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MICROWAVE DRYING OF TOMATO SLICES: AN EVALUATION OF ARTIFICIAL NEURAL NETWORK (ANN) AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) MODELS

Hussein J.B.[1], Oke M.O.[2]✉, Ajetunmobi-Adeyeye R.I.[2] and Adegoke A.F.[3]

[1]*Department of Food Science and Technology, Modibbo Adama University, Yola, Adamawa State, Nigeria.*
[2]*Department of Food Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.*
[3]*Department of Food Science and Technology, Federal University of Agriculture, Abeokuta, Ogun State, Nigeria.*

✉*mooke47@lautech.edu.ng*

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ABSTRACT

This study used two methodologies to model microwave drying kinetics of tomato slices: artificial neural networks (ANN) and the adaptive neuro-fuzzy inference system (ANFIS). The tomatoes were pre-treated with water blanching (WBP), ascorbic acid (AAP), and sodium metabisulphite (SBP). The tomatoes were then dried in the microwave at 90, 180, and 360 W after being sliced into 4-, 6-, and 8-mm thicknesses. After fitting ANN and ANFIS models to the experimental drying data, the optimal model topology was identified. The predictive accuracy of these models was assessed through these metrics: the coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE), by contrasting the projected results with experimental data. The results showed a range of 0.92 to 3.75 h for drying time, 0.28 to 2.86 x 10^{-8} m^2/s for D_{eff}, and 0.0027 to 0.0063 kWh/kg for SEC. The results indicated a high-performance capacity of ANFIS compared to ANN, with a higher R^2 of 1.0000 and a lower MSE of 0.9999 to 1.0000, an RMSE of 1.45x10^{-11} to 0.00309, and a MAE of 1.15x10^{-11} to 0.00296. Consequently, the ANFIS model demonstrated superior predictive capabilities compared to the ANN model, achieving a strong fit with the observed data.

1. Introduction

Tomatoes (*Solanum lycopersicum* L.var) hold a crucial position in human diets and contribute significantly to a country's economic growth. They are a rich source of essential nutrients and offer various health benefits (Hussein et al., 2019). Nonetheless, their perishable nature, characterized by high moisture content, increased respiration rate, and soft texture, renders them susceptible to spoilage and presents challenges in terms of transportation. To address these issues, drying has become a widely adopted method for extending the shelf life of tomatoes. Traditional drying methods include sun drying and solar drying, which are relatively cost-effective and straightforward. However, these methods come with several drawbacks, such as prolonged drying times, low energy efficiency, and considerable loss of food quality, including colour degradation and nutrient loss. Therefore, there is a need for more advanced and efficient methods to dry and preserve food.

Microwave drying serves as an alternative approach to address these challenges. This method offers advantages such as reduced drying time, enhanced product quality, and decreased energy consumption, as pointed out by Darvishi et al. (2013) and Hussein et al. (2019). According to Wray and Ramaswamy (2015), this technique uses microwaves to speed up the drying process by creating volumetric heating. But just like traditional drying, microwave drying uses the disparity in water vapour pressure between the material's interior and outside to propel the transfer of moisture. This complexity results in the microwave drying of tomato fruit being an intricate thermal process involving the simultaneous transfer of heat and moisture. As a result, it demands a significant amount of energy and time.

The complexity of microwave drying has given rise to a variety of mathematical models, both empirical and semi-empirical, to predict the drying patterns of tomatoes. Nevertheless, empirical and semi-theoretical models are generally only applicable within the specific temperature, air velocity, and humidity ranges for which they have been developed (Tohidi et al., 2012). Consequently, they cannot serve as universal correlations for a wide range of drying parameters. In contrast, theoretical models are derived from solutions to partial differential equations based on heat and mass balance principles. While theoretically sound, these models often involve complex calculations and rely on assumptions that may not align with real-world drying systems. As a result, there is a clear need for predictive models to better understand and anticipate drying kinetics. These models can greatly improve the efficiency of the drying process and the quality of the final products. With more precise predictions, they can assist in optimizing drying conditions and enhancing the performance of drying systems.

