated and a comparison between regression analysis and ANN was conducted in the process of dynamic drying of carrot layers. Among the four mathematical models of drying, the best model for estimating carrots dryness was the surface response method. Then, this model was compared with the ANN (ANN). It was observed that the ANN is more than 0.05% higher than the modified version of the model, and the neural network model has been proved to be very successful in predicting the dynamical drying systems.

In addition, Zbysinsky et al. [3] for modeling the moisture evaporation process in a fluid bed dryer, Zubisinsky et al. [23] to predict the heat transfer coefficient of various materials, Mittal and Zang [24] to estimate moisture and temperature in thermal processes, Brüyart et al. [25] to model the heat and mass transfer phenomenon and to study the process of qualitative changes in biscuit processing, Hernandez et al. [26] for estimating heat and mass transfer in the process of drying starch and mango, Poonnoy et al. [27,28] to model the prediction of the moisture content of the fungus and predict the temperature and moisture content of the thin layer of tomato in the microwave-vacuum dryer used the neural network (ANN). All of the above studies show the effectiveness of thin-layer models as well as the neural network model for determining the kinetics of drying agricultural products.

Study Procedure

Thin layer models were used to predict the instantaneous moisture content. Calculation of coefficients and computer simulation of pistachio drying can be used to optimize and control the relevant drying systems. In this research, the data are obtained from an experimental cabinet dryer at temperatures of 50, 55 and 60℃ and air velocity of 0.75 and 1.25 m/s. Before the experiment, the moisture content of pistachios was measured in the range of 37-36% (based on wet weight). During the drying process, the moisture dropped from 37% to 5%.

Designing an artificial neural network to predict instantaneous moisture

The purpose of this section is to predict the moisture content of pistachios during drying by taking into account three input parameters such as velocity of hot air temperature, temperature and time using artificial neural networks. Hence, the MLP networks with the learning algorithms of Leungberg-Marguerite were used to train the network. A neural network was designed with three input neurons (temperature, air velocity, and time) and a neuron output layer (moisture content).

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In this research, Matlab 7.12 software has been used. Also, for increasing the accuracy and speed of the artificial neural network, input and output data are obtained in the form of a dimensionless unit in the range of [0,1].

$$M_R = \frac{M - M_e}{M_o - M_e} \tag{1}$$

$$T_n = \frac{T_i - T_{\min}}{T_{\max} - T_{\min}} \tag{2}$$

$$t_n = \frac{t_i - t_{\min}}{t_{\max} - t_{\min}} \tag{3}$$

$$v_n = \frac{v_i - v_{\min}}{v_{\max} - v_{\min}} \tag{4}$$

M_e and M_i express the final moisture content and the initial moisture content, respectively. T_n , t_n and v_n indicate the temperature, time, and the input air velocity in the dimensionless form.

Calculate the coefficients of the thin layer drying equations

Table 1 presents the semi-experimental thin-layer drying equations. In each of the following forms, a prevalent thin layer model was examined.

Table 1. Sub-equations of thin layer drying

	Thin-layer drying models	
Name	**Model equation**	**References**
Newton	**MR=exp(-kt)**	**O'callaghanetal(1971)**, [48]
Page	**MR=exp(-kt^n)**	**Agrawal and Singh(1977)**, [49]
Henderson and Pabis	**MR=a exp(-kt)**	**Chhinman(1984)**, [50]

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Logarithmic (1995)	**$MR=a_0+a\exp(-kt)$**	**Chandra and Singh**, [51]
Logistic (1995)	**$MR=a_0/(1+a\exp(kt))$**	**Chandra and Singh**, [51]
Two-term exponential	**$MR=a_1\exp(-k_1t)+a_2\exp(-k_2t)$**	**Henderson(1974)**, [52]
Linear	**$MR=at+b$**	**Chandra and Singh(1995)**, [51]
Wang and Singh	**$MR=1+a_1t+a_2t^2$**	**Wang and Singh(1978)**, [53]
Midilli	**$MR=a\exp(-kt^n)+bt$**	**Midilli et al(2002)**, [54]
Diffusion approach	**$MR=a\exp(-kt)+(1-a)\exp(-kbt)$**	**Kassem(1998)**, [55]

For all models, the model equation coefficients, the Mse and R values, as well as the regression line were evaluated. The Midilli thin-layer model has the best matching (lowest error, highest regression coefficient) compared to other models (Figure 1).

