Modeling the Moisture Content and Drying Rate of Zucchini (Cucurbita pepo L.) in a Solar Hybrid Dryer Using ANN and ANFIS Methods

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Estimating product drying kinetics is critical to obtain the best drying process without compromising product quality and necessitates the development of numerical drying models. This research aims to compare the prediction models developed using artificial neural network (ANN) and adaptive network-based fuzzy inference system (ANFIS), two popular machine learning approaches in the recent years. Zucchini slices were chosen as samples and dried in a solar-assisted microwave belt dryer at 0.245 m/min belt speed and microwave powers of 0.7, 1, and 1.4 kW. On the data set obtained by computing the moisture content and drying rate values, prediction models were developed using ANN and ANFIS approaches. These models were evaluated using the coefficient of determination, mean absolute percent error, and root mean square error data. The ANFIS-based prediction model outperformed the ANN model in terms of drying rate performance, but the ANN model outperformed the ANFIS model in terms of moisture content values. Results showed that both methods established can be utilized to estimate zucchini slices.

Keywords: ANFIS, ANN, conveyor, microwave drying, zucchini

INTRODUCTION

Zucchini (Cucurbita pepo L.) differs significantly from other vegetables depending on the seasons of cultivation and the way it is evaluated (Ulusay 2019). It is frequently sold fresh, eaten raw in salads, and cooked with the skin in soups or other dishes. Zucchini vegetables are essential in most daily diets and alleviate most micronutrient deficiencies (Eissa et al. 2013). Dried zucchini can be used in soup mixes, stews, spice mixes or simply consumed as a nutritious snack (Çelen et al. 2017a; Kutlu and Isci 2017).

Drying is the process of removing liquid substances such as water in the solid material in order to slow down or stop chemical reactions and microbial deterioration (Çelen et al. 2018). The drying process not only extends the shelf life of the food but also provides volume and weight advantages during transportation and storage (Çelen and Karataşer 2019). Drying is a complicated process that involves simultaneous heat, mass, and momentum transfer events. To design, optimize, and regulate the drying process, effective models are required (Khazaei et al. 2013). This study is about establishing a model to predict the moisture content and drying rate of dried zucchini.

Mathematical modeling, which usually consists of equations describing the behavior of a process or system, provides conveniences such as reducing dryer cost and energy consumption and determining drying time. It is used in agriculture as well as in many industries such as construction, textiles, and food, among others (Şevik et al. 2014). Artificial intelligence techniques such as artificial neural network (ANN) and adaptive-network based fuzzy inference system (ANFIS) are effective for predicting optimum conditions as they do not need to include any assumptions or simplifications. These methods attempt to imitate the human brain's ability to learn patterns. In both methods, the models aim to derive the relationship between a previously obtained set of model inputs and their corresponding outputs (Mousavifard et al. 2015).
An artificial neural network is created by combining artificial neurons which are often organized into three interconnected layers that are parallel to one another to form a network with three layers: the input layer, the hidden layer, and the output layer (Akkaya 2007). The input layer is in charge of receiving data from the outside environment and passing it along to the intermediate layers. There is no information processing in this layer in certain artificial neural networks. The middle layer is in charge of processing and sending data from the input layer to the output layer. There can be more than one middle layer, commonly known as the concealed layer. The artificial neural network’s interlayers comprise a significant number of artificial neurons that are connected to other cells in the artificial neural network. The output layer is in charge of sending the processed data from the middleware to the outside environment (Gökçe and Sonugür 2016).

ANN is an alternative computational simulation consisting of a neuron network or circuit (Bhagya Raj and Dash 2020). Artificial neural networks are computer software that execute basic operations such as producing new data from data collected by the human brain through learning, remembering, and generalizing by emulating its learning path (Öztürk and Şahin 2018). ANNs are networks of functions that establish relationships similar to those of nerve cells called neurons. Recently, they have become widespread in many areas (such as agriculture, industry, health, and finance, etc.) in parallel with the development of computer technologies (Yildiz et al. 2020; Akkaya 2007). They provide accurate and fast solutions in science and engineering, especially for regression and classification problems. In terms of drying technologies, ANNs are used for many purposes such as modeling drying kinetics, dryer design and optimization, process control, and energy control (Yildiz et al. 2015). Modeling and optimization are the most critical steps in the drying process and help increase drying efficiency and preserve product quality characteristics. Because of its capacity to specifically discover nonlinear correlations between independent variables and dependent variables through training and retraining of input-output systems, ANN is frequently used in complex systems (Ram Talib et al. 2019).