Artificial Neural Network (ANN) is a versatile mathematical model that draws inspiration from human perception. It has proven to be a useful tool for tackling challenging and nonlinear problems, particularly in the field of drying systems (Oke et al., 2017). Its high learning capacity and ability to discern input and output relationships make it well-suited for modelling the intricate, nonlinear dynamics involved in the drying process. Moreover, ANN enables precise management of the drying process in industrial settings. A significant advantage of ANN over conventional mathematical models is its ability to process vast quantities of noisy data from dynamic and nonlinear systems, particularly when the underlying physical relationships are not completely understood (Aghbashlo et al., 2015). Indeed, numerous studies have utilised ANN to predict drying kinetics in different drying processes. For example, Pedren et al. (2005) employed ANN to predict the drying kinetics in microwave-assisted drying. Poonnoy et al. (2007a) used ANN to model the temperature and moisture content of tomato slices during microwave-vacuum drying. Similarly, Poonnoy et al. (2007b) used ANN and regression models to estimate the moisture ratio in mushrooms during microwave-vacuum drying. Sarimeseli et al. (2014) used the ANN model to describe how thyme leaves dry quickly in microwaves. Bai et al. (2018) also used the ANN model to predict how Ginkgo biloba seeds dry quickly in microwaves and how their colour changes during drying. The examples provided underscore the efficiency of ANN in diverse drying applications. They showcase ANN's capability to optimize drying procedures and enhance the quality of the resulting dried products.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is an integrated modelling approach that combines the strengths of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS). According to Oke et al. (2018), by merging the benefits of both methods, ANFIS provides a robust solution for tackling complex and nonlinear issues, yielding superior outcomes. Kaveh et al. (2021) highlighted the ability of ANFIS to simulate nonlinear systems with high precision and reduced modelling time, distinguishing it among computational models. ANFIS has been applied in numerous studies to model the drying characteristics of a variety of agricultural products. For example, Bousselma et al. (2021) employed ANFIS to model the microwave drying of pre-treated whole apricots. Zadhossein et al. (2021) utilized the ANFIS system to forecast the exergy and energy aspects of drying cantaloupe slices in a microwave dryer. Ojediran et al. (2020) employed ANFIS to predict the drying kinetics of yam slices. In another study, Jahanbakhshi et al. (2020) applied the ANFIS system to model various aspects of drying pistachio kernels, including speed, effective moisture diffusivity, specific energy consumption, shrinkage, and colour, during microwave heating followed by ultrasound treatment. The analysis results offer significant insights into the ideal conditions for microwave drying with ultrasonic pretreatment. These examples highlight the flexibility and efficiency of ANFIS in modelling the drying processes for various agricultural products.

ANN and ANFIS models have been used successfully to predict the drying kinetics of other agricultural products, but there is a significant gap in the literature when it comes to using them to predict the drying kinetics of microwave-dried tomatoes. This study aims to bridge this gap by creating both ANN and ANFIS models designed specifically for forecasting the drying kinetics of microwave-dried tomatoes, offering a more precise and effective prediction method. By utilizing these advanced modelling techniques, this research seeks to improve the accuracy and efficiency of predicting the drying behavior of tomatoes under microwave drying conditions. The findings from this study can provide valuable insights for optimizing the drying process and enhancing the quality of microwave-dried tomatoes in the food industry.

2. Materials and methods

2.1. Materials

The tomatoes used in this study were UTC varieties, obtained from the Teaching and Research Farm at Modibbo Adama University of Technology, Yola, Adamawa State, Nigeria. The selection of these tomatoes was based on visual appearance, firmness, and size uniformity, ensuring they met the quality and consistency standards for commercial production.

2.2.1. Samples

Initially, the tomatoes were meticulously cleaned by washing under tap water, then rinsed with distilled water, and dried with a tissue towel, adhering to the method outlined by Hussein et al. (2016). Each pretreatment involved 12 kg of tomatoes. Three separate pretreatment methods were employed: one minute of water blanching pretreatment (WBP), five minutes of 5% w/v sodium metabisulphite pretreatment (SMP), and one minute of 5% w/v ascorbic acid pretreatment (AAP). The 1:10 (w/v) ratio of tomatoes to the dipping solution, as used by Hussein et al. (2019), was retained. Subsequent to pretreatment, the tomatoes were cut into slices of three varying thicknesses: 4 mm, 6 mm, and 8 mm, utilising a Tomato Slicer (NEMCO 56610-13/16” Roma).

