Modeling Drying Kinetics of Pistachio Nuts with Multilayer Feed-Forward Neural Network

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Drying kinetics of pistachio nuts (Akbari v.) was simulated using a multilayer feed-forward neural network (MFNN). Experiments were performed at five drying air temperatures (ranging from 40 to 80°C) and four input air flow velocities (ranging from 0.5 to 2 m/s) with three replicates in a thin-layer dryer. Initial moisture content in all experiments was held at about 0.3 kg/kg d.b. To find the optimum model, various multilayer perceptron (MLP) topologies, having one and/or two hidden layers of neurons, were investigated and their prediction performances were evaluated. The (3-8-5-1)-MLP, namely, a network having eight neurons in the first hidden layer and five neurons in the second hidden layer resulted in the best-suited model estimating the moisture content of the pistachio nuts at all drying runs. For this topology, $R^2$ and MSE values were 0.9989 and 4.20E-06, respectively. A comparative study among MFNN and empirical models was also carried out. Among the empirical models, the logarithmic model, with $MSE = 7.29E-6$ and $R^2 = 0.9982$, gave better predictions than the others. However, the MFNN model performed better than the Lewis, Henderson and Pabis, two-term, and Page models and was marginally better than the logarithmic model.

Keywords  Drying kinetics; Moisture content; Neural network; Pistachio nuts

INTRODUCTION

Pistachio (Pistacia vera L.) is a dry-climate deciduous tree, producing nuts in clusters. Based on FAO statistics, Iran produced about 275,000 Mt of pistachio nuts in 2003, which represents approximately 54.7% of the world’s pistachio production. Iran exported 184,946 Mt of its pistachio nuts in the same year, and the total export revenue from pistachio nuts was about US$679,940,000 (http://www.fao.org). Therefore, pistachio nut are of great economic value for Iran. Pistachios are served principally as salted nuts. A large percentage of pistachios are marketed in the shell for snack food. Nonsplit, filled nuts are used for processing. The food industry uses pistachios for cakes, biscuits, pies, candies, ice cream, and pistachio butter. They are also used as the main ingredient of many Iranian desserts and as stuffing for both meat and snacks. Pistachio nuts contain 25% protein (mainly essential amino acids), 16% carbohydrate (mainly sucrose), and 55% oil (80% unsaturated fatty acids). Pistachios are an excellent source of dietary fiber, containing 2.8 g of fiber per ounce.[1]

The preparation process of pistachio nuts consist of (a) dehulling, to separate the soft hull from nuts; (b) trash and blank separation, to remove blank pistachios and trash such as small branches, remaining shells, and leaves; (c) unpeeled pistachios separation, to remove unpeeled and unripe nuts; (d) washing, which involves spraying water at high pressures on the pistachios to clean the nuts; (e) drying, to decrease moisture content of pistachios from 37–40% to the appropriate level; (f) split nuts separation, to separate split nuts from nonsplit ones; (g) salting; (h) roasting; and (i) packaging.[2] Among these processes, drying, which is defined as a process of moisture removal due to simultaneous heat and mass transfer, plays an important role in the preservation of pistachio nuts. The most important reasons for the popularity of dried products are longer shelf life, product diversity, minimal packaging requirements, as well as substantial volume reduction. This could be expanded further with improvements in product quality and process applications.[3] This complicated process depends on different factors such as drying air temperature, air flow velocity, relative humidity of air, air flow rate, physical nature, initial moisture content of the drying material, exposed area, and pressure, etc.[4]

Drying behavior of different natural materials has been studied by several investigators.[5–8] In particular, Middli and Kucuk[6] presented a mathematical modeling of thin-layer drying of pistachio by using solar energy. Ghazanfari et al.[7] designed and tested a thin-layer forced air solar dryer for drying pistachio nuts. Kashaninejad et al.[8] studied the thin-layer drying characteristics of pistachio nuts under different drying conditions and determined the effect of different parameters (temperature, velocity, and relative humidity of drying air) on drying time and rate of pistachio nuts.

