Modeling drying kinetics of tomato slices under convective hot-air using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models

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Abstract: The study aimed to model the drying kinetics (drying time (DT), effective moisture diffusivity (D_{eff}), and specific energy consumption (SEC) of tomato slices dry with a convective hot-air dryer using artificial neural networks (ANN) and neuro-fuzzy inference system (ANFIS). The tomatoes were pretreated with water blanching (*WBP*), ascorbic acid *(AAP*) and sodium metabisulphite (*SBP*); sliced into 4, 6, and 8 mm thickness and dried at 40°C, 50°C, and 60°C air temperatures. The experimental drying data were fitted to ANN and ANFIS models, while the best topology was obtained. The model's predictive performance was determined using the coefficient of determination (R^2), means squared error (*MSE*), root means squared error (*RMSE*), and mean absolute error (*MAE*) between predicted and experimental results. The *DT* ranged between 11.5 and 22.5 h, D_{eff} (0.98 $\times 10^{-10}$ to 6.36 $\times 10^{-10}$ m^2 s^{-1}) and *SEC* (0.6247 to 1.9514 kWh kg^{-1}). Higher R^2 (0.9056–0.9834) with lower *MSE* (0.0014–2.2044), *RMSE* (0.00035 – 1.49 $\times 10^{-13}$) and *MAE* (0.00026 – 1.08 $\times 10^{-13}$) for ANFIS compared to ANN showed that ANFIS methodology could precisely predict experimental data. This study found that ANFIS is highly accurate in predicting the drying kinetic, thereby demonstrating its ability to find a meaningful relationship between drying kinetic and drying conditions. Therefore, the model developed in this study can be a valuable tool in accurately predicting drying kinetic in dried tomatoes.

Keywords: Drying kinetic, ANN**,** ANFIS, Hot-air drying, Modelling

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1 Introduction

Tomatoes are a seasonal crop that provides consumers with many health benefits and nutrients (Oke et al., 2017a). They are produced in surplus amounts during harvesting, but their physiological nature, including high moisture content, increased respiration rate, and soft texture, make them more vulnerable to spoilage and challenging to transport. Since tomatoes are highly perishable and seasonal, drying can be used to preserve them. At the same time, the acceptability of the final product depends on the method and processing variables used for the drying (Hussein et al., 2016a).

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Many studies have been conducted in the field of tomato drying. However, the complex nature of the drying system led to the use of drying mathematical models in estimating the drying kinetics, the behavior, and the energy needed to dry tomatoes. Many mathematical models, empirical and semi-empirical, have been proposed to estimate the drying characteristics of tomatoes. But these models are generally solutions of simultaneous heat and mass transfer differential equations, and the final result may be very complicated and difficult to use in actual drying systems (Oke et al., 2017b). Therefore, it is inevitable to consider different models like artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) for precise simulation of the drying process.

As a data processing system inspired by biological neural systems, ANN is a generalized mathematical model for human perception and an adequate tool for solving complex and nonlinear problems like drying systems (Oke et al., 2017b). ANN has been used to model the complex nonlinear relationships that occur in the drying process due to its high learning ability and capability to identify a system's input and output. ANN also permits adequate and precise drying process control in industrial applications. ANN has advantages over mathematical modeling, including its ability to handle large amounts of noisy data from dynamic and nonlinear systems, especially when the underlying physical relationship is not fully understood (Aghbashlo et al., 2015). An ANN model was created by Nadian et al. (2015) to forecast the color changes that occur when apple slices are dried using hot air. The ANN topology was shown to have a good ability to predict the network outputs with a minor error because there was a good agreement between experimental and estimated values. In order to predict changes in the moisture ratio of green bell peppers during hot air fluidized bed drying, Jafari et al. (2016) found that the ANN model was more effective and precise than the mathematical modeling method. The moisture ratio and color parameters of Ginkgo Biloba seeds during the microwave drying process were predicted by Bai et al. (2018) using ANN. The experimental data were successfully predicted with high accuracy using the ANN methodology with a high correlation coefficient (0.9056-0.9834) and a small mean square error (0.0014-2.2044). ANN was used to model the bael pulp's drying kinetics during microwave vacuum drying (Dash et al., 2020). The ANN that used a 3-6-1 topology, a tansig transfer function, and the Levenberg-Marquardt training algorithm performed the best in terms of minimum mean square error. By using ANN, Choudhary et al. (2022) investigated the simulation and modeling aspects of the hot air-drying kinetics of ginger. The 3-5-1 ANN architecture was selected as the top candidate for simulating the drying behavior of ginger slices.

ANFIS is an integrated modeling technique that combines the strength of ANN and fuzzy inference system (FIS) (Oke et al., 2018a). ANFIS employed the benefits from both methods to solve complex and nonlinear problems and achieve optimum results. Many researchers have applied the ANFIS method to explain the drying properties of many agricultural products. Bagheri et al. (2015) reported the ability of ANFIS models to predict the energy efficiency of a forced-convection solar dryer adequately. This study confirmed the ability of the developed model to determine and predict the drying behavior of leafy vegetables. Al-Mahasneh et al. (2016) compared ANFIS modeling with the conventional thin-layer drying models to predict roasted green wheat's moisture ratio in an open sun drying. The ANFIS model showed superior performance in comparison with two-term exponential mode with R^2 = 0.999, RMSE = 1.2×10^{-6} and R^2 = 0.988, RMSE = 0.038, respectively. The application of ANFIS and ANN models in predicting moisture diffusivity and specific energy consumption (SEC) of potato, garlic, and cantaloupe drying under a convective hot-air drier was compared by Kaveh et al. (2018); ANFIS had the best prediction ability.

Notwithstanding the good reports of ANN and ANFIS in modeling the drying characteristics of a various agricultural materials, there was a dearth of information on the ANN and ANFIS models to predict the drying kinetic of dried tomatoes. The study, therefore, aims to develop ANN and ANFIS models to predict the drying kinetics of tomatoes during drying in a convective hot-air dryer.

2 Materials and methods

2.1 Materials

The UTC varieties of tomatoes used in this study were obtained from the Teaching and Research Farm of the Modibbo Adama University of Technology, Yola, Adamawa State, Nigeria (latitude 9° 13′ – 9° 37′ N, longitude 12° 16′ – 12° 42′ E). The appearance, firmness, and size uniformity served as the basis for selection from the lot.

2.2 Methods

2.2.1 Sample preparation

Tomatoes were thoroughly cleaned by washing them under tap water. After that, it was rinsed with distilled water and wiped with a tissue towel, as described by Hussein et al. (2016b). Twelve (12) kg of tomatoes were subjected to each water blanching pretreatment (WBP) for 1 minute, 5% w/v of ascorbic acid pretreatment (AAP), and 5% w/v of sodium metabisulphite pretreatment (SMP) for 5 minutes. The ratio of 1:10 (w/v) for tomatoes to dipping solution, as used by Hussein et al. (2021), was adopted. After the pretreatment process, each portion was sliced into 4, 6, and 8 mm thick, respectively, with the aid of a Tomato Slicer (NEMCO 56610-13/16” Roma).

2.2.2 Taguchi experimental plan and drying procedure

The Taguchi experimental plan was designed with Minitab 16 (Minitab, Inc. Coventry, UK) software for three factors at three levels, having an array of L9 (3×3). The outline that gave nine experimental runs (Table 1) was obtained and used to evaluate the responses of the drying kinetics with the interactions between pretreatment, slice thickness, and drying temperature. The drying was carried out in a convective hot-air dryer (Model: TO008GA-34, AKAI-Tokoyo, Japan) following the procedure used by Hussein et al. (2021). The drying time, moisture ratio, and effective moisture diffusivities of the dried tomato slice were evaluated as described by Hussein et al. (2021). The SEC consumed for drying a kilogram of tomato slices is calculated using Equation 1 below, as described by Motevali et al. (2011) and Samadi and Loghmanieh (2013).

Table 1 Outline of Taguchi experimental design L_9 (3×3) for conventional hot-air oven drying

Experimental runs	Independent variables in coded form			Experimental variables in their natural units		
	A	B	C	Pretreatment	Thickness (mm)	Temperature (°C)
1	1.0	1.0	1.0	WBP	4.0	40.0
2	1.0	2.0	2.0	WBP	6.0	50.0
3	1.0	3.0	3.0	WBP	8.0	60.0
4	2.0	1.0	2.0	AAP	4.0	50.0
5	2.0	2.0	3.0	AAP	6.0	60.0
6	2.0	3.0	1.0	AAP	8.0	40.0
7	3.0	1.0	3.0	SMP	4.0	60.0
8	3.0	2.0	1.0	SMP	6.0	40.0
9	3.0	3.0	2.0	SMP	8.0	50.0

Note: WBP = Water blanched pretreated sample

AAP = Ascorbic acid pretreated sample

SMP = Sodium metabisulphite pretreated sample.

$$SEC = (\frac{\rho_a A v C_{pa} \Delta T}{M_w})t \quad (1)$$

Where,

SEC = specific energy consumption (kWh kg^{-1} $_{water}$),

ρ_a = density of air at a temperature (kgm^{-3})

A = the cross-sectional area of the channel that samples are placed (m^2)

v = the air velocity (ms^{-1})

C_{pa} = heat capacity of air at constant pressure ($kJkg^{-1}$ $℃^{-1}$),

t = total drying time (h),

M_w = mass of water evaporated (kg)

ΔT = change in temperature [i.e. between inlet and ambient air temperature] (°C).