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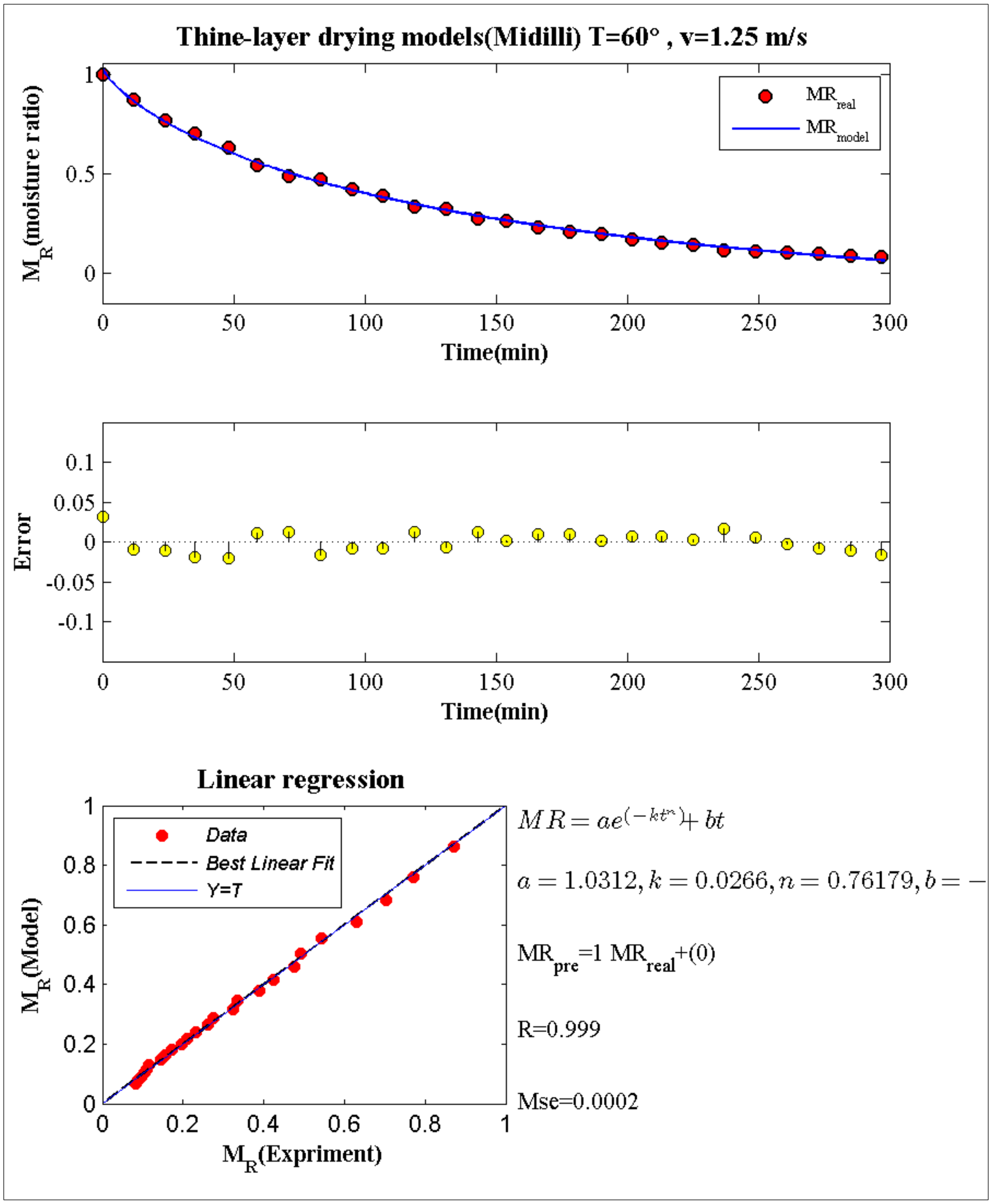

Figure 1. Midili thin layer model for the first experiment (air temperature 60 ° C and speed 1.25 m / s), the constant amounts of the thin layer model are shown in the figure. Also, correlation coefficient, regression line, and sum square error are also provided for the proposed mode.