Several researchers have also developed simulation models for drying processes. Artificial neural networks...
(ANN), which are heuristic models, are recognized as good tools for dynamic modeling. ANN is a useful statistical tool for nonparametric regression. The advantage of ANN over simpler parametric models (such as linear regression) is the increased flexibility and reduction in assumptions of the model. One can get an improved fit for the data when the relationship between the explanatory and response variables is complicated. ANN has been successfully used in prediction of drying kinetics of seeds, vegetables, and fruits food process parameters.[9–17] For example, Erenturk and Erenturk[9] compared the use of genetic algorithm and ANN approaches to study the drying of carrots. They demonstrated that the proposed neural network model not only minimized the $R^2$ of the predicted results but also removed the predictive dependency on the mathematical models (Newton, Page, modified Page, Henderson-Pabis). They also suggested that the application of the artificial neural networks could be used for the on-line state estimation and control of the drying process. Chen et al.[10] used multilayer ANN models with three inputs (concentration of osmotic solution, temperature, and contact time) to predict five outputs (drying time, color, texture, rehydration ratio, and hardness) during osmo-convective drying of blueberries. The optimal configuration of the neural network consisted of one hidden layer with 10 neurons. The predictability of the ANN models was compared with that of multiple regression models. The results confirmed that ANN models had much better performance than the conventional empirical or semiempirical mathematical models. The effects of different drying conditions (temperature, air velocity, drying time, and sample thickness) and different osmotic treatments (use of sorbitol, glucose, and sucrose solutions) on the drying time and quality of osmotically dried pumpkins through the application of ANNs and image analysis was predicted.[11]

Optimum artificial neural network (ANN) models were developed based on one to two hidden layers and 10–20 neurons per hidden layer. Recently, Lertworasirikul[18] presented a comparative study among mechanistic and empirical models to estimate dynamic drying behavior of semifinished cassava crackers using a hot air dryer. The prediction performance of different approaches such as the diffusion model, Newton model, Page model, modified Page model, Henderson and Pabis model, ANN model, and Adaptive-Network-Based Fuzzy Inference System (ANFIS) in modeling the drying processes of semifinished cassava crackers under different drying air temperatures was investigated. Overall, the ANN model performed superior to the diffusion model but was marginally better than ANFIS and modified Page models.

In drying processes, complex and highly nonlinear phenomena are involved. Consequently, analytical models are difficult or impossible to obtain. The knowledge of drying behavior is important in the design, simulation, and optimization of drying processes.[19] However, the improvement of performance and reliability of dryers requires accurate modeling and prediction of these phenomena. For this purpose, ANN possesses a number of properties for modeling processes or systems: universal function approximation capability, learning from experimental data, tolerance to noisy or missing data, and good generalization capability.

This work aims at evaluating the usefulness of ANN in such applications, as it is reflected in some relevant papers. The intent is to apply ANN for estimating the moisture content of pistachio nuts (Akbari v.) during the drying process in a hot air dryer by considering time, drying air temperature, and air flow velocity. A comparative study between an optimal ANN model and empirical models will also be presented and discussed.

MATERIALS AND METHODS

Drying experiments were performed in a tray dryer. Figure 1a shows the diagram of the fully automated dryer designed and fabricated by authors for experimental works.[20] The dryer consists of a of a PC (1) for data collection; main microcontroller circuit (2); centrifugal fan (4); four electronic heaters for heating input air flow to the dryer chamber, three sensors for measuring of air temperature (8), relative humidity of the air (9), and air flow...
A block diagram of the proposed data-acquisition system is shown in Fig. 1b. During the experiments, ambient temperature and relative humidity, outlet velocity of drying air in the duct, and dryer chamber were recorded. For continuous recording of the sample mass loss during drying, a digital balance was used. Detailed specifications of the dryer, main controlling board, measurement instruments, and their rated accuracy as well as software used for data acquisition, recording, and processing are available in the literature.[20,21]