2.2.3 ANN modelling design

The Neural Network Toolbox 8.0 of MATLAB software was used for the modeling. In designing the ANN, three significant stages are involved. The organization of the initial model to be developed is the first stage. In this first stage, the input, hidden, and output neurons, the initial numbers of hidden layers, and the learning methods were selected based trial and error method reported by Witek-Krowiak et al. (2014). The second stage was optimizing the ANN model's initial values to produce stable and accurate outputs. Thus, the most widely used ANN learning algorithm, back-propagation, which attempts to minimize the error at each iteration reported by Turan et al. (2011), was used. The last stage was evaluating the prediction performance of the optimized ANN model. This was done by comparing the predicted values with the numerically simulated ones. This work's input variable is; pretreatment, drying air temperature, and slice thickness. The corresponding outputs were drying time, effective moisture diffusivities, and SEC, as shown in Figure 1.

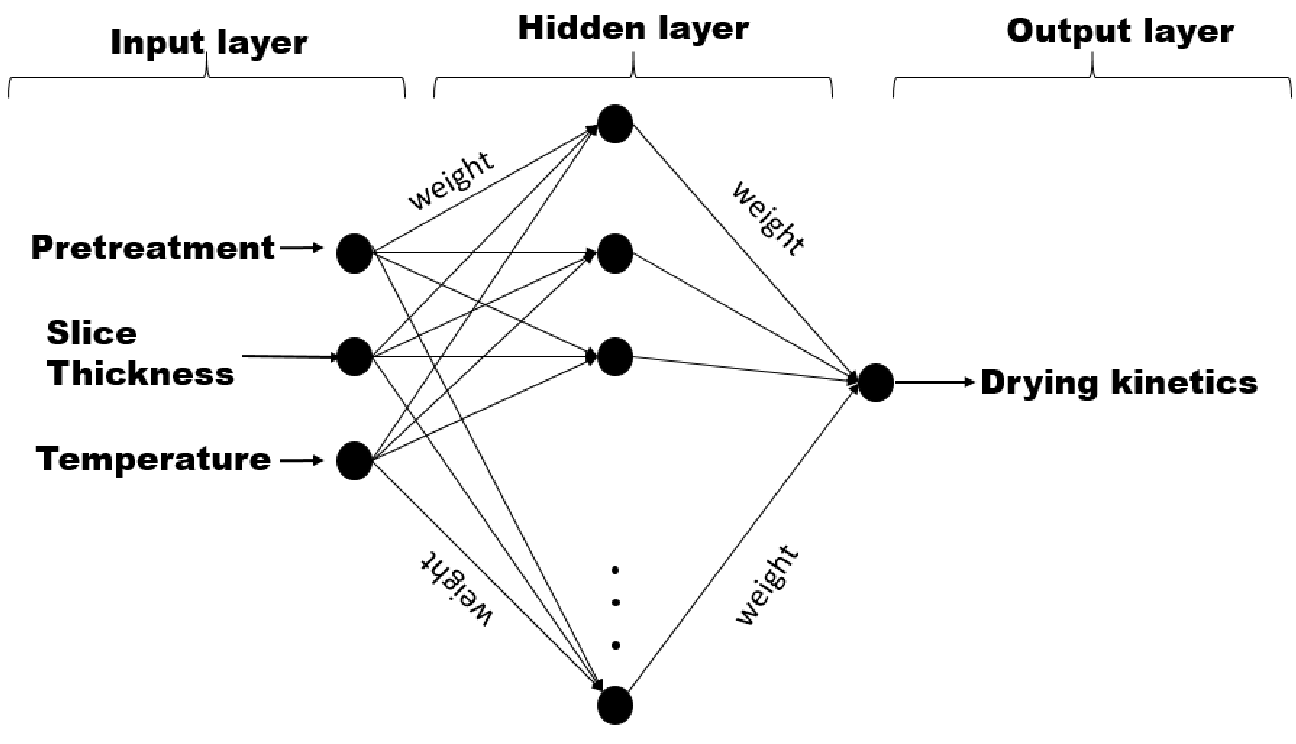


Figure 1 Schematic diagram developed ANN model

The experimental data obtained were divided randomly into three groups, 70% for training, 15% for validation, and the residual 15% for the testing set. The training data was used to train the neural network's weights to produce the desired outcome. The validation data find the best ANN configuration, training parameters, and monitor the network error during the training process. The testing data sets confirmed the actual predictive power of the developed neural network. The regression plots of the validation data set and that comparing the ANN's output and its target values were used as the stopping criterion for the training process. The input and output variables or responses were normalized between 0 and 1 to achieve fast convergence to minimal mean square error. The normalization was carried out using Equation 2 as described by Abdalla et al. (2014).

$$y_n = \frac{y_a - y_{min}}{y_{max} - y_{min}} \quad (2)$$

where; y_n, y_a, y_{min}, and y_{max} are normalized, actual, minimum, and maximum values, respectively.

The network predicted values, which were in the range of (0 – 1), were then transformed into real-world values using Equation 3 as described by Abdalla et al. (2014).

$$y_a = y_n(y_{max} - y_{min}) + y_{min} \quad (3)$$

2.2.4 ANFIS modelling design

The Takagi–Sugeno ANFIS in MATLAB (The MathWorks Inc., Natick, Massachusetts, USA) software was used to develop the model for the drying characteristics and changes in the qualities of dried tomatoes. The ‘exhsrch’ function in the MATLAB software environment was used for an exhaustive search within the available inputs to select the most influential inputs that affect the drying kinetics. Exhaustive search is a combinatorial function that determines the required number of inputs combination that has an optimal effect on the output performance (Aremu et al., 2014). The ANFIS model was developed by combining the least square method and back-propagation, as Oke et al. (2018b) described. The back-propagation was used for the input membership function parameters, while least-squares estimation was used for the output membership function parameters. The developed model was optimized with different types and numbers of membership functions to detect the optimized functions and their quantities. The effectiveness of ANFIS models in prediction depends on the number and type of membership functions and the number of training epochs (Tao et al., 2016).

Therefore, in the ANFIS model’s construction, 2 membership functions were assigned to each input variable to reduce divergence between experimental and predicted results. Three input parameters applied were pretreatment, slice thickness, and drying temperature, while the drying kinetics were set as output parameters. The output parameters were changing, while the input parameters were kept constant. Figure 2 shows the ANFIS model structure using the set parameters**.** The ANFIS modeling was launched, and the input and output data points were set. The data order was first randomized and divided into three groups: 70% for training, 15% for validating, while the residual 15% was used for testing. The triangular, trapezoidal, and Gaussian membership functions were used in line with the model's bivariate input alongside 2 membership functions to detect the optimized model, as Farzaneh et al. (2017) and Tao et al. (2016) described. A preliminary simulation study was first conducted to obtain the optimum epoch needed for the ANFIS setting, and 500 to 1000 epoch values were chosen as the best epoch value, thus used for the subsequent simulation.

2.2.5 Model performance

The performance and effectiveness of the models were calculated using the following criteria, namely; correlation coefficient (*R*), coefficient of determination (R^2), mean square error (*MSE*), root mean square error (*RMSE*), and mean absolute error (*MAE*) which are defined in Equations 4, 5, 6, 7 and 8. *R* and R^2 inform the correctness of model fitting. *R* and R^2 closer to 1 are counted as reliable. The values of *MSE* and *RMSE* indicate the difference between the predicted and experimental values. The network was considered satisfactory when the values of *MSE* and *RMSE* were closer to 0. *MAE* indicates the predictions' closeness to the final outcomes (Nazghelichi et al., 2011; Hussein et al., 2022).

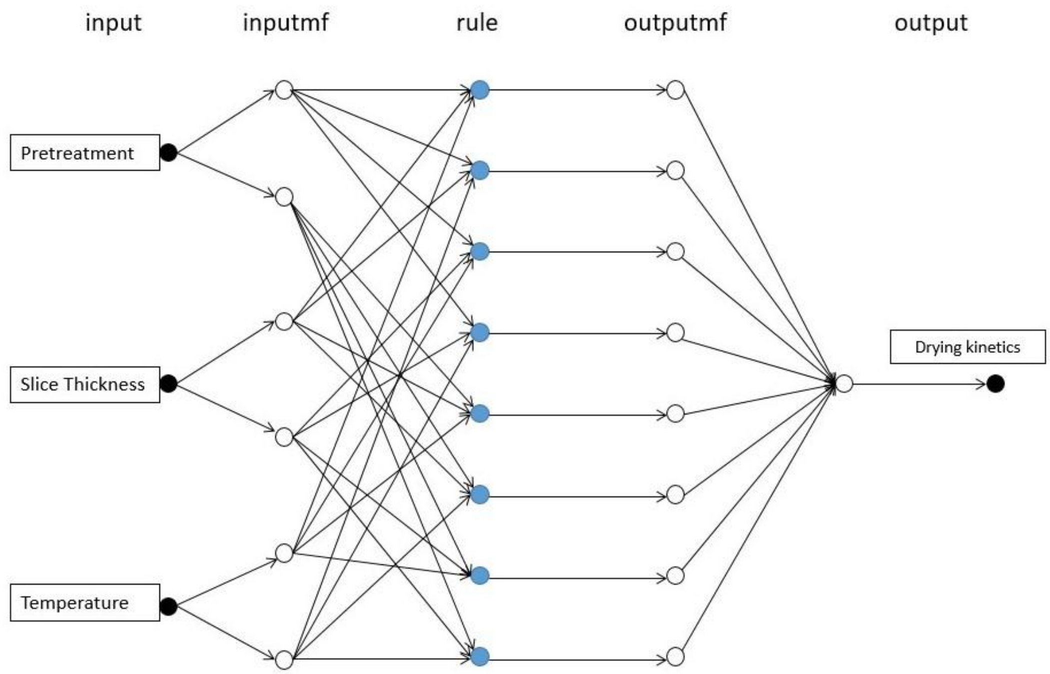


Figure 2 Schematic diagram developed for ANFIS model

$$R = \frac{\sum(y_o - y_o^1)(y_e - y_e^1)}{\sqrt{\sum(y_o - y_o^1)^2 \sum(y_e - y_e^1)^2}} \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_0 - y_e)^2}{\sum_{i=1}^{n}(y_0 - y_o^1)^2} \quad (5)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_o - y_e)^2 \quad (6)$$

$$RMSE = \left(\frac{1}{N}\sum_{i=1}^{n}(y_o - y_e)^2\right)^{1/2} \quad (7)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_o - y_e|^2 \quad (8)$$