Comparison of the accuracy associated with different models of thin-layer drying

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The comparison of the correlation coefficient (R^2) for ten thin-layer models is shown in Figures 2 and 3.

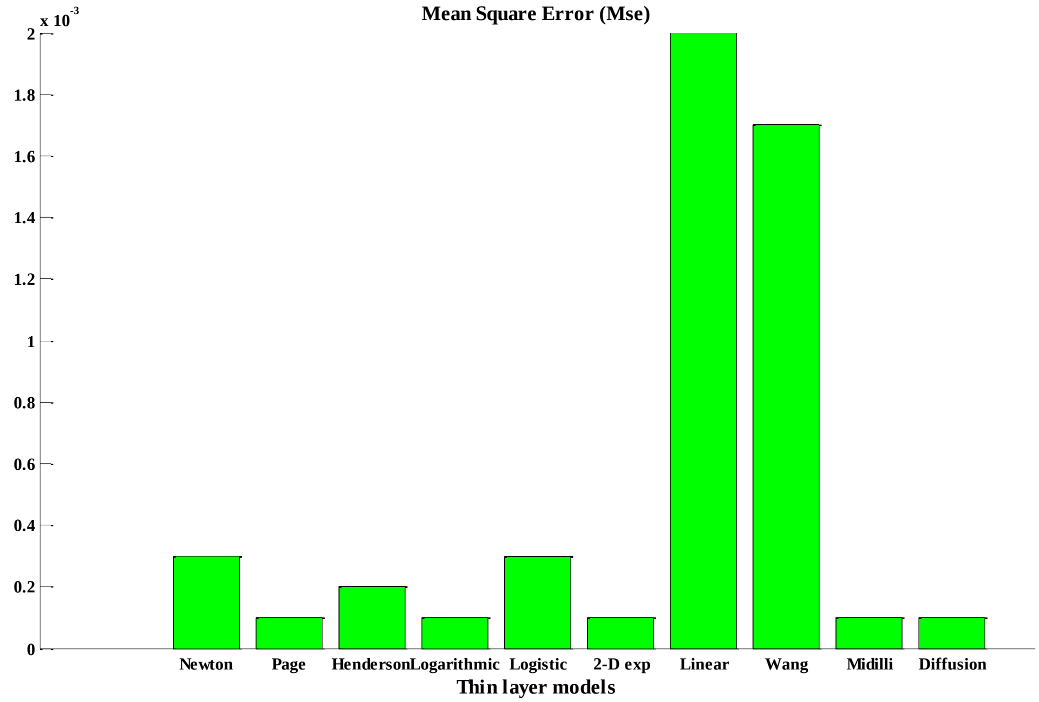

Figure 2. Comparison of sum of squared errors for ten thin-layer models

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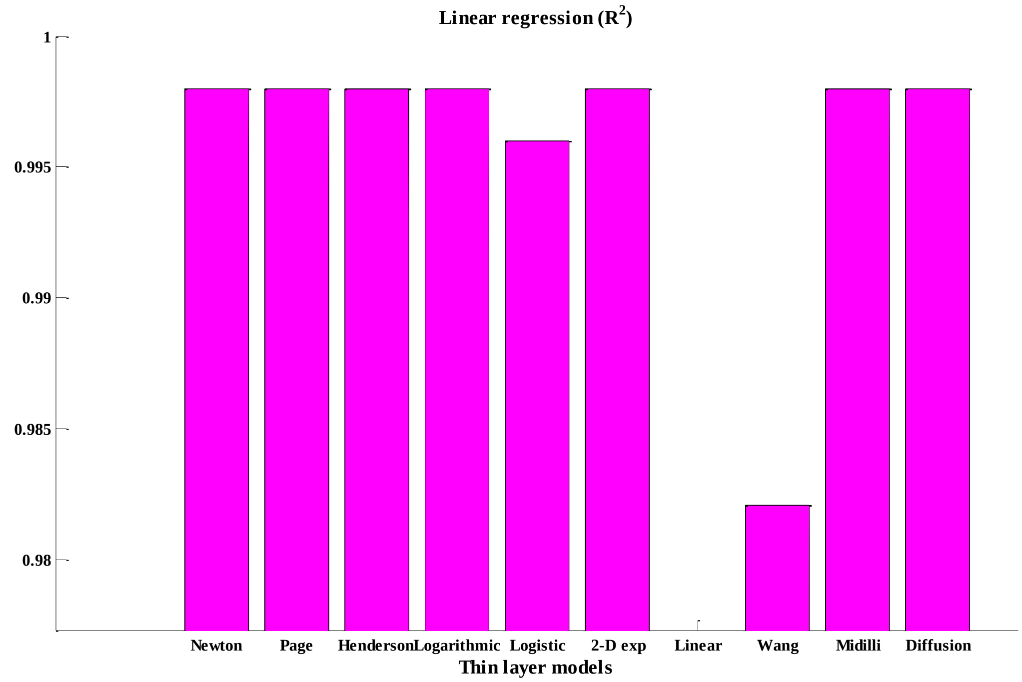