Figure 2 shows the process flow diagram of drying pursued in this work for pistachio nuts samples. The preparation of the dryer was done by running the PC, microcontroller, fan blower, digital balance, and heaters as well as the settings of the drying conditions (temperature and air velocity) in the software installed on the PC. Then, the trays containing thin layers of pistachio nuts samples were placed in the dryer chamber. Data collection by the PC was done at five drying temperatures (40, 50, 60, 70, and 80°C) four air flow velocities (0.5, 1, 1.5, and 2 m/s) in triplicate. Each experiment was started approximately 30 min after setting up the dryer, in order to meet the steady state for the system conditions. The measurement was carried out from initial moisture content of 0.3 to 0.05 kg/kg db. The final moisture content was considered as the value of equilibrium moisture content (EMC).

Moisture ratio (MR) is the ratio of the amount of moisture remaining in the nuts to the original moisture content and is given by:[22]

\[
MR = \frac{M - M_e}{M_0 - M_e}
\]

where \( MR \) is the moisture ratio (dimensionless), \( M_0 \) is the initial moisture in kg (H\(_2\)O)/kg (DM), \( M \) is the mean moisture in kg (H\(_2\)O)/kg (DM) at time \( t \) in s, and \( M_e \) is the EMC; i.e., the mean moisture at equilibrium in kg (H\(_2\)O)/kg (DM). In the calculations, the dry basis values were used.

Once the moisture ratio of pistachio nuts is found, other information such as drying rate, effective diffusivity, and activation energy may be easily calculated, if needed, using simple mathematical expressions and curve fitting procedures.

**Data Preparation**

For each treatment on average, 4500 data points were obtained. In total, about 90,000 data were recorded. Considering the fact that the sampling times between data points were very short (5 s) and the limited accuracy of digital balance (±0.01 g), the difference between successive data points was indistinguishable. Therefore, the time interval between sample points was taken as 3 min. Of the 2500 remaining data points, a random sample of 1500 cases (50%) was used as training, 500 (20%) for cross-validation (CV), and 500 (20%) for testing. Training data were used to train the application, validation data were used to monitor the neural network performance during training, and the test data were used to measure the performance of the trained application. As training progressed, the error was calculated in the CV subset and when it reached a minimum after a certain number of epochs (or cycles), the process stopped.[23] Before training the different networks, some preprocessing operations are carried out: Firstly, all sample data were randomized. Then, data standardization (0, 1) was achieved thru the min-max function.

**Statistical Analysis**

Empirical modeling of the drying behavior of agricultural products often requires the statistical methods of regression and correlation analysis.[23] Linear and nonlinear regression models are important tools to find the relationship between different variables, especially those for which no established empirical relationship exists. The empirical coefficients in Table 1 can be estimated by fitting the total

![Flow diagram of thin-layer drying process of agricultural products.](Image)

**TABLE 1**

<table>
<thead>
<tr>
<th>Model name</th>
<th>Model equation ( a )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lewis</td>
<td>( MR = \exp(-kt) )</td>
</tr>
<tr>
<td>Henderson-Pabis (HP)</td>
<td>( MR = a \exp(-kt) )</td>
</tr>
<tr>
<td>Page</td>
<td>( MR = \exp(-kt') )</td>
</tr>
<tr>
<td>Logarithmic (LOG)</td>
<td>( MR = a \exp(-kt) + c )</td>
</tr>
<tr>
<td>Two-term (TT)</td>
<td>( MR = a \exp(-k_1t) + b \exp(-k_2t) )</td>
</tr>
</tbody>
</table>

\( a, b, c \) and \( k, k_1, k_2 \) are constants and coefficients in the drying models, respectively.
model employed to the experimental drying curves. The goodness of fit of the tested models to the experimental data are the coefficient of determination, $R^2$, and the mean square error (MSE) of the difference between the experimental and calculated values for the tested models. These statistical parameters are as follows:

$$R^2 = 1 - \frac{\sum_{j=1}^{N} (m_j - \bar{m})^2}{\sum_{j=1}^{N} (m_j - \bar{m})^2}$$  \hspace{1cm} (2)$$

$$MSE = \frac{\sum_{j=1}^{N} (m_j - \bar{m})^2}{N}$$  \hspace{1cm} (3)$$

where $\bar{m}_j$ is the network (predicted) output from observation $j$, $\bar{m}$ is the average value of experimental output, and $N$ is the total number of data observation.