Where,

n = the number of experiments used for developing the model,

y_o = the predicted value of the model,

y_o^1 = the average value of the predicted model,

y_e = the actual or experimental value and

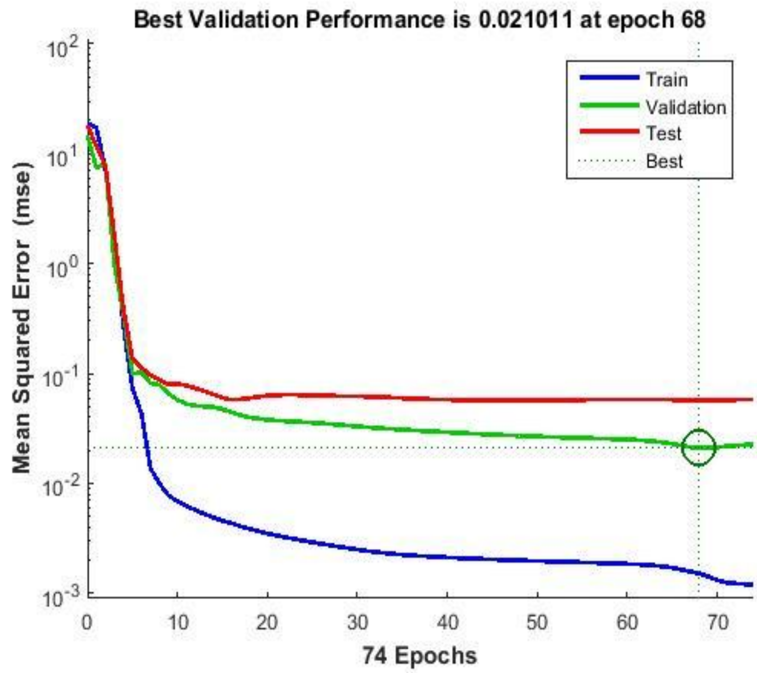
y_e^1 = the average of actual values.

3 Results and discussion

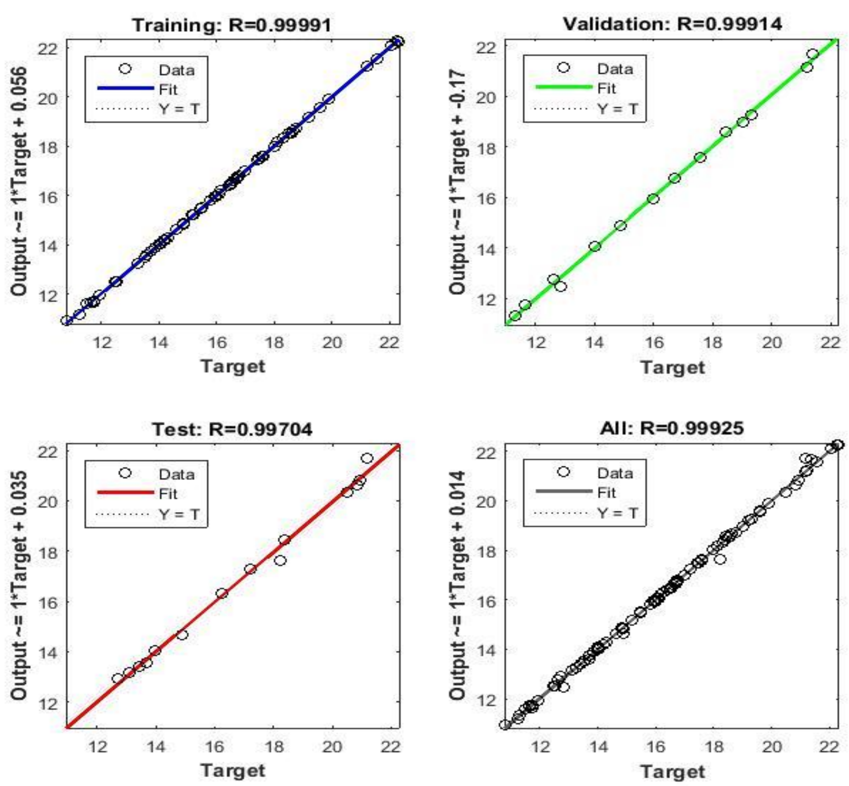
3.1 Drying kinetics of the pretreated tomato slices

The total drying time required to dry the pretreated tomato slice to the equilibrium moisture content of 15.67% to 0.12% (dry basis) ranged from 11.5 to 22.5 h, with the experimental run (WBP, 4 mm, 40°C) having the highest value. In contrast, the experimental run (SMP, 4 mm, 60°C) had the lowest value. The result showed an accelerated rate in the drying process as the drying temperatures increased. This showed that the higher the drying air temperature, the shorter the drying time for a given thickness. The ease of this moisture migration was due to higher temperature gradients created by higher air temperature, which eased water migration from the tomato's inner part to the surface to evaporate (Hussein et al., 2016b). The values of the D_{eff} of the pretreated tomato samples varied between 0.98×10^{-10} to 6.36×10^{-10} m^2s^{-1}. These values are within range of 10^{-12} to 10^{-8} m^2s^{-1} for drying agricultural materials (Doymaz, 2010).

The SEC in the drying of pretreated tomato slices ranges from 0.6247 to 1.9514 kWh kg^{-1}, with the experimental run (WBP, 8 mm, 60°C) having the highest value while the experimental run (SMP, 6 mm, 40°C) had the lowest value. This showed that the SEC increases with increasing the slice thickness and drying temperature. In other words, each factor causing an increase in input energy rate also causes the SEC to increase. A similar result was reported by Chayjan (2012) for potato slices and Pillai et al. (2010) for plaster of paris. The highest SEC was obtained for WBP and the thickest sample. This was probably due to the high energy utilized in transferring heat to the internal regions of the slice and the heat transfer distance. Similar results have been observed for ginger slices by Afolabi et al. (2014).



(a) ANN training performance



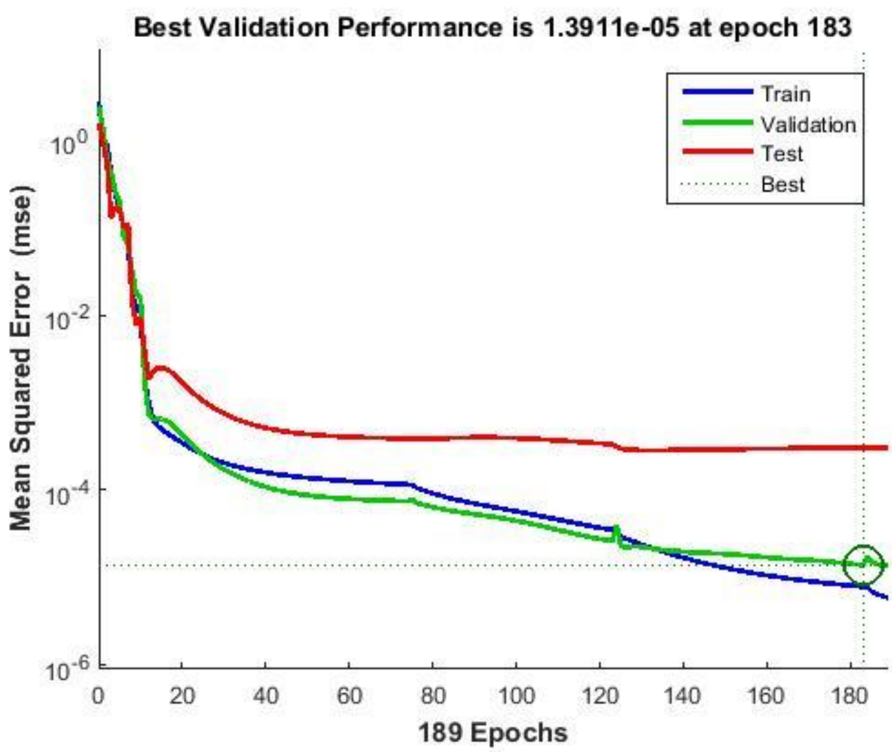
(b) Regression analysis

Figure 3 The ANN training performance and regression analysis for training and validation datasets for hot-air drying time