Figure 3. Correlation coefficient (R2) for ten thin-layer models

For the Midili model, the coefficients of the thin-layer equation for all experiments are presented in Table 2.

Table 2. Implementing the Midili Model for All Data

MIDILI						
RUN NO	**Temp©**	**V(m/S)**	**A**	**K**	**n**	**B**
RUN 1	60	1.25	1.002705	0.015509	0.885033	-4.11E-05
RUN 2	55	1.25	1.036377	0.034653	0.649945	-0.00046
RUN 3	50	1.25	1.020234	0.020321	0.729967	1.41E-05
RUN 4	60	0.75	1.012155	0.016581	0.805009	-0.00024
RUN 5	55	0.75	1.005385	0.014143	0.784523	-0.00025
RUN 6	50	0.75	1.024748	0.02253	0.621478	-0.00021

As shown in Table 2, for the Page model at a specific air velocity with decreasing air temperature, the coefficient *K* increases at first, then decreases. Also, power *n* reduces then increases. Also, at a constant temperature, with decreasing air velocity, k increases and power *n* decreases.

Neural Network Modeling

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To evaluate the performance of multi-layer perceptron network, multi layers of different topologies with various neurons were used. In the first step after learning the network, the MSE error of the network was calculated and based on that, the most appropriate topology was selected. During the modeling, 60% of the data were randomly assigned as training data and the rest of them were taken as test data and validator. The network with the LM (Levenberg-Marquardt) learning algorithm has produced the least educational error in comparison with other topologies. This topology for the test data predicted the moisture content with an error of MSE= 0.0005 and regression coefficients of R = 0.996. The obtained results indicate the ability of the neural network as a tool for predicting changes in the content of moisture with time that can be used in dry control systems. In Table 3, the numerical values of the regulatory parameters of the neural network used in the modeling are presented. In the following, only the results of the best neural network topology are presented in the prediction of moisture content.

Table 3. Regulatory Parameters of Artificial Neural Network

0.996	**Regresion**
0.0005	Prediction error
50	repeat
MSE	Objective function
LM	Training algorithm
tansig	Transfer function
3-9-1	Topology
FF-BP	Network type