The empirical models, shown in Table 1, were fitted by using nlintool in Statistic Toolbox of MATLAB R2007b. The Gauss-Newton method was used for the nonlinear data fitting to estimate the coefficients and constants in the drying models using least squares of the difference between the experimental data and fitted values. The effects of some parameters related to the product or drying conditions of pistachio nuts such as drying air temperature, relative humidity, etc., were investigated by many researchers.[4,8,24] The higher the values of $R^2$ and the lower the values of MSE and MAE, the better the goodness of fit.

**Multilayer Feed-Forward Neural Network**

The model considered in the multilayer feed-forward neural network (MFNN) included one output variable (the moisture content of the dried pistachio nuts) and three input variables including temperature, air velocity, and time. This topology is shown in Fig. 3. Input variables were drying air temperature ($T$), air flow velocity ($V$), and time ($t$) and the output is the moisture content ($M$) of the pistachio nuts; i.e., $M=f(T, V, t)$. For illustration purposes, in Fig. 3 a network having one hidden layer (with a log-sigmoid activation function) and one output layer (linear function) is drawn. We name this network a (3-25-1)-MLP topology; that is, $n=3$ and $m=25$.

In general, the value at the output unit is always the same for a certain set of input values. Therefore, the output $\hat{m}$ (predicted moisture content) can be seen as a function of the input values $T$, $V$, and $t$. The bias parameters, $b^{(h)}_i$ and $b^{(o)}$, may be viewed as weights from an extra input having a fixed value of one. The general expression for a feed-forward (FF) operation can compactly be cast into:

$$\hat{m} = \sum_{j=1}^{m} w^{(o)}_{ji} f \left( \sum_{i=1}^{n} w^{(h)}_{ji} O_i + b^{(h)}_i \right) + b^{(o)}$$  \hspace{1cm} (4)$$

where $\hat{m}$ is the predicted value of the pistachio nuts moisture content in the network, $i=1, \ldots, n$, $j=1, \ldots, m$ and

$$O_j = f(\text{net}_j) = \frac{1}{1+e^{-\text{net}_j}}$$  \hspace{1cm} (5)$$

Notice the use of log-sigmoid activation function, $O_j=f(\text{net}_j) = 1$, for the hidden layer neurons and in the output layer, the outputs of the hidden layer are summed linearly to produce moisture content estimates, $\hat{m}$. Expressions similar to Eqs. (4) and (5) can be derived for more complex networks.

The first step in developing MFNN deals with the definition of the network architecture, which was defined by the basic processing elements (neurons) and by the way in which they are interconnected (layers). In the feed-forward networks, error minimization can be obtained by a number of procedures including gradient descent (GD), Levenberg-Marquardt (LM), and conjugate gradient (CG). Multilayer perceptrons (MLP) are normally trained with an error back-propagation (BP) algorithm.[25] The knowledge obtained during the training phase is not stored as equations or in a knowledge base but is distributed throughout the network in the form of connection weights between neurons.[26] It is a general method for iteratively solving for weights and biases. BP uses a GD technique that is very stable when a small learning rate ($\eta$) is used but has slow convergence properties. Several methods for speeding up BP have been used, including adding a momentum term or using a variable learning rate. In this article, GD with a momentum (GDM) algorithm that is an improvement to the straight GD rule in the sense that a momentum term is used to avoid local minima, speeding up learning and stabilizing convergence, is used. In GDM, weights in the $n$th training iteration are updated by the following rule:

$$w^{(n)}_{ji} = w^{(n-1)}_{ji} + \Delta w^{(n)}_{ji}$$  \hspace{1cm} (6)$$

where the computation of the weight changes ($\Delta$) can be accomplished by:

$$\Delta w^{(n)}_{ji} = \eta \delta^{(n)}_i + \alpha \Delta w^{(n-1)}_{ji}$$  \hspace{1cm} (7)$$

where $w_{ji}$ is the weight between the $j$th node (neuron) of the upper layer and the $i$th node of the lower layer, $\delta_i$ error