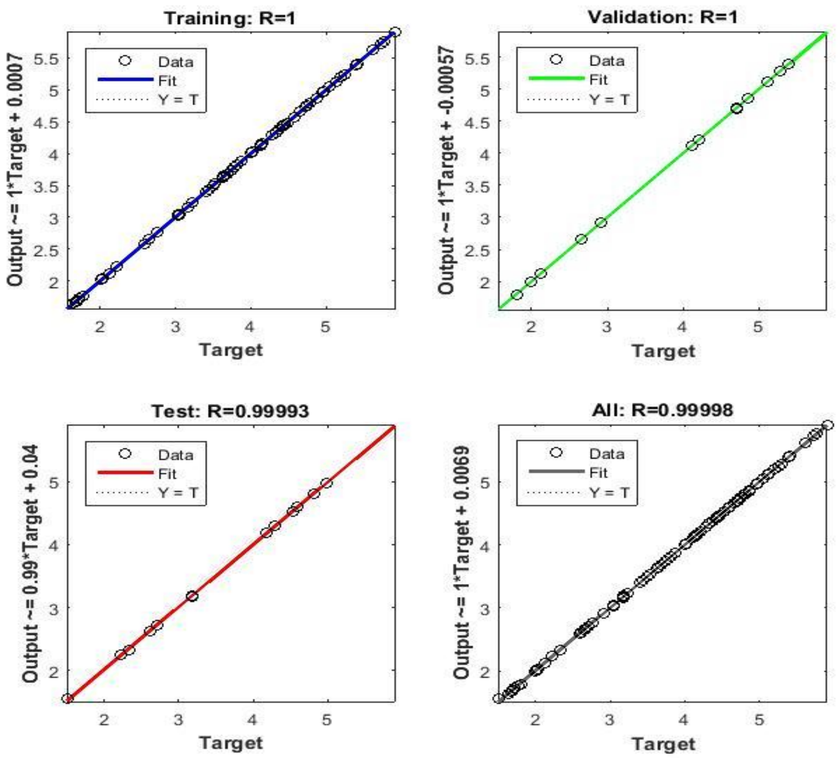
3.2 Modeling the effect of drying conditions on the drying time of hot-air dried tomato slices using ANN

The optimum topology and transfer function for predicting drying time was achieved after repeated trials of different topologies and transfer functions. The neural network architecture with 3-11-1 topology was observed to produce the best performance model. That is, three (3) inputs (pretreatment, slice thickness, and drying temperature), one hidden layer consisting of 11 neurons, and tangent sigmoid function (tansig) at both the hidden and output layer. The generated ANN model was used to simulate the effect of input data on the output data. The best optimal architecture was terminated at a high *R* and low *MSE*. Figure 3 shows the ANN training performance and regression analysis for training and validation datasets for drying time. The training was stopped after 74 epochs, as shown in Figure 3a, to prevent overfitting the network. The best ANN network was identified at 68 epochs after stopping the training. The regression analysis between ANN outputs and the experimental data for drying time gave a precise and effective prediction at *R* of 0.99991, 0.99914, 0.99704, and 0.99925 for training, validation, testing, and all data, respectively (Figure 3b). The MSE value was found to be 0.02101 at 68 epochs for the optimal architecture.

The simulated result was plotted to show the fitness between experimental values and predicted drying time to verify the model. The simulated regression plot's R^2 was 0.99810. The *RMSE* and *MAE* were 0.13090 and 0.07719, respectively. Zaibunnisa et al. (2009) and Hussein et al. (2022) reported that when R^2 is closer to unity, the better will the empirical model fits the experimental data. The obtained R^2, RMSE, and MAE values for the drying time showed a good correlation between the actual and predicted drying time. Thus, the ANN model fits well for predicting the drying time. Comparable results were reported for dehydration of other fruits such as carrot (Erenturk and Erenturk, 2007), pumpkin (Zenoozian et al., 2007), and ginger (Choudhary et al., 2022).



(a) ANN training performance



(b) Regression analysis

Figure 4 The ANN training performance and regression analysis for training and validation datasets for effective moisture diffusivity of hot-air drying

3.3 Modeling the effect of drying conditions on the effective moisture diffusivity of hot-air dried tomato slices using ANN

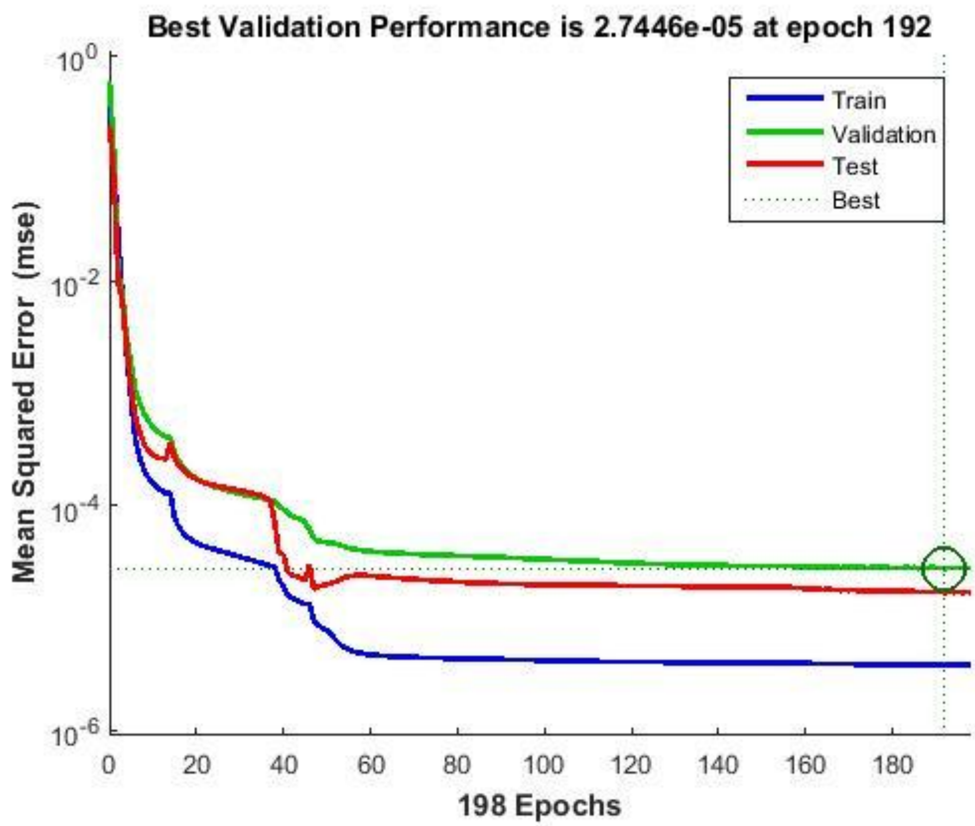
Different topologies and the number of neurons in the hidden layer were tried to determine the optimum number. It was observed that neural network architecture with a 3-9-1 topology produced the best performance model. Three (3) inputs (pretreatment, slice thickness, and temperature), one hidden layer consisting of 9 neurons, and tangent sigmoid function at both hidden and output layers. The generated ANN model was used to simulate the effect of input data on the output data. The best optimal architecture was terminated at high *R* and *MSE*. Figure 4 shows the ANN training performance and regression analysis for training and validation datasets for effective moisture diffusivity. The training was stopped after 189 epochs, as shown in Figure 4a, to prevent overfitting the network. After stopping the training process, the best ANN network was identified at 183 epochs. The regression analysis between ANN outputs and the experimental data of the effective moisture diffusivity gave a precise and useful prediction of the ANN model with *R* of 1.00000, 1.00000, 0.99993, and 0.99998 for training, validation, testing, and all data, respectively (Figure 4b). The MSE value was 0.00001 at 183 training epochs for the optimal architecture.

The fitness between experimental and predicted moisture diffusivity was verified. The R^2 of the simulated regression plot was 1.0. The RMSE and MAE were 0.00743 and 0.00337, respectively. The R^2, RMSE, and MAE values of the effective moisture diffusivity gave a good correlation between the actual and predicted values. Thus, the ANN model fits well for predicting the effective moisture diffusivity of the pretreated tomato slice. A similar result was reported by Zhang et al. (2002) for the moisture and drying rate of rough rice predicted with the ANN model. This result also corroborated ANN modeling of moisture diffusivity of carrot (Aghbashlo et al., 2011), pomegranate seed (Chayjan et al., 2012), and terebinth fruit (Kaveh and Chayjan, 2015).