Table 1. Layout of Taguchi experimental design L9 (3x3)

Test runs	Coded independent variables			Variables of experiment in their natural units		
	Pretreatment	Thickness (mm)	Microwave power (W)	Pretreatment	Thickness (mm)	Microwave power (W)
1	1.0	1.0	1.0	WBP	4	90
2	1.0	2.0	2.0	WBP	6	180
3	1.0	3.0	3.0	WBP	8	360
4	2.0	1.0	2.0	AAP	4	180
5	2.0	2.0	3.0	AAP	6	360
6	2.0	3.0	1.0	AAP	8	90
7	3.0	1.0	3.0	SMP	4	360
8	3.0	2.0	1.0	SMP	6	90
9	3.0	3.0	2.0	SMP	8	180

2.2.2. The Taguchi experimental plan and the drying process

The Taguchi experimental design was developed using Minitab 16 software, which is tailored to handle three factors at three distinct levels. This approach led to the creation of an L9 (3x3) array, resulting in nine experimental runs. These runs, detailed in Table 1, evaluated the drying kinetics, considering the interactions among pretreatment, slice thickness, and microwave power. The drying was performed with a BOSCH 25 L compact microwave oven (model number: HMT84G451), which has a maximum power of 900 W and operates at a frequency of 2450 MHz. The drying procedure followed the procedures set forth by Hussein et al. (2019).

2.2.3. Determination of drying kinetic of the dried tomato slices

The methodology outlined by Hussein et al. (2022) was employed to calculate the drying time and moisture ratio. The effective moisture diffusivities were determined based on molecular diffusion, the primary mechanism for moisture transfer within the food material. Assuming a uniform initial moisture distribution, negligible external resistance to moisture migration, and moisture release from both bottom surfaces of the tomato slices, the equation used by Workneh and Oke (2013) was utilised.

$$MR = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp\left(-\frac{(2n+1)^2 D_{eff}\pi^2}{4L^2}t\right) \quad (1)$$

where;

Deff denotes the effective moisture diffusivity in dried tomato slices (m^2/s).

t represents the drying time (in seconds).

n is a positive integer.

L indicates the total thickness of the tomato slice (measured on a non-perforated dish).

It is crucial to recognise that the first term of Equation 1 gains significance with the increase in drying time. Consequently, the simplified expression is as follows:

$$MR = \frac{8}{\pi^2}\exp\left(-\frac{D_{eff}\pi^2}{4l^2}t\right) \quad (2)$$

The aforementioned equation can be further reduced to the form of a linear equation;

$$\ln(MR) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{D_{eff}\pi^2}{4l^2}t\right) \quad (3)$$

The determination of the effective moisture diffusivity in dried tomato slices involved plotting the natural logarithm of the moisture ratio (ln MR) against the drying time. The resulting straight line's slope provided the necessary calculation for the effective moisture diffusivity;

$$slope = -\frac{D_{eff}\pi^2}{4l^2} \quad (4)$$

Therefore, with the thickness of the tomato slices and the slope derived from the aforementioned plot, the moisture diffusivity was calculated. The Specific Energy Consumed (SEC) for the microwave oven drying of tomato slices was estimated following the method described by Hosain (2012).

$$SEC = \frac{Pt_{on}}{M_w} \quad (5)$$

where;

SEC represents the specific energy consumption for microwave drying, measured in kWh per kg of water evaporated.

P denotes the power of the microwave in watts (W).

t_{on} refers to the total duration for which the microwave power is on, measured in hours (h).

Mw is the mass of water that has been evaporated, measured in kilograms (kg).

2.2.4. ANN and ANFIS modelling design

In order to model ANN and ANFIS, the Neural Network Toolbox 8.0 in MATLAB was used, in accordance with the method described by Hussein et al. (2023). The efficacy and performance of the model were assessed using various metrics, as outlined by Hussein et al. (2022) and Nazghelichi et al. (2011), including the following: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

3. Results and discussions

3.1. Drying kinetics of the microwave dried tomato slices

The required drying time to decrease the moisture content in pretreated tomato slices from 15.67% to 0.12% varied between 0.92 and 3.75 hours. The longest drying time was recorded for the experiment using water blanching (WBP), a 4 mm slice thickness, and 90 W of microwave power. Conversely, the shortest drying time was achieved with sodium metabisulphite (SMP), a 4 mm slice thickness, and 360 W of microwave power. A higher microwave power and increased exposure time were noted to significantly reduce moisture content, thus decreasing drying time, corroborating the findings of Talih et al. (2017). These results suggest that the choice of pretreatment method and microwave power level can have a significant impact on the efficiency of the drying process for tomato slices.

The effective moisture diffusivity (D_{eff}) values for pretreated tomato samples varied from 0.28 to 2.86 x 10^{-8} m^2/s. The highest D_{eff} value was observed in the experimental run with water blanching (WBP), an 8 mm slice thickness, and 360 W microwave power, while the lowest was in the run with water blanching (WBP), a 4 mm slice thickness, and 90 W microwave power. These D_{eff} values fall within the range of 10^{-12} to 10^{-8} m^2/s reported by Doymaz (2010) for various agricultural products. They are also in line with the findings of other studies, such as Zarein et al. (2013), who reported values for apple dried at 200 W to 600 W (ranging from 3.79 x 10^{-7} to 22.7 x 10^{-7} m^2/s), Mahdhaoui et al. (2014) for olive fruit dried at 90 W to 900 W (ranging from 5.96 x 10^{-9} to 13.00 x 10^{-9} m^2/s), and Workneh and Oke (2013) for microwave-assisted hot-air dried tomato slices at 1.13 - 3.11 W/g plus hot air at 50°C (ranging from 1.68 x 10^{-9} to 4.77 x 10^{-9} m^2/s). These studies collectively demonstrate the impact of different drying methods and power levels on the effective moisture diffusivity of various agricultural products. The range of values reported highlights the importance of optimising drying conditions for specific products to achieve desired results. It also provides valuable insights for optimising drying processes in the agricultural industry.

The mass transfer process during microwave oven drying of tomatoes is complex. As microwave power penetrates the slices, it generates internal heat. This creates a vapour pressure gradient within the slice, enabling moisture to move gently to the surface and evapourate. According to Hussein et al. (2019), this leads to a moisture pumping effect that pushes water out, preventing case hardening. The study suggests that effective diffusivity rises with increased microwave power and thinner tomato slices, a finding that echoes Sadin et al. (2014) regarding infrared drying of tomatoes. Notably, the intricate interplay between microwave energy, heat, and moisture migration can enhance drying efficiency and uniformity. Nonetheless, factors such as microwave power, tomato characteristics, and slice preparation can influence the effectiveness of this method.

The Specific Energy Consumption (SEC) ranges from 0.0027 to 0.0063 kWh/kg. The minimum SEC was recorded for SMP pretreatment with 6 mm slices at 90 W microwave power, whereas the maximum SEC was noted for WBP pretreatment with 8 mm slices at 360 W microwave power. Notably, an increase in slice thickness and microwave power corresponded to a rise in SEC, indicating that factors leading to higher energy inputs also escalated the SEC. This observation is consistent with prior research by Chayjan (2012) on potato slices and Pillai et al. (2010) on plaster of Paris.

The type of pretreatment applied significantly affected the SEC, with SMP pretreatment showing a more pronounced effect compared to AAP and WBP pretreatments. This suggests that pretreatment effectively lowers the specific energy needed for drying tomato slices, thus decreasing energy consumption during the process, which is beneficial. It corroborates the initial observation that pretreatment aids in the drying of tomato slices and shortens the drying time. Consequently, applying pretreatment before drying tomatoes could enhance energy efficiency, particularly in areas where energy costs are substantial. This result aligns with the findings of Tunde-Akintunde et al. (2014) regarding bell pepper drying. The study also highlights the importance of considering pretreatment methods in the overall energy optimisation of food drying processes.