![FIG. 3. Schematic diagram of MFNN with (3-25-1)-MLP topology.](image-url)
signal of the \( j \)th node, \( o_i \) output value of the \( i \)th node of the previous layer, and \( \eta \) and \( \alpha \) are the learning rate and the momentum term, respectively. The terms \( \Delta w_{ij}^{(n)} \) in Eqs. (6) and (7) are in fact the gradient vector associated with the weights. The gradient vector is the set of derivatives for all weights with respect to the output error. In developing MFNN models, the values of \( \eta = 0.1 \) and \( \alpha = 0.7 \) were used in Ghazanfari et al.\cite{7}

NeuroSolutions 5.0 software was used for the design and testing of MFNN models.\cite{23} The number of neurons in input and output layers depends on independent and dependent variables, respectively. Because one dependent variable (the moisture content of the dried pistachio nuts) depends on three variables (temperature, air velocity, and time), therefore one and three neurons are chosen for output and input layers, respectively. One and three neurons were devoted to output and input layers, respectively. The number of hidden layers and their neurons depend on the complexity of the problem to be investigated.\cite{27} In this study one and two hidden layer(s) including various neurons were used for the MFNN model.

To develop a statistically sound model, the networks were trained three times and the average values were recorded for Each parameter. To avoid overfitting, the MSE of the CV subset was calculated after adjusting of weights and biases. The training process continued until the minimum MSE of the validating sets was reached (early stopping scheme\cite{23}). The network weights and biases were then adapted and employed for validation in order to determine the neural network model overall performance. The MSE and \( R^2 \) of the MFNN model on test sets were then calculated (Table 2) and compared with different empirical equations in Table 1.

### RESULTS AND DISCUSSION

Various MFNNs were designed and trained as two and three layers to find an optimal model prediction for the pistachio nuts' moisture content. Training procedures of the networks was as follows: Initially, an experimental network having one hidden layer was considered. Hidden layer neurons varied from 2 to 30 and the number of epochs varied from 50 to 2000. This initial network was trained in order to find rough estimates on the number of neurons and training epochs. The diagram of MSE changes versus the number of hidden layer neurons (\( N_h \)) for different training epochs.

![Percentage error of various MFNNs versus the number of hidden layer neurons (\( N_h \)) for different training epochs.](image)

The results indicate that by selecting about 20 neurons in the hidden layer and the number of epochs of more than 150, stable results may be produced.

In our investigation, different hidden layer neurons and arrangements were adapted to select the best production results. More specifically, the number of neurons in one hidden layer network was varied from 5 to 30, whereas in two hidden layers cases were varied from 5 to 8 (in the first)