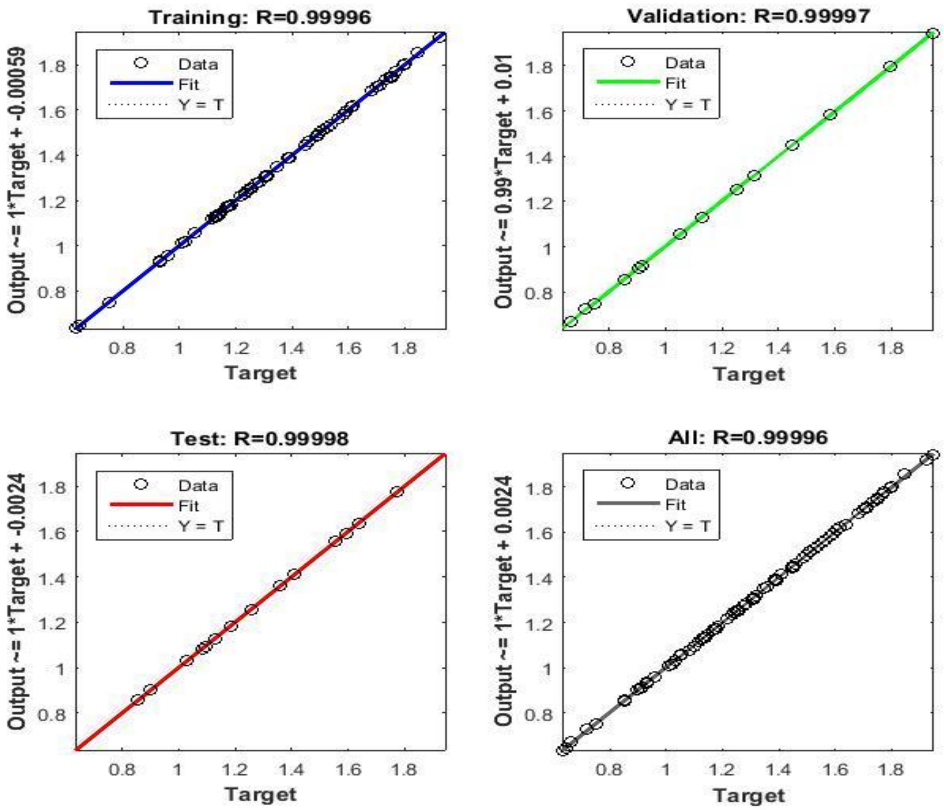
3.4 Modeling the effect of drying conditions on the SEC of hot-air dried tomato slices using ANN

The optimum topology and transfer function for predicting the energy consumption during convective hot-air drying of pretreated tomato slices was achieved after repeated trials of different topology and transfer functions. It was observed that the ANN architecture with 7 neurons at the hidden layer and one neuron at the hidden layer produced the best performance model. The optimal architecture of the developed ANN model for SEC was three (3) inputs (pretreatment, slice thickness, and temperature), one hidden layer with 7 neurons, and a logarithmic sigmoid function at the hidden layer and tangent sigmoid function at the output layer. Beigi et al. (2017) applied a similar ANN with a 3-6-1 topology to predict the SEC of rough rice in a laboratory-scale convective dryer. They reported that the Levenberg-Marquardt training algorithm with the sigmoid transfer function gave the most accurate network.

The generated ANN model was simulated, and the best optimal architecture was terminated at low *MSE*, and high *R*. Figure 5 shows the ANN training performance and regression analysis for training and validation datasets for SEC. The training was stopped after 198 epochs (Figure 5a), and the best ANN network was identified at 192 epochs after stopping training. The regression analysis between ANN outputs and the experimental data gave a precise and effective prediction of the ANN model with a *R* of 0.99996, 0.99997, 0.99998, and 0.99996 for training, validation, testing, and all data, respectively (Figure 5b). The MSE value was 0.00003 at 192 epochs for the optimal architecture.



(a) ANN training performance



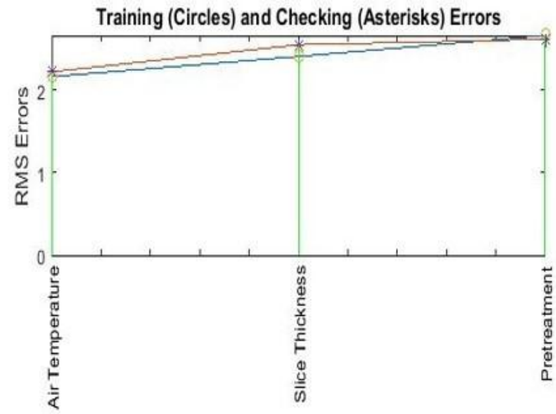
(b) Regression analysis

Figure 5 The ANN training performance and regression analysis for training and validation datasets for SEC of hot-air drying

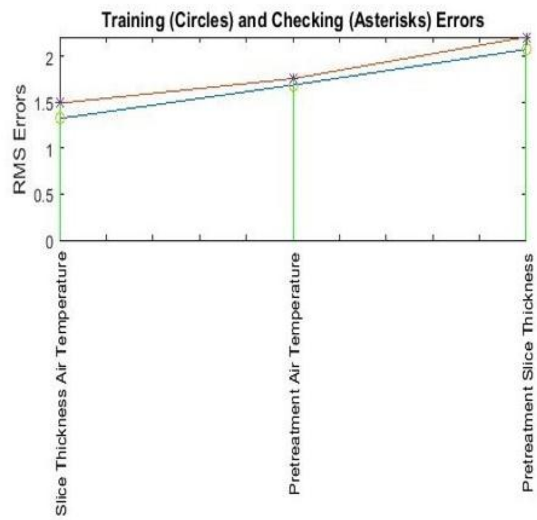
The experimental versus predicted values for the simulated SEC for hot-air drying of pretreated tomato slices was plotted. The R^2 of the simulated regression plot was 0.9999. The *RMSE* and *MAE* were 0.00309 and 0.00220, respectively. The obtained R^2, *RMSE*, and *MAE* values for the SEC showed that the model simulated the experiments satisfactorily. The developed ANN model had an excellent generalization in predicting the SEC in tomato slices' drying. Furthermore, the result gave good agreement between the predicted and the experimental values of SEC. This result corroborated with what was reported by Beigi et al. (2017) and Kaveh et al. (2018) for the SEC of rough rice, potato, garlic, and cantaloupe dried in a convective hot-air dryer.

3.5 Modeling the effect of drying conditions on drying time of hot-air dried tomato slices using ANFIS

An exhaustive search was performed on the experimental results to get the optimal effect of different input variable combinations on the drying time. Figure 6 shows an exhaustive search of the ANFIS model for one and two variables, respectively. For one input variable, the air temperature was found to have the lowest training error of 2.1654 and a checking error of 2.2236. This indicated that this input variable was the most relevant variable concerning the pretreated tomato slice's drying time in the hot-air drying. For two input variables, the combination of slice thickness and the air temperature was found to have the lowest training error of 1.3227 and a checking error of 1.4893. Thus, the most significant input variables controlling the output performance. This result corroborated with Kulanthaisami et al. (2010) and Hussein et al. (2016b), which stated that the drying time decreased significantly as the slice thickness decreased. This is because the resistance to moisture migration is relatively higher in thicker slices than in thinner ones. Also, pretreatment reduces the resistance to moisture migration, thereby increasing the drying rate, as Doymaz and Ozdemir (2014) reported.



(a) One input variable



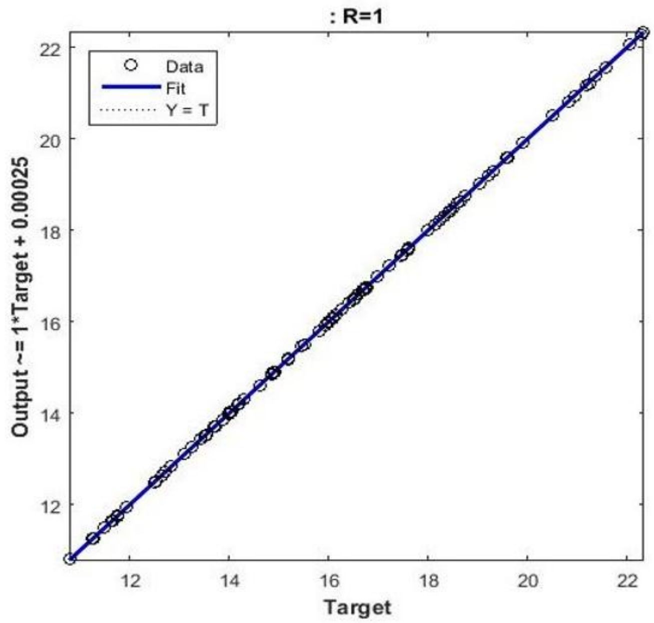
(b) Two input variables combination

Figure 6 ANFIS exhaustive search for one and two input variables and their influence on the hot-air drying time

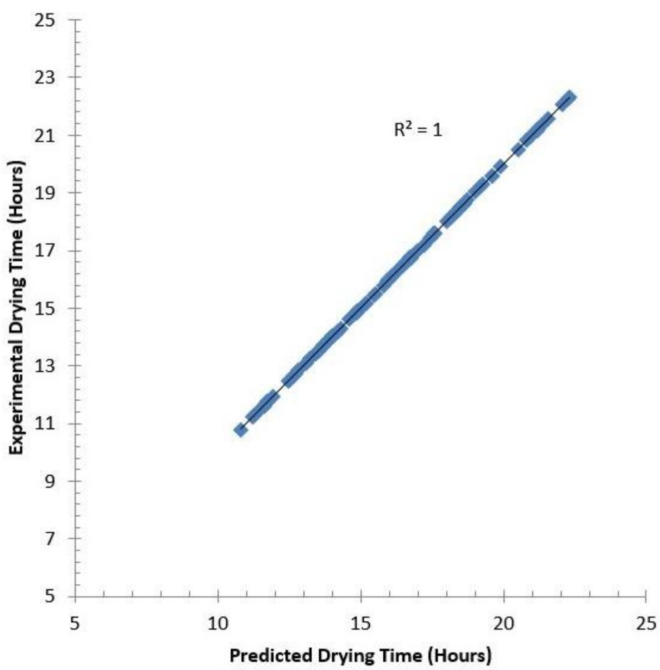
The three input parameters, pretreatment, slice thickness, and air temperature, were used for the ANFIS predictive technique to predict the drying time. The effects of different input membership functions (IMF), such as tri, trap, gbell, gauss, gauss2, pi, psig, and dsig, with high epoch numbers (1000) were tested and verified to determine the best input MF and training number for ANFIS model for the prediction of drying time. The effects of the two output membership functions (OMF), linear and constant, were evaluated. It was observed that the ANFIS architecture with 2 type membership functions (MFs), gauss IMF and linear OMF, had the highest predictive accuracy. The regression analysis of the ANFIS outputs and the experimental data gave a prediction with a R^2 of 1 (Figure 7a). The regression plot observed that the data bound around the ideal trend line indicating the model adequacy for predicting the test data. The *RMSE* for both the training (0.00878) and testing (0.00987) of ANFIS are very small, reflecting the ability of ANFIS to capture the essential components of underlying dynamics governing the relationships between the input and the output variables.