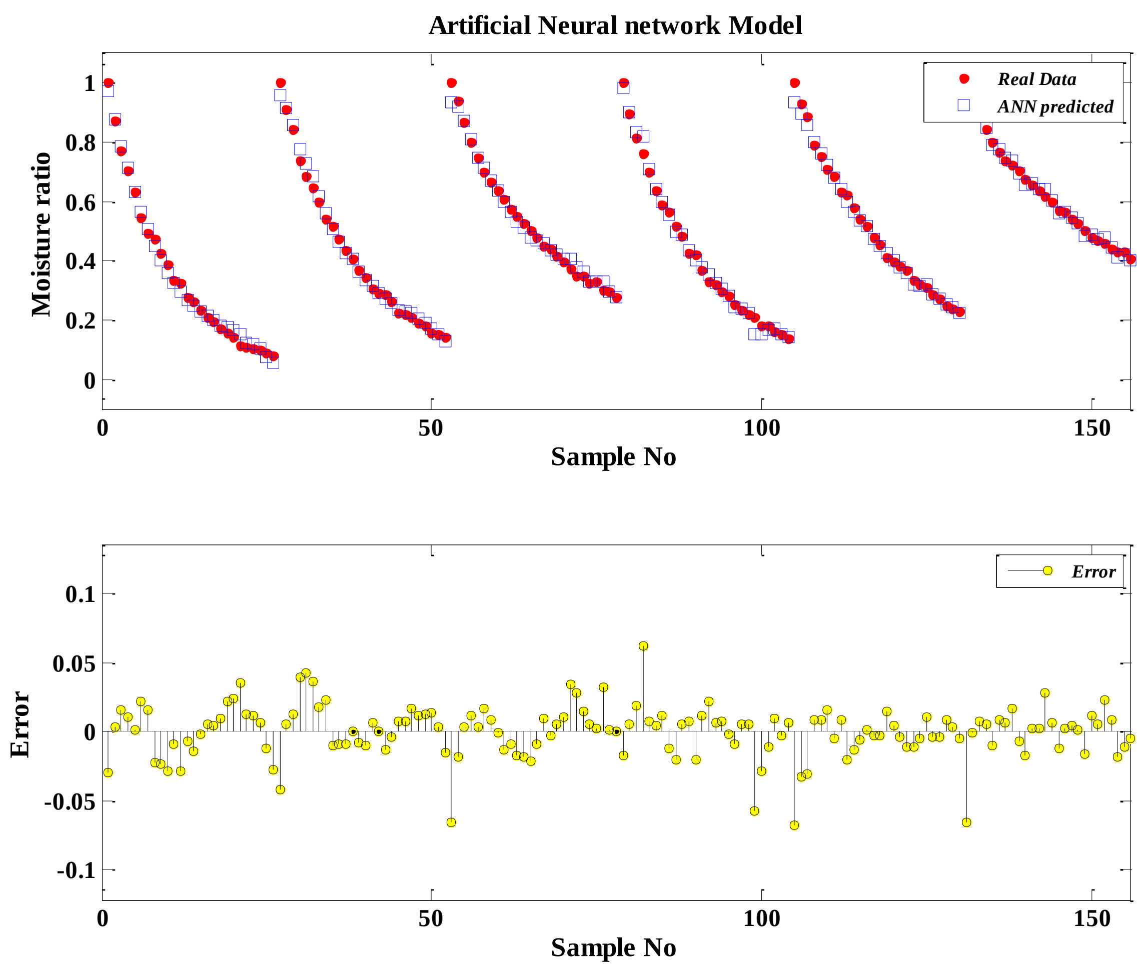

Figure 4. The actual and predicted data by the neural network and error rate.

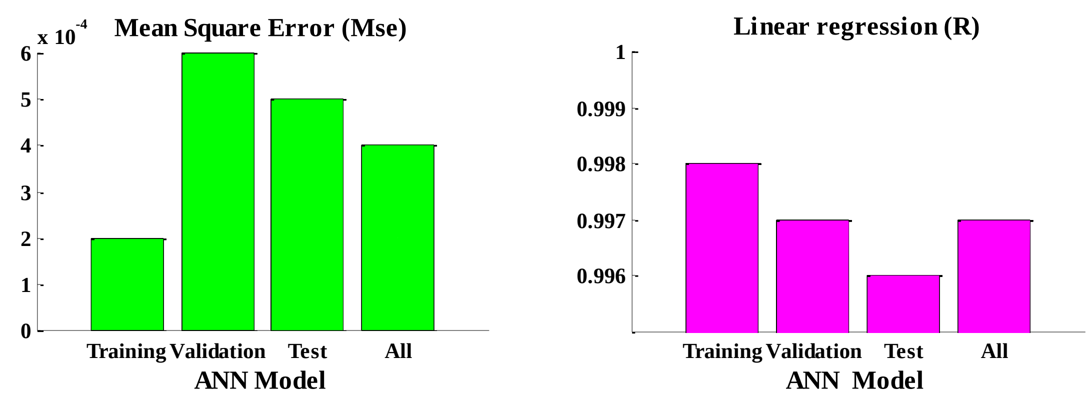

Figure 5. Linear regression coefficient and MSE error for training data, validation and testing

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The evaluation of the actual data matching with the data obtained from the neural network are divided into three categories: training 60%, validation 20%, testing20%. The value of root-square error and linear regression coefficient were calculated for each of the three groups. In Figure 4, the predicted values by the neural networks were evaluated with the experimental results, and in Fig. 4, the values of the correlation coefficient and the mean value of the errors were evaluated.