3.2. Modelling the effect of drying conditions on the drying kinetic of microwave dried tomato slices using ANN

Exploration of various neural network topologies and neuron counts in the hidden layer was conducted to identify the optimal configuration for drying kinetics. The architecture with a 3-9-1 topology was found to be the most effective for modelling drying time and moisture diffusivity. In contrast, an ANN structure with 11 neurons in the hidden layer demonstrated superior performance for Specific Energy Consumption (SEC).

Figure 1 depicts the optimal ANN model structure for predicting drying time and moisture diffusivity, which includes three inputs (pretreatment, slice thickness, and microwave power), a hidden layer with 9 neurons employing a logarithmic sigmoid activation function, and a tangent sigmoid function at the output layer. Conversely, the best structure for SEC features a single hidden layer with 11 neurons and a tangent sigmoid activation function at both the hidden and output layers.

It is significant to mention that Lertworasirikul and Tipsuwan (2008) reported a comparable network setup featuring nine neurons in the hidden layer and a logarithmic sigmoid transfer function in the initial layer for the drying of semi-finished cassava crackers. This indicates that the selected architecture has proven successful in modelling drying processes across different applications. Moreover, the consistent use of this architecture suggests its versatility and effectiveness in capturing the complex dynamics of drying phenomena. It may be beneficial for future studies to explore its applicability in other food drying processes.

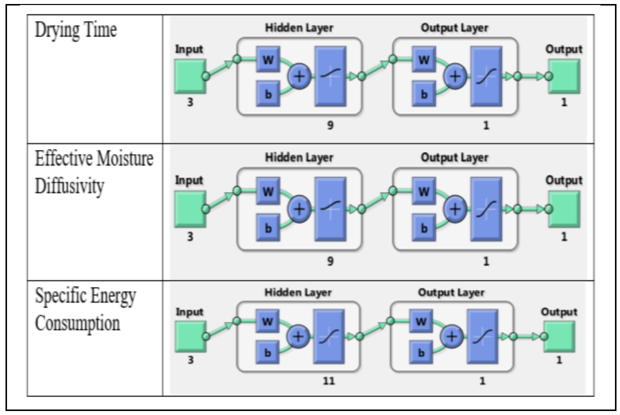
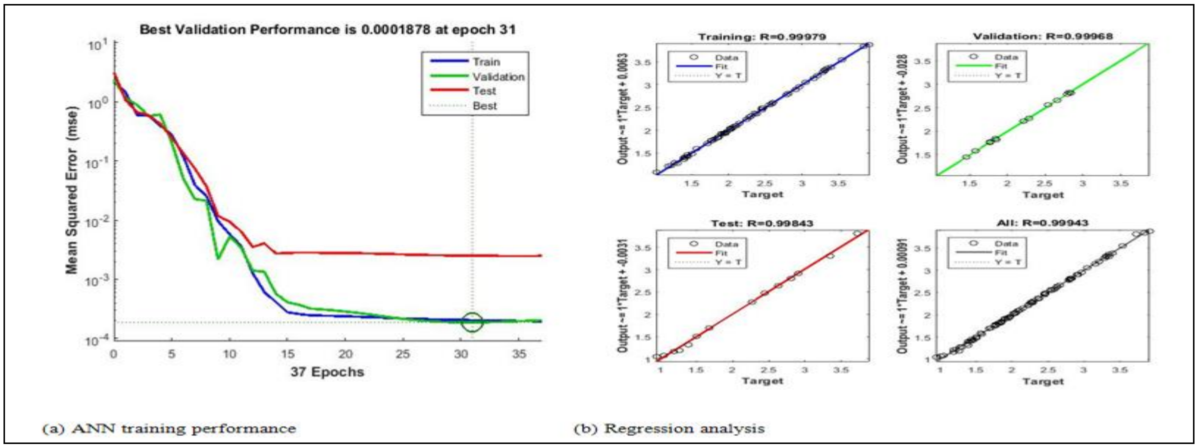


Figure 1. The optimised ANN model for drying kinetic (drying time, D_{eff} and SEC) of microwave dried tomatoes