The simulation accuracy of the developed ANFIS model was performed to validate the reliability of the network. The predicted and experimental value of the drying time was plotted in Figure 7b. The R^2 of the simulated regression plot was 1. The *RMSE* and *MAE* were 0.00879 and 0.00670, respectively. Chong et al. (2015) and Tao et al. (2016) reported that R^2 value of an ANFIS model should be more than 0.8 to have a satisfactory agreement between experimental and predicted data. This high value of R^2 and relatively low

RMSE and *MAE* values implies that the developed ANFIS model could simulate the drying time of the pretreated tomato slice dried in the hot-air dryer.



(a) ANFIS model correlation coefficient



(b) Coefficient of determination

Figures 7 Regression between the experimental and predicted drying time in hot-air drying using ANFIS model

The ANFIS decision surface plot for the effect of the pretreatment, slice thickness, and air temperature on the drying time is shown in Figure 8. It was observed from the plot that increasing the drying air temperature reduced the drying time. While increasing the slice thickness increased the drying time. This could be due to high-temperature gradients created by higher air temperature, which ease water migration from the inner part to the surface to evaporate. The ease of this migration could depend on the samples' porosity, drying air temperatures, and the surface area available, as Hussein et al. (2016b) reported.

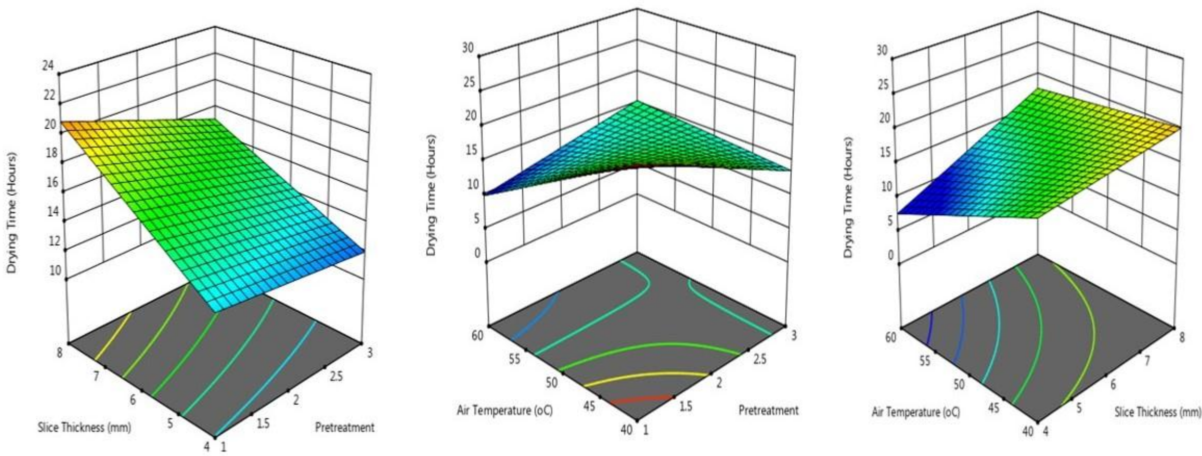
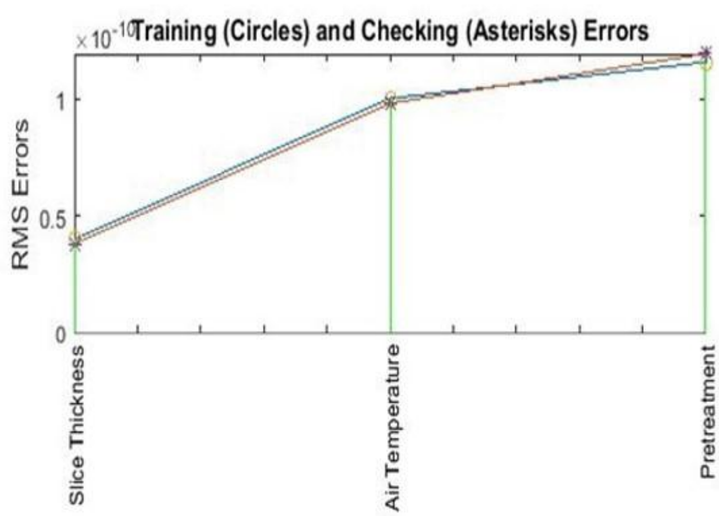


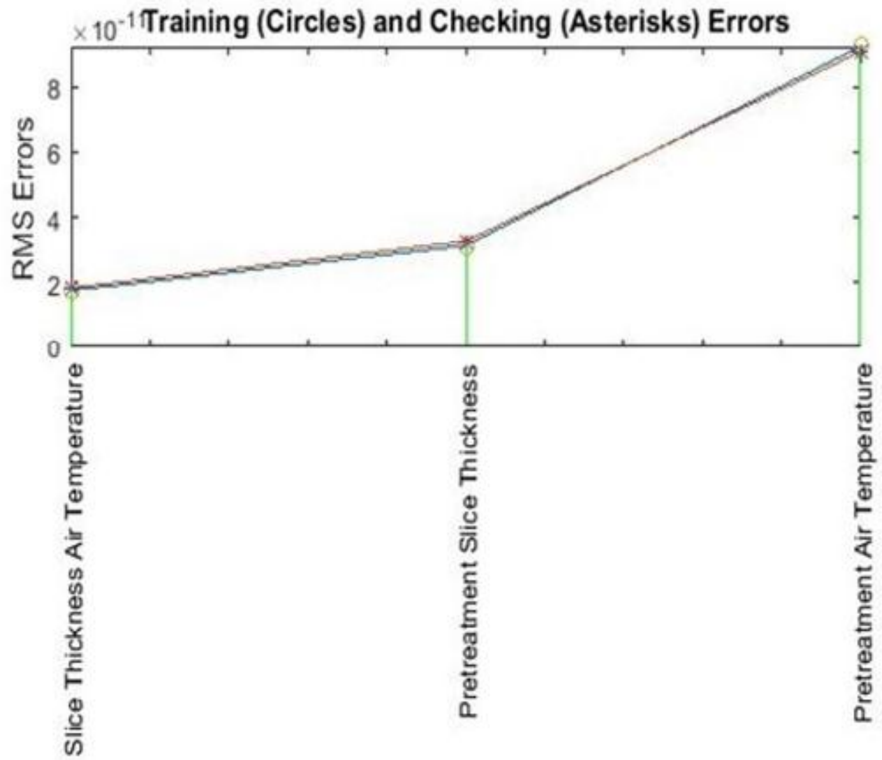
Figure 8 The ANFIS decision surface plot for the effect of pretreatment, slice thickness and air temperature on the value of drying time

3.6 Modeling the effect of drying conditions on the effective moisture diffusivity of hot-air dried tomato slices using ANFIS

An exhaustive search was performed on the experimental results to know the optimal effect of different input variable combinations on the hot-air effective moisture diffusivity. Figure 9 shows the results of the exhaustive search ANFIS model for one and two variables, respectively. For one input variable, the slice thickness was found to have the least training error of 0.4018 and a checking error of 0.3807. This indicated that this input variable was the most relevant variable concerning moisture diffusivity of pretreated tomato slices with hot-air drying. For two input variables, the slice thickness and the air temperature combination were found to have the least training error of 0.1760 and the checking error of 0.1836. Thus, the most significant input variables to the output performance. This supported the results of Touil et al. (2014), Afolabi et al. (2014), and Onu et al. (2016) that the effective moisture diffusivity content of a material is significantly affected by the shorter distance the moisture needs to travel before it evaporates to the surroundings. However, there was a high difference between the training and checking errors, as shown in Figure 9. Aremu et al. (2014) and Oke et al. (2018a) reported that a high difference between the training and checking errors implied overfitting during the exhaustive search.