#### TABLE 2

<table>
<thead>
<tr>
<th># Hidden layer</th>
<th>Hidden layer nodes</th>
<th>MSE</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>5</td>
<td>3.14E-05</td>
<td>0.9929</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>1.49E-05</td>
<td>0.9964</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>1.20E-05</td>
<td>0.9973</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.10E-05</td>
<td>0.9971</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>6.49E-06</td>
<td>0.9986</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>1.79E-05</td>
<td>0.9982</td>
</tr>
<tr>
<td>Two</td>
<td>5, 3</td>
<td>2.01E-05</td>
<td>0.9951</td>
</tr>
<tr>
<td></td>
<td>5, 5</td>
<td>1.52E-05</td>
<td>0.9966</td>
</tr>
<tr>
<td></td>
<td>6, 3</td>
<td>2.22E-05</td>
<td>0.9972</td>
</tr>
<tr>
<td></td>
<td>6, 5</td>
<td>1.43E-05</td>
<td>0.9965</td>
</tr>
<tr>
<td></td>
<td>7, 3</td>
<td>7.76E-06</td>
<td>0.9980</td>
</tr>
<tr>
<td></td>
<td>7, 5</td>
<td>1.07E-05</td>
<td>0.9974</td>
</tr>
<tr>
<td></td>
<td>7, 6</td>
<td>6.77E-06</td>
<td>0.9986</td>
</tr>
<tr>
<td></td>
<td>8, 3</td>
<td>1.59E-05</td>
<td>0.9961</td>
</tr>
<tr>
<td></td>
<td>8, 5</td>
<td>4.20E-06</td>
<td>0.9989</td>
</tr>
<tr>
<td></td>
<td>8, 6</td>
<td>1.07E-05</td>
<td>0.9983</td>
</tr>
<tr>
<td></td>
<td>8, 7</td>
<td>7.82E-06</td>
<td>0.9981</td>
</tr>
</tbody>
</table>

![Error of training and cross-validating sets versus number of epochs.](image)
Results of the network performance for different arrangement are presented in Table 2. As indicated in Table 2, among the trained networks, the (3-8-5-1)-MLP, namely, a network having three input variables ($T, V, a$, and $t$), 8 neurons in the first hidden layer and 5 neurons in the second hidden layer, and single output variable (moisture content) resulted in the best-suited model estimating the moisture content of the pistachio nuts (Akbari v.). For this topology, $R^2$ and MSE values were 0.9989 and 4.201E-06, respectively. Figure 5 shows the average values of training and validating errors versus the number of training epochs for the optimal network. Among the one hidden layer networks, the (3-25-1)-MLP topology provided comparable errors with $R^2 = 6.49E-06$ and MSE = 0.9986. Comparison of the experimental (actual) data and the MFNN output (predicted) data of the best network trained, (3-8-5-1)-MLP with $R^2 = 0.9989$, is shown in Fig. 6. More results of other studied topologies for different experimental conditions can be found in Baharlooei.\cite{21}

Comparison of drying curves based on the experimental data and the (3-8-5-1)-MLP for air velocities of 0.5, 1.0, 1.5, and 2 m/s (and different drying air temperatures) are shown in Figs. 7a–7d, respectively. Excellent correlation between the experimental and predicted results is obtained. From Fig. 7, it is observed that at the beginning of drying process, the drying rate is higher. Drying rate decreases continuously with decreasing moisture content or improving drying time. In this curve, there is no constant rate period and the drying occurs in the falling rate period.\cite{20}

The results indicate that diffusion is the most likely physical

![FIG. 6. Comparison of experimental and predicted (MFNN) moisture content.](image)

![FIG. 7. Comparison of the fit of the optimum MFNN model for pistachio nuts dried at various temperatures ($T = 40, 50, 60, 70, \text{ and } 80^\circ C$) and air velocity of (a) $V = 0.5 \text{ m/s}$, (b) $V = 1 \text{ m/s}$, (c) $V = 1.5 \text{ m/s}$, and (d) $V = 2 \text{ m/s}$, respectively.](image)
mechanism governing moisture movement in the pistachio nut samples. These results are in agreement with some literature studies on drying of various food products.\[4,5,8,20]\n
As expected from Fig. 7, increasing the air temperature and velocity increases the drying rate (and consequently decreases drying time). The experimental results showed that the drying air temperature has a significant effect on the evolution of the moisture content, whereas the drying air velocity has small effect. Different authors reported similar results on drying of grains and nuts.\[8,20,28\]