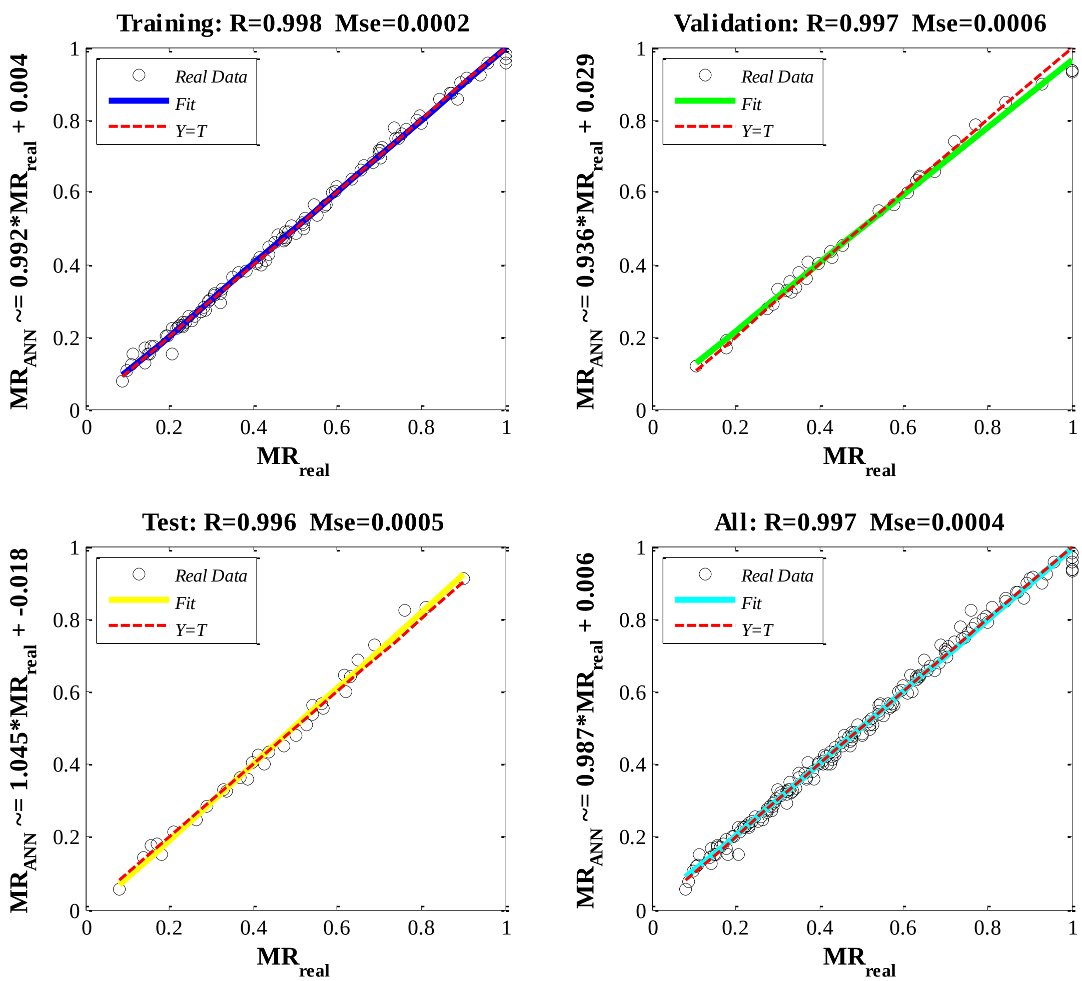

Figure 6. Neural Network Efficiency in Training, Validation, and Prediction

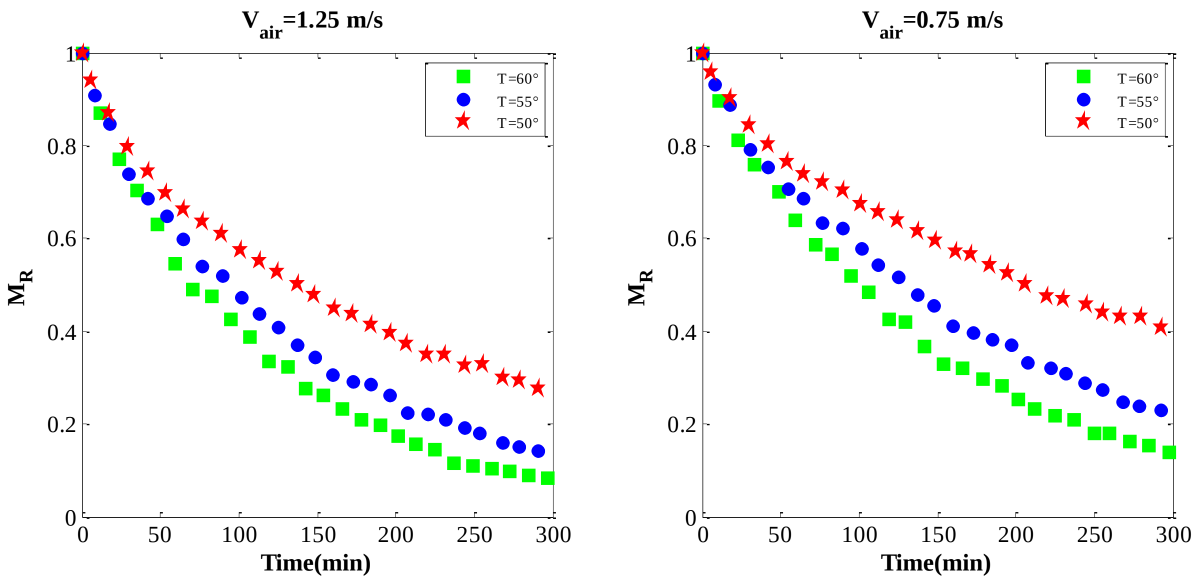

Figure 7. Moisture drop of the product in 300 minutes for three temperatures and two different air velocities

According to Fig. 7, the amount of product moisture loss in 300 minutes for three temperatures of 50, 55, 60 ° C and two air velocities of 0.75 and 1.25 m/s is depicted. Convective heat transfer augments with increasing the temperature difference (ΔT) and the convection coefficient (h). As shown in the figure above, the rate of moisture loss is higher for higher air velocity. Because the convection coefficient increases with rising the air velocity. Also, as shown in the figure, the rate of convective heat transfer increases with increasing air temperature for a constant air velocity.

Conclusion

The moisture content of the drying product was measured by the time affected by three air temperatures, two different velocities. According to the results of the experimental results, at higher air velocities, the product is dried faster, due to the fact that with increasing air flow, the difference in the partial pressure of water vapor between the product and the drying air increases. As the result, the moisture transfer rate from the product to the dry air is increased and the product is dried faster. Considering the slope of the moisture change curve, it can be understood that the drying speed is faster at the beginning of the operation (especially at higher speeds), but the drying rate is lessen by passing the time. The lowest error (Mse) in the prediction of moisture content in the pistachio drying process is related to the model of the midilli thin-layer model and the Page and the neural network. The air temperature is the most important factor in controlling the quality

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of pistachios during the drying process. As the temperature increases, the drying time and the M_R decreases and the drying rate increases. The results of this analysis showed that the air flow rate has a significant effect on the drying rate of pistachios. Although the effect of air flow velocity on drying rate is quite significant, its effect is less than air temperature. Furthermore, by referring to the experimental data and the good fitting of R^2 associated with each data series with semi-experimental models, it was clear that the models showed the perfect agreement with the experiments and could easily be used to predict the equilibrium moisture for each variety at the given temperatures. Also, the trained neural network, with 60% of the experimental data has the ability to predict moisture at any desired temperature and velocity within the test range. To ensure this, 20% of the experimental data were considered as test data. The regression coefficient for the test data is approximately $R^2 = 0.992$, which indicates its proper performance in predicting moisture.

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