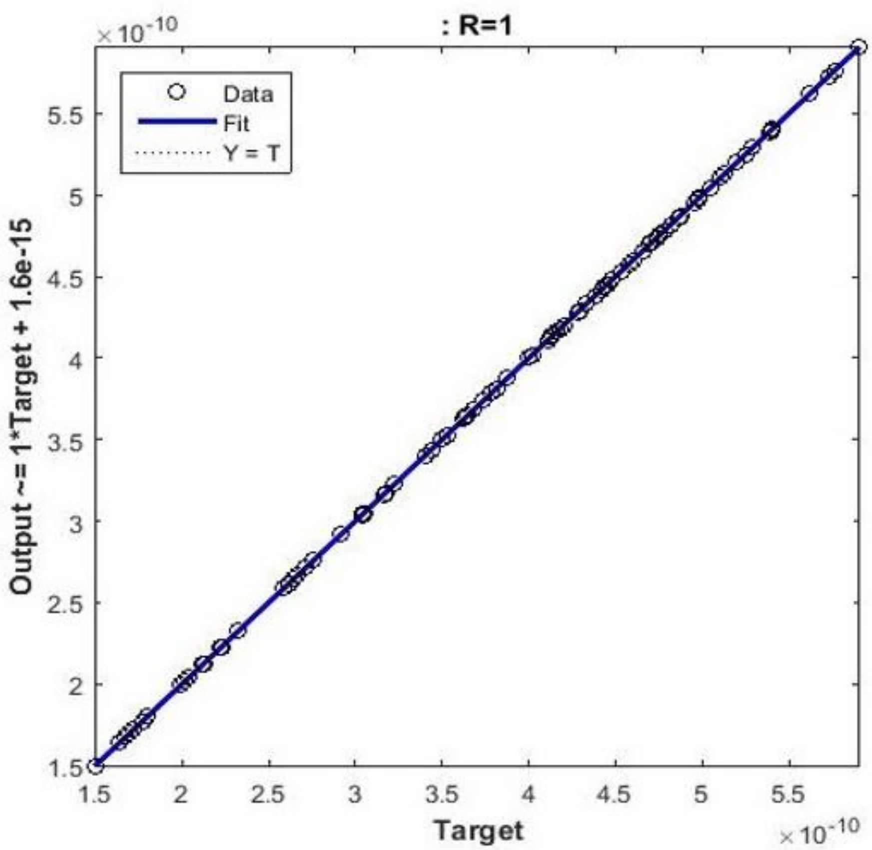


(a) One input variable

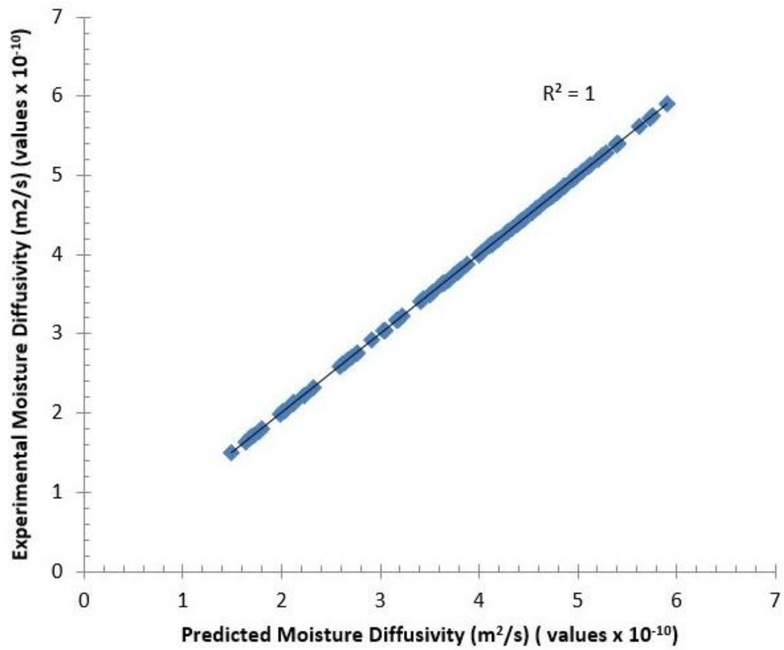


(b) Two input variables combination

Figure 9 ANFIS exhaustive search for one and two input variables and their influence on the hot-air moisture diffusivity



(a) ANFIS model correlation coefficient



(b) Coefficient of determination

Figure 10 Regression between the experimental and predicted moisture diffusivity in hot-air drying using ANFIS model

The 3 input parameters, including pretreatment, slice thickness, and air temperature, were used for ANFIS predictive technique to predict the moisture diffusivity. Different IMF effects such as tri, trap, gbell, gauss, gauss2, pi, psig, and dsig, with high epoch number (500), were tested and verified to determine the best input MFs and training number for the ANFIS model for the prediction of moisture diffusivity. The training's epoch value of 500 was used to minimize the error measure. Also, the effects of the two OMF, linear and constant, were evaluated. It was observed that the ANFIS architecture with 2 type MFs, gbell IMF and linear OMF had the highest predictive accuracy. A similar ANFIS structure was reported by Tao et al. (2016) for ANFIS modeling of dried cherry tomatoes' water activity.

The regression analysis of the ANFIS outputs and the experimental data gave a prediction with a R^2 of 1 (Figure 10a). The regression plot observed that the data bounded around the ideal trend line explaining the model adequacy in predicting the test data. The *RMSE* for both the training (1.49×10^{-13}) and testing (1.55×10^{-13}) of ANFIS are very small, reflecting the capacity of ANFIS to capture the essential components of underlying dynamics governing the relationships between the input and output variables. The simulation accuracy of the developed ANFIS model was performed to validate the reliability of the network. The predicted and experimental value of the moisture diffusivity was plotted in Figure 10b. The R^2 of the simulated regression plot was 1. The *RMSE* and *MAE* were 1.49×10^{-13} and 1.08×10^{-13}, respectively. Nazghelichi et al. (2011) and Hussein et al. (2022) reported that the closer the R^2 to unity, the better the empirical model would fit the experimental data. Based on this high value of R^2 and low *RMSE* and *MAE* values, the developed ANFIS model could simulate the moisture diffusivity of the dried pretreated tomato slice in the convective hot-air dryer.

The ANFIS decision surface plot for the effect of pretreatment, thickness, and air temperature on the value of moisture diffusivity is shown in Figure 11. From the plot, it was observed that increasing the air temperature reduced the moisture diffusivity. Likewise, increasing the slice thickness also decreased the moisture diffusivity. This is probably because the water needs to migrate a long thickness from the inside to the surface of the product before it evaporates, as Hussein et al. (2016b) reported. The SMP pretreatment showed a higher increase in moisture diffusivity compared to others. This could be due to the SMP reducing the tomato surface's hardening by destroying the cell membrane stability and changing the resistance to internal moisture diffusion by altering of the microstructure the tomato samples under processing.

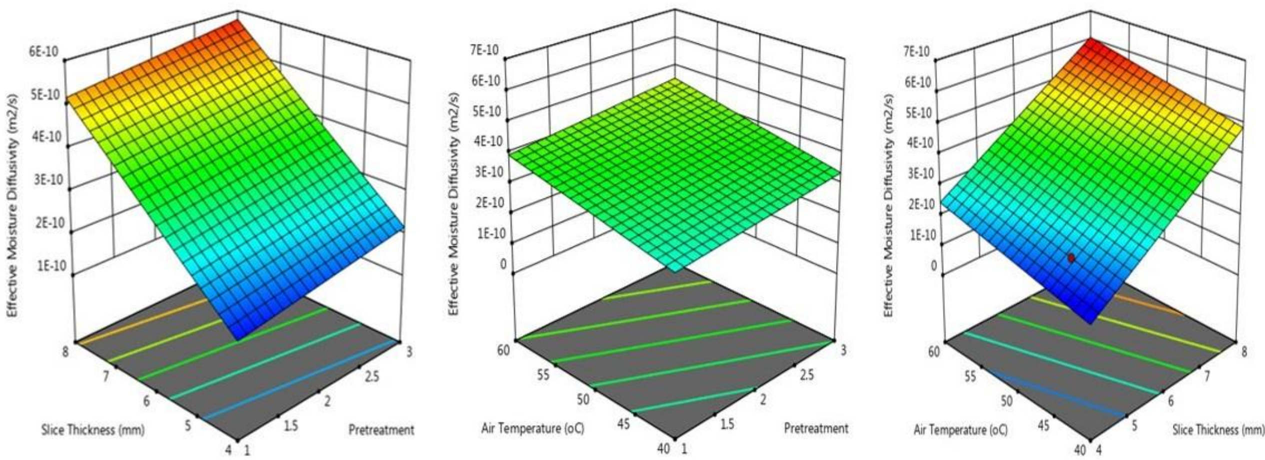
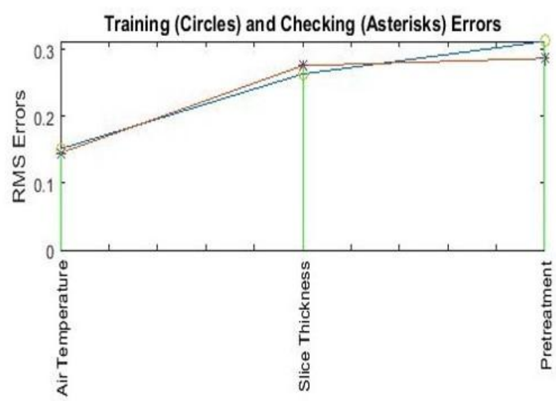
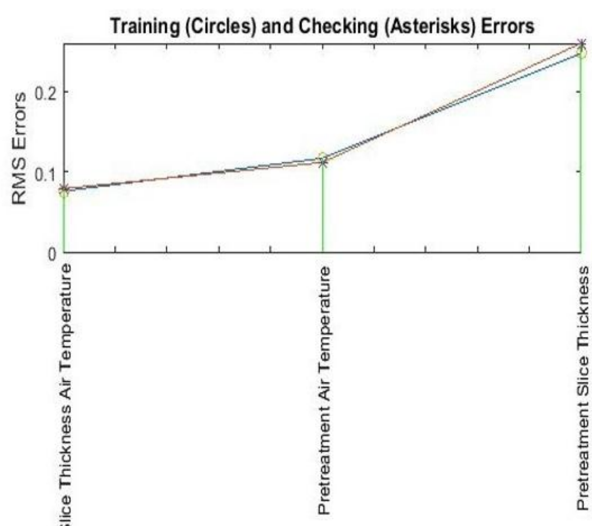