Finally, a comparative study among MFNN and empirical models (Table 1) of Lewis, Henderson and Pabis (HP), Page, logarithmic (LOG) and two-term (TT) models,\[18,22\] for different experimental conditions. The R^2 and MSE were performance criteria for comparing these models. Only the results for air velocity of V = 1.0 m/s and drying air temperatures of T = 40, 50, 60, 70, and 80°C are presented and discussed in Table 3. Other results are available in Baharlooei.\[21\] Among the studied models, LOG with R^2 = 0.9982 and MSE = 7.29E-6 gave better predictions than other models for estimating dynamic drying behavior of pistachio nuts. The corresponding values for HP model were R^2 = 0.9741 and MSE = 1.46E-04. In Table 3, constants and coefficients in the drying models (k, a, c) of these empirical models are also presented. It is clear from Table 3 that the values of constants for each correlation vary considerably from one experimental condition to another. Although the values of these constants in different experimental conditions had no logical relations with each other, the average MSE and R^2 values of the empirical equation for whole range of experiments were compared with the results of the unique ANN model in Table 3. The values in Table 3 clearly show that although the constants of the empirical equations are allowed to change from one experimental condition to another, the results of the ANN model are more accurate than each of them. As shown in Table 3, both (3-8-5-1)-MLP and (3-25-1)-MLP outperform regression models (LOG and HP). Overall, the MFNN model performed superior to Lewis, HP, TT, and Page models but was marginally better than LOG model. MFNN is a universal approximator, whereas the regression approach is not.\[27\]

It is interesting to note that, in the case of LOG we would end up with 20 different equations (five for each air velocity) and a total of 60 values for k, a, and c to cover all drying conditions. But MFNN uses only one set of weights for all drying conditions. The number of weights and biases required for an optimal MFNN model is given in Table 3. Of course, empirical models are physically interpretable, whereas the MFNN cannot be easily interpreted. Its behavior has properties of a “black box,” not giving exact information on weighting factors of individual components to the user, although various sensitivity tests and model comparisons may provide insight into their physical meanings.

CONCLUSION
In this study, drying kinetics of pistachio nuts were investigated experimentally. A comparative study was performed between a regression analysis and MFNN to estimate their abilities for prediction of moisture content. MFNN models are able to describe a range of experiments,
whereas the application of empirical equations is limited to a specific experiment. More than 30 different empirical equations, similar to those considered in this article, may be fitted to a drying system in different conditions, whereas a single MFNN model is able to describe the whole range of experimental conditions more accurately.

Based on this study, the following conclusions can be drawn:

1. The (3-8-5-1)-MLP, namely, a network having eight neurons in the first hidden layer and five neurons in the second hidden layer, resulted in the best-suited model estimating the moisture content of the pistachio nuts at all drying runs. For this topology, MSE = 4.2E-06 and \( R^2 = 0.9989 \) were obtained. Among the one-layer models, the optimal model in predicting the moisture content of pistachio nuts has a (3-25-1)-MLP topology. The \( R^2 \) of greater than 0.99 is obtained for all MFNN models fitted to all drying air temperatures and air flow velocities.

2. Among the empirical models, the logarithmic model with MSE = 7.29E-6 and \( R^2 = 0.9982 \) gave better predictions than other models for estimating drying behavior of pistachio nuts. For the logarithmic model, 20 different sets of parameters for \( a, k, c \) have to be calculated to cover all drying conditions.

3. When function approximation is the goal, the MFNN model will often deliver close to the best fit. The present work was motivated in this direction. Apart from model accuracy and generalization capability, other important issues such as computational time, credibility, tactical issues, and replicating the results have to be considered when using empirical versus ANN to estimate moisture content. For example, although outperforming the empirical modeling techniques, MFNN has one big offset—it is hard to draw any physical information out of it; i.e., no information from the neurons’ weights and biases can be drawn about the weights of each predictor in the final score. Nevertheless, because of their better results, ANNs have been commonly used during the past 10 years to solve nonlinear problems of high complexity. In future similar modeling efforts, the best solution will represent a trade-off between the simplicity of empirical models and the higher capacity of ANNs to simulate nonlinear effects.

ACKNOWLEDGEMENTS

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