With the trained ANN, the estimation of a new drying curve is done with great accuracy within a few seconds, thus avoiding time-consuming new experiments. Extending the neural model (adding new inputs and/or outputs) is also made simple. Moisture content is considered one of the most important parameters in drying procedure research and defines where the amount of water or steam is present in a material (Fabani et al. 2021).

The ANFIS method, in addition to artificial neural networks, has been a popular method for prediction models in recent years (Doğan 2016). ANFIS is a network topology made up of several nodes connected by directional links. A node function with fixed or changeable parameters characterizes each node (Vazifehkhah 2012). Machine learning-based methods such as artificial neural networks and adaptive neuro-fuzzy inference system models employ information to forecast complex system outcomes such as drying technologies (Kaveh et al. 2021). The main advantage of ANFIS is that it provides self-learning capabilities to fuzzy controllers, allowing them to achieve the lowest steady-state error possible (Elijah et al. 2020).

Among the modeling tools available, ANFIS simulates the properties of various food products and the complex nonlinear relationship between food properties and processing factors. ANFIS is a multilayer feedforward network that establishes the relationship between inputs and target outputs using a neural network learning algorithm and fuzzy inference systems (Tao et al. 2016).

Since drying is a complex process, there are many approaches that model the drying rate and product moisture content according to the drying process under various drying conditions. ANN and ANFIS have also been used by different researchers in the drying studies of agricultural products (Beigi et al. 2017; Kaveh et al. 2018; Chasiotis et al. 2020; Kaveh et al. 2020; Fabani et al. 2021; Kaveh et al. 2021; Sun et al. 2021).

The overall goal of the study was to mathematically model the drying process using experimentally obtained drying data of zucchini slices. Simulations based on these models help reduce the time and energy invested in laboratory experiments and help scientists determine the optimum conditions for drying. Specifically, the study aimed to generate mathematical models of the drying process using ANN and ANFIS methods and compare the performance of the mathematical models.

**MATERIALS AND METHODS**

**Drying Equipment and Experimental Procedure**

Zucchini (*Cucurbita pepo* L.), which is widely grown in Turkey, was used for the drying experiments. Samples were obtained from local markets in Tekirdağ province and kept in a refrigerator at +4°C until drying.

The microwave belt dryer consisted of a drying tunnel, 2 microwave power units, a 0.55 kW electric...
motor, and a control panel. The drying tunnel is 3.5 m long and 0.5 m wide. The collector used to generate hot air in the experiments was 1.5 m in diameter and made of acrylic. The heat generated by the solar collector was transferred to the dryer tunnel via a cylindrical tube connected to the solar collector and a 0.035 kW fan (Fig. 1) (Arda 2016; Çelen and Arda 2019).

Before the drying process, the zucchini was washed and sliced in 5, 10, and 15 mm thicknesses. No pre-treatment was applied other than washing. Before starting the drying experiments, the initial moisture values of the sample slices of 5, 10, and 15 mm thickness were determined as 85 ± 0.7 % (wet basis). Experiments were carried out at 0.7, 1, and 1.4 kW power levels. During the trials, the belt speed was set to 0.245 m/min. When the hot air produced in the collector reached a constant value, it was transferred to the tunnel at a constant rate. In all experiments, moisture loss was calculated by measuring the weight of the product every 5 min using a Precisa XB 620M precision balance (Precisa Instruments AG, Dietikon, Switzerland). In the drying processes, the moisture content of the products was maintained up to 10 ± 0.5% (wet basis). The experiments were repeated thrice and the averages of the data were used.

**Moisture Content Determination**

The moisture content of the products used in the drying experiments was calculated using equation (1) according to the wet basis and equation (2) according to the dry basis. The changing moisture content values of the products during the drying process were also calculated using equation (3).

\[
m_f = m_s/(m_s + m_k) \quad (1)
\]

\[
m = m/m_d \quad (2)
\]

\[
m_e = m - m_k/(m_s + m_k) \quad (3)
\]

where \( m_f \) = moisture content on a wet basis, \( m_s \) = wet mass of the product (g), \( m_k \) = the dry mass of the product (g), \( m_e \) = equilibrium moisture content, \( m_0 \) = initial moisture content.

For long drying times, the values of \( m_e \) are small when compared to \( m \) or \( m_0 \). In the microwave oven, the equilibrium moisture content \( (m_e) \) is assumed to be zero and simplified as \( m/m_0 \) (Çelen et al. 2017b; Kaveh et al. 2018).

**Drying Rate**

The drying rate is the pace at which the moisture content of a dried product changes over time. Eq.(4) is used to compute the drying rate (Ojediran et al. 2020).

\[
DR = (m_t+\Delta t - m_t)/\Delta t \quad (4)
\]

Here, \( DR \) (drying rate; g.water/g.dry matter.min) shows the moisture content at the moment of \( m_t \), and \( m_{t+\Delta t} \) shows the moisture content according to the dry base at the moment of \( \Delta t \).

**ANN Modeling**

In this study, MATLAB software was used to create and test ANN models. Since one hidden layer is sufficient for solving many complex problems in general, a multi-layer ANN architecture consisting of an input layer, a hidden layer, and an output layer has been preferred while creating ANN models. While creating ANNs, there is no generally accepted rule for determining the number of neurons in the hidden layer. However, in a few studies, empirical methods have been established to determine this number (Kurtulmuş et al. 2020). In the ANN architecture created in this study, the number of neurons in the hidden layer is accepted as 25. The illustration of one of the ANN architectures used in the study is shown in Fig. 2. Another factor affecting ANN performance is transfer functions. While the linear transfer function is used in the output layer of the generated ANNs, the tangent sigmoid function is used in the hidden layer (Lertworasirikul and Tipsuwan 2008).
296 Philipp Agric Scientist (2023)106(3):293-305

Moisture Content and Drying Rate Using ANN and ANFIS Methods

Halil Nusret Buluș et al.

Different learning algorithms may show different prediction performances due to the unique structure of the data. In this study, "Levenberg-Marquardt" (trainlm) — one of the algorithms frequently used in literature — was used. While drying time, slice thickness, and microwave power are given as inputs to the ANN, the network is expected to predict moisture and drying rate. In each ANN trial, 70% (98 data) of the total drying trial data was used for the training of the network, 15% (21 data) for the validation in the training iterations, and the remaining 15% (21 data) data was randomly selected as the test data to reveal the prediction success of the model.

ANSI Modeling

ANSI is a combination or hybrid intelligent system that is a subset of other single intelligent systems. The openness of a fuzzy inference system is combined with the learning ability of a neural network in the ANSI function. As shown in Fig. 3, ANSI is made up of three hidden of input and output layers, a multilayer neural network, and a back-propagation algorithm based on the Sugeno fuzzy type, according to its theory (Ojediran et al. 2020; Pusat et al. 2016).

There are 5 layers in the ANSI model (Tao et al. 2016; Taşova et al. 2020). In this model, in the first layer, the input values are drying time, slice thickness, and microwave power. These input values exit the layer by taking their membership degrees through a membership function. In the second layer, the inputs are multiplied and exit a node. In the third layer, the MR values are normalized by proportioning the total MR values. After the fourth layer, the Sugeno model is run. At the end of the fifth layer, the total output values are obtained from the model. The ANSI tool of the MATLAB platform does not allow multiple outputs. For this reason, 2 different ANSI models were created to perform MR and DR...
predictions. Exactly the same training and test set were used for these two models, and 27 rules were created.

**Statistical Analysis**

The proximity between the actual measured values and the estimation of the model was evaluated with the coefficient of determination ($R^2$), error terms (Root of Square Mean Error (RMSE), and mean absolute percent error (MAPE), which are the most commonly used measures for evaluating machine learning models. In this study, regression analysis was performed using MATLAB for the estimation of model parameters. The predictive ability of the created ANFIS models was evaluated using the coefficient of determination $R^2$, RMSE, and MAPE. The model with the highest $R^2$, lowest RMSE, and MAPE below 10% has the best performance in experimental MR and DR estimation against drying time (Table 1). (Çelen et al. 2015; Tınmaz Köse et al. 2019).

The results of the MR and DR tests were examined using analysis of variance, depending on the microwave power level (one-way ANOVA). To see if the differences were significant, the LSD (Least Significant Different) test was used. SPSS was used for all statistical analyses (PASW Statistics 18, SPSS Ltd, Hong Kong, China). Significant differences were defined as those with $p$ values less than 0.05.

**RESULTS AND DISCUSSION**

**Performance and Prediction Using ANFIS and ANN**

The moisture ratios of zucchini slices obtained for different drying times at 3 test thicknesses and 3 microwave power levels are shown in Fig. 4. The decrease in drying time with increasing drying power may be due to the increased water vapor pressure in the zucchini slices, which favors moisture migration. The moisture ratio of zucchini dropped rapidly with increasing drying time. The continued decrease in the moisture ratio suggests that diffusion dominates the internal mass transfer. Similar observations were made with papaya slices (Yousefi 2017).

Fig. 5 shows the experimental moisture ratio versus ANFIS and ANN predictions for the test data points (data not visible). It can be seen that the system is fully efficient in estimating the moisture ratio values obtained under all conditions.
experimental conditions. While creating the ANN architecture, different neuron numbers were tried with preliminary studies on the data of zucchini drying experiments and it was seen that the use of 25 neurons in the hidden layer provided better results than the use of more neurons in estimating the drying rate and moisture values.

Model predictions and experimental measurements were observed to have the same trends and overlap. Looking at the numbers, it can be seen that the MR values reported as a function of drying time are in agreement with the experimental results and the ANN and ANFIS predictions. Similar results were reported by Kırbaş et al. (2019) for pomelo fruit peel.

Because of the high moisture value early in the drying process, the absorbed power is likewise high. More power will have a greater impact on the polar molecules in the product, resulting in more heat (Workneh et al. 2011; Çelen 2019). As can be seen in Fig. 4, drying was quick at first but slowed as the moisture level dropped in subsequent intervals. As evidenced by this, diffusion is the mechanism that controls moisture movement (Darvishi 2012). The drying rate increased when the microwave power was increased, similar to the results of Doymaz (2012), Hanif et al. (2015), and Chahbani et al. (2018).

Of the 140 experimental data available for the creation of the models, 70% were used for training, 15% for testing, and 15% for validation. These data were randomly distributed and training, validation, and test sets were created. To create the ANN model, 3 inputs — time, microwave power, and slice thickness — were selected, while moisture rate and drying rate were selected as outputs. In the ANN model with 1 hidden layer, the hidden layer function is tangent sigmoid, the transfer function is linear transfer function, and Levenberg–Marquardt (trainlm) is used as the learning algorithm. According to the results obtained from various experiments in the hidden layer, the number of neurons was set to 25. In Fig. 6, the error log graph of the ANN training, which gave the most successful result, is given.

The regression graphs created for the training, testing, and validation as well as all data for the created ANN model are shown in Fig. 7.

The drying data was applied to the ANN model created in the MATLAB program. In this model, a single hidden layer neural network sensor model with 3 inputs and 2 output values is created. Time, microwave power, and slice thickness values were used as input data for the network, while moisture and drying rate were obtained as output data.

In this study, an ANN model was developed for the estimation of MR and DR parameters in zucchini drying. A model in which drying curves can be created without experimentation under different drying conditions in a solar assisted hybrid dryer has been successfully implemented. Accordingly, MR and DR parameters can be successfully estimated at different microwave powers and slice thicknesses values. In this way, it will be possible to easily predict how the system will behave at which temperatures, saving both time and energy. This method can also be applied by creating a prediction model for other products or other drying temperatures. It
can be said that this ANN model is useful in practice for designing and controlling the drying process of zucchini slices. This model can be improved by extending the database and can be retrained in case of emergence of new information and changes in the system.

ANFIS was used to estimate the moisture content and drying rate of zucchini slices at different thicknesses and microwave power values over time. ANFIS is an inference system based on the Takagi-Sugeno fuzzy inference system and has two main components: membership functions and fuzzy inference rules. Membership functions are the mapping of each point in the input space to the membership value (or degree of membership) in the combined fuzzy set, which takes a value between 0 and 1. Fuzzy inference rules are some if-then rules that reveal the character of the output values according to the input values.

In this study, 140 data obtained from experimental results — 119 (85%) training data and 21 (15%) test data — were applied to the ANFIS model. The model was implemented in MATLAB software using the ANFIS toolbox.

The training and test data sets formed by the experimentally obtained data in zucchini drying at the specified rate are given in Fig. 8 for both ANFIS models.

Fig. 8. Training and Test data for (a) MR (b) DR.

The number of training rounds of the 2 models with 3 inputs and 1 output, created with the given sets, was determined as 1000 and the training error graph formed as a result of the realization of this training was obtained. This training error graph is given in Fig. 9.

ANFIS rules were formed by training the developed models — Fig. 10 shows these rules, while Fig. 9a shows the rules created for the estimation of the MR parameter and Fig. 9b shows the rules created for the estimation of the DR parameter. In this model, 27 rules emerged and were then used to make predictions.

The ANFIS model was able to predict DR values closer to the experimental data than the ANN model. On the other hand, the ANN model outperformed the ANFIS model in predicting the MR value. Similar results were obtained using the Takagi-Sugeno fuzzy model on mango slices to estimate the effective diffusivity (Vaquiro et al. 2008). Ganjeh et al. (2013) also reported that the combination of fuzzy logic and neural networks is a suitable and reliable method to model and predict the drying kinetics of onions and similar products.

The variation between the experimental result and the analytical model's forecast result is shown by error parameters. The model error parameters show that the RMSE and MAPE values are low and the $R^2$ value is near to 1, indicating that the model is accurate. When reviewing the literature, it is clear that $R^2$ values are
Moisture Content and Drying Rate Using ANN and ANFIS Methods

Halil Nusret Buluş et al.

Table 2. F values obtained as a result of analysis of variance for Moisture Content and Drying Rate Using ANN and ANFIS Methods

<table>
<thead>
<tr>
<th>Variables</th>
<th>ANN (MR)</th>
<th>ANN (DR)</th>
<th>ANFIS (MR)</th>
<th>ANFIS (DR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M.P</td>
<td>334.16**</td>
<td>63.07**</td>
<td>6669.61**</td>
<td>3412.79**</td>
</tr>
<tr>
<td>5 mm Time</td>
<td>657.74**</td>
<td>196.47**</td>
<td>8968.24**</td>
<td>3299.95**</td>
</tr>
<tr>
<td>M.P * Time</td>
<td>31.04**</td>
<td>4.63**</td>
<td>483.78**</td>
<td>527.86**</td>
</tr>
<tr>
<td>M.P * Time</td>
<td>196697.30**</td>
<td>413.26**</td>
<td>213080.50**</td>
<td>433.41**</td>
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<tr>
<td>10 mm Time</td>
<td>1430808.00**</td>
<td>1901.61**</td>
<td>1381183.00**</td>
<td>1518.10**</td>
</tr>
<tr>
<td>M.P * Time</td>
<td>28951.89**</td>
<td>165.83**</td>
<td>20528.65**</td>
<td>483.59**</td>
</tr>
<tr>
<td>M.P</td>
<td>669603.50**</td>
<td>510.13**</td>
<td>668225.80**</td>
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<tr>
<td>15 mm Time</td>
<td>1669896.00**</td>
<td>909.17**</td>
<td>1649433.00**</td>
<td>930.90**</td>
</tr>
<tr>
<td>M.P * Time</td>
<td>14974.65**</td>
<td>64.02**</td>
<td>14072.16**</td>
<td>111.45**</td>
</tr>
</tbody>
</table>

** Significant at the 1% level. * Significant at the 5% level. M.P: Microwave Power.

Table 3. MR mean values and significance groups for ANN and ANFIS at 5 mm thickness.

<table>
<thead>
<tr>
<th>M.P(W)</th>
<th>0</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
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<tr>
<td>0.7</td>
<td>0.9962**</td>
<td>0.9900**</td>
<td>0.9860**</td>
<td>0.9920**</td>
<td>0.9011**</td>
<td>0.8721**</td>
<td>0.8412**</td>
<td>0.7825**</td>
<td>0.8923**</td>
<td>0.5714**</td>
<td>0.4332**</td>
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<tr>
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<td>1.0041**</td>
<td>0.9845**</td>
<td>0.9562**</td>
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<td>0.7561**</td>
<td>0.6417**</td>
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</tr>
<tr>
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<td>1.0077**</td>
<td>0.9755**</td>
<td>0.9516**</td>
<td>0.9159**</td>
<td>0.8861**</td>
<td>0.8537**</td>
<td>0.8150**</td>
<td>0.7585**</td>
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<tr>
<td>0.7</td>
<td>1.0093**</td>
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<td>0.8945**</td>
<td>0.8548**</td>
<td>0.8139**</td>
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<tr>
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<td>0.9524**</td>
<td>0.9240**</td>
<td>0.8932**</td>
<td>0.8599**</td>
<td>0.8230**</td>
<td>0.7628**</td>
<td>0.7384**</td>
<td>0.6344**</td>
<td>0.4681**</td>
</tr>
</tbody>
</table>

M.P: Microwave power, M.P *: Time interaction, LSD: Least Significant Difference, Means with the same letter are not significantly different from each other.

Table 4. DR mean values and significance groups for ANN and ANFIS at 5 mm thickness.

<table>
<thead>
<tr>
<th>M.P(W)</th>
<th>0</th>
<th>5</th>
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<tr>
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<td>0.0000**</td>
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<td>0.0088**</td>
<td>0.0089**</td>
<td>0.0168**</td>
<td>0.0186**</td>
<td>0.0202**</td>
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<td>0.0223**</td>
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<tr>
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<td>0.0026**</td>
<td>0.0059**</td>
<td>0.0090**</td>
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<td>0.0143**</td>
<td>0.0167**</td>
<td>0.0197**</td>
<td>0.0227**</td>
<td>0.0252**</td>
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<td>0.0177**</td>
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<td>0.0014**</td>
<td>0.0032**</td>
<td>0.0050**</td>
<td>0.0070**</td>
<td>0.0090**</td>
<td>0.0114**</td>
<td>0.0135**</td>
<td>0.0162**</td>
<td>0.0204**</td>
<td>0.0258**</td>
</tr>
<tr>
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<td>0.0000**</td>
<td>0.0020**</td>
<td>0.0060**</td>
<td>0.0089**</td>
<td>0.0145**</td>
<td>0.0191**</td>
<td>0.0242**</td>
<td>0.0294**</td>
<td>0.0348**</td>
<td>0.0345**</td>
<td>0.0131**</td>
</tr>
<tr>
<td>1.4</td>
<td>0.0016**</td>
<td>0.0028**</td>
<td>0.0037**</td>
<td>0.0049**</td>
<td>0.0062**</td>
<td>0.0075**</td>
<td>0.0090**</td>
<td>0.0105**</td>
<td>0.0121**</td>
<td>0.0161**</td>
<td>0.0241**</td>
</tr>
</tbody>
</table>

M.P: Microwave power, M.P *: Time interaction, LSD: Least Significant Difference, Means with the same letter are not significantly different from each other.

Fig. 10. Rules created for ANFIS Models.

widely employed to assess model performance. Rezai et al. (2019) used artificial neural networks to model the microwave drying of potato slices and calculated R² values in the 0.93 – 0.96 range, while Behroozi Khazaei et al. (2013) discovered comparable R² value results in the drying process of grapes.

ANOVA was performed on the obtained values and the statistical significance of the differences between the averages was determined by Tukey’s test. The difference between the MR and DR values was found to be statistically significant at the level of 1% according to the Tukey’s test (Tables 2–8).

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Table 5. MR mean values and significance groups for ANN and ANFIS at “10 mm” thickness.

<table>
<thead>
<tr>
<th>M.P (W)</th>
<th>Drying Time (s)</th>
<th>ANN</th>
<th>LSD</th>
<th>M.P * Time: 0.00093</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>5</td>
<td>0.9971</td>
<td>0.9951</td>
<td>0.9971</td>
</tr>
<tr>
<td>1.0</td>
<td>15</td>
<td>0.9731</td>
<td>0.9725</td>
<td>0.9731</td>
</tr>
<tr>
<td>1.4</td>
<td>30</td>
<td>0.9441</td>
<td>0.9435</td>
<td>0.9441</td>
</tr>
</tbody>
</table>

Table 6. DR mean values and significance groups for ANN and ANFIS at “10 mm” thickness.

<table>
<thead>
<tr>
<th>M.P (W)</th>
<th>Drying Time (s)</th>
<th>ANN</th>
<th>LSD</th>
<th>M.P * Time: 0.00093</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>5</td>
<td>0.9971</td>
<td>0.9951</td>
<td>0.9971</td>
</tr>
<tr>
<td>0.9731</td>
<td>0.9725</td>
<td>0.9731</td>
<td>0.9725</td>
<td>0.9731</td>
</tr>
<tr>
<td>0.9441</td>
<td>0.9435</td>
<td>0.9441</td>
<td>0.9435</td>
<td>0.9441</td>
</tr>
</tbody>
</table>

Table 7. MR mean values and significance groups for ANN and ANFIS at 15 mm thickness.

<table>
<thead>
<tr>
<th>M.P (W)</th>
<th>Drying Time (s)</th>
<th>ANN</th>
<th>LSD</th>
<th>M.P * Time: 0.00093</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>5</td>
<td>0.9971</td>
<td>0.9951</td>
<td>0.9971</td>
</tr>
<tr>
<td>1.0</td>
<td>15</td>
<td>0.9731</td>
<td>0.9725</td>
<td>0.9731</td>
</tr>
<tr>
<td>1.4</td>
<td>30</td>
<td>0.9441</td>
<td>0.9435</td>
<td>0.9441</td>
</tr>
</tbody>
</table>

Table 8. DR mean values and significance groups for ANN and ANFIS at “15 mm” thickness.

<table>
<thead>
<tr>
<th>M.P (W)</th>
<th>Drying Time (s)</th>
<th>ANN</th>
<th>LSD</th>
<th>M.P * Time: 0.00093</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>5</td>
<td>0.9971</td>
<td>0.9951</td>
<td>0.9971</td>
</tr>
<tr>
<td>1.0</td>
<td>15</td>
<td>0.9731</td>
<td>0.9725</td>
<td>0.9731</td>
</tr>
<tr>
<td>1.4</td>
<td>30</td>
<td>0.9441</td>
<td>0.9435</td>
<td>0.9441</td>
</tr>
</tbody>
</table>

In Tables 3 to 8, the estimation values are shown as a result of applying the MR and DR values to the ANN and ANFIS models. Estimated values were determined for each thickness, taking into consideration the same drying times. Considering all the tables, it is seen that the ANN and ANFIS values are proximity to each other. Statistically, means with the same letter as a result of the F test are not significantly different from each other.

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Philipp Agric Scientist (2023)106(3):293-305 301
CONCLUSION

In this study, the ANN model was chosen as the single hidden layer model, and the number of neurons in the hidden layer was determined to be 25. Similar to the ANFIS model, 15% of the experimental data was chosen as the test data in the ANN model. The ANFIS model, which includes 27 rules, created the most successful network through 140 data inputs, 85% training, and 15% test partitioning. These estimation models aim to minimize the number of tests for drying processes in the future. In this way, it is possible to easily predict how the system will behave at different powers, saving both time and energy. This method can also be applied by creating prediction models for different products and microwave powers. More data can be obtained using products with longer drying periods, and more successful predictive models can be obtained using different computational intelligence methods.

REFERENCES CITED


MOISTURE CONTENT AND DRYING RATE USING ANN AND ANFIS METHODS


YILDIZ AK, POLATCI H, ÜÇUN H. 2015. Drying of the banana (Musa cavendishii) fruit and modeling the kinetics of drying with artificial neural networks.