Figure 11 The ANFIS decision surface plot for the effect of pretreatment, slice thickness and air temperature on the value of moisture diffusivity



(a) One input variable



(b) Two input variables combination

Figure 12 ANFIS exhaustive search for one and two input variables and their influence on the hot-air SEC

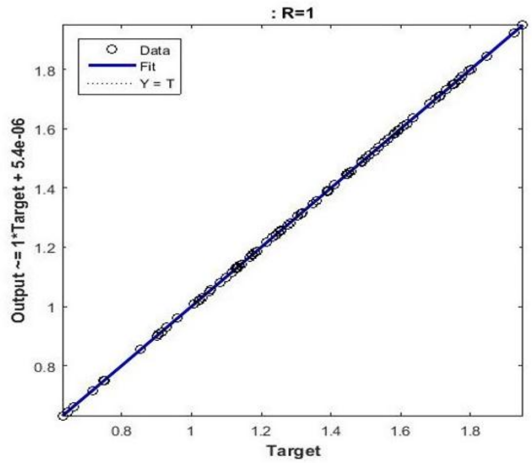
3.7 Modeling the effect of drying conditions on the SEC of hot-air dried tomato slices using ANFIS

An exhaustive search was performed on the experimental results to get the optimum effect of the different input variable combinations on the hot-air SEC. Figure 12 shows the exhaustive search ANFIS model results for one and two variables, respectively. For one input variable, the air temperature was found to have the lowest training error of 0.1515 and a checking error of 0.1455. This indicated that this input variable was the most relevant variable concerning SEC of pretreated tomato slices with hot-air drying. For two input variables, the slice thickness and the air temperature combination was found to have the lowest training error of 0.0759 and a checking error of 0.0790. Thus, the most significant input variables to the output performance. As indicated in the figure, the training and checking errors were slightly different, implying overfitting during the exhaustive search. Aremu et al. (2014) and Oke et al. (2018a) reported that the low difference between training and checking errors implied less overfitting during the exhaustive search.

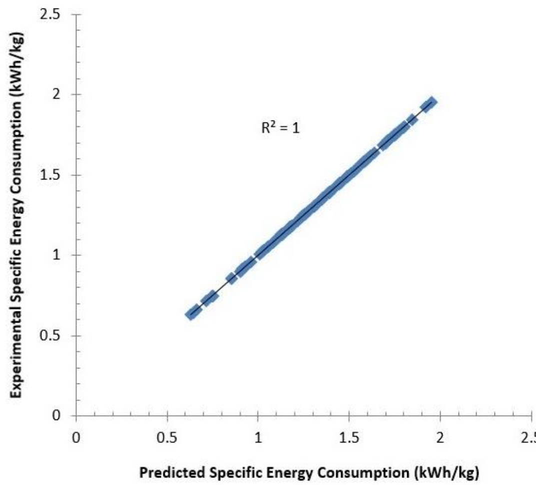
The 3 input parameters, including pretreatment, slice thickness, and air temperature, were used for the ANFIS predictive technique to predict the SEC. Different IMF effects such as tri, trap, gbell, gauss, gauss2, pi, psig, and dsig, with high epoch number (500) were tested and verified to determine the best input MFs and training number for the ANFIS model for the prediction of SEC. Also, the effects of the two OMF, linear and constant, were evaluated. It was observed that the ANFIS architecture with 2 type MFs, gbell, gauss, and gauss2 IMF with linear OMF, had the highest predictive accuracy. A similar ANFIS structure was reported by Kaveh et al. (2018) for the ANFIS modeling of SEC of dried garlic, potato, and cantaloupe.

The regression analysis of the ANFIS outputs and the experimental data gave a prediction with a R^2 of 1 (Figure 13a). It was observed from the regression plot that the data bounded around the ideal trend line satisfying the model adequacy in predicting the test data. The *RMSE* for the training (0.00035) and testing (0.00028) of the ANFIS model is very small, showing the model's ability to capture the essential components underlying the dynamics governing the relationships between the input and output variables. The developed ANFIS model's simulation accuracy was performed to validate the network's reliability. The predicted and experimental *value* of the SEC was plotted in Figure 13b. The R^2 of the simulated regression plot was 1. The *RMSE* and *MAE* were 0.00035 and 0.00026, respectively. Chong et al. (2015) and Tao et al. (2016) reported that the R^2 values of an ANFIS model greater than 0.8 have a satisfactory agreement between the actual and predicted data. Thus, based on this high value of R^2 and low values of *RMSE* and *MAE*, it implies that the developed ANFIS model is reliable for simulating the SEC of the pretreated tomato slice dried in the hot-air dryer.

The ANFIS decision surface plot for the effect of pretreatment, thickness, and air temperature on the value of SEC is depicted in Figure 14. It was observed from the plot that increasing the air temperature increases the SEC. Also, increasing the slice thickness increased the SEC. This is probably because the water needs to move a long thickness from the inside to the product's surface before evaporating, thereby increasing the energy taken. A similar observation was reported by Afolabi et al. (2014) for the ginger slice SEC. It was also observed that the highest SEC was obtained for WBP samples, followed by AAP and SMP pretreatment. This shows that each factor responsible for an increase in the input energy rate also aids the SEC increase. This result corroborates with what was reported by Pillai et al. (2010) for plaster of Paris, Chayjan (2012) for potato slice, Tunde-Akintunde et al. (2014) for bell pepper, and Kaveh et al. (2018) for ANFIS modeling of the SEC of the dried potato, garlic, and cantaloupe. Tunde-Akintunde et al. (2014) also reported that pretreatment before drying bell pepper could be used to optimize energy utilization, especially in areas where the cost of energy usage is high.



(a) ANFIS model correlation coefficient



(b) Coefficient of determination

Figure 13 Regression between the experimental and predicted specific energy consumption in hot-air drying using ANFIS model

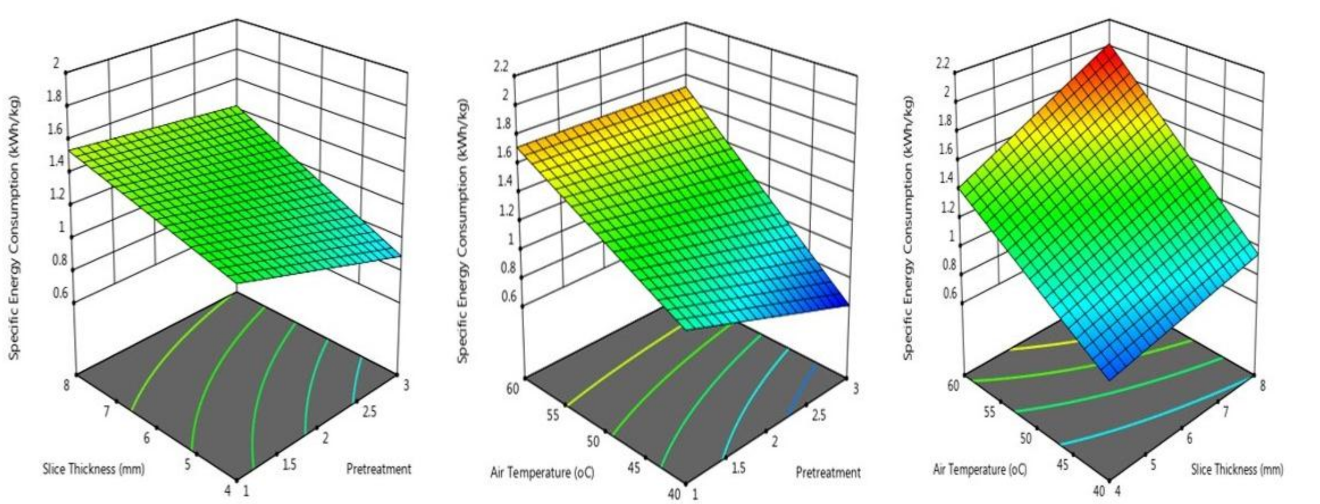


Figure 14 The ANFIS decision surface plot for the effect of pretreatment, slice thickness and air temperature on the value of specific energy consumption

4 Conclusions

This study investigated the drying kinetics of pretreated tomato slices at three drying temperatures and thicknesses in a hot-air dryer. Like most agricultural materials, drying time reduced with increasing drying temperature, while the effective moisture diffusivity increased. The SEC was within the range of 0.6247 to 1.9514 kWh kg^{-1} over the experimental domains. A comparison of the constructed models indicated that the ANFIS model exhibited better performance with high accuracy for predicting the drying kinetics compared to ANN, although the performance was similar to each other. Therefore, the model developed in this study has an acceptable generalization capability and accuracy. It is concluded that ANFIS provides an effective analyzing and generalizing model to understand and simulate the non-linear behavior of drying tomatoes.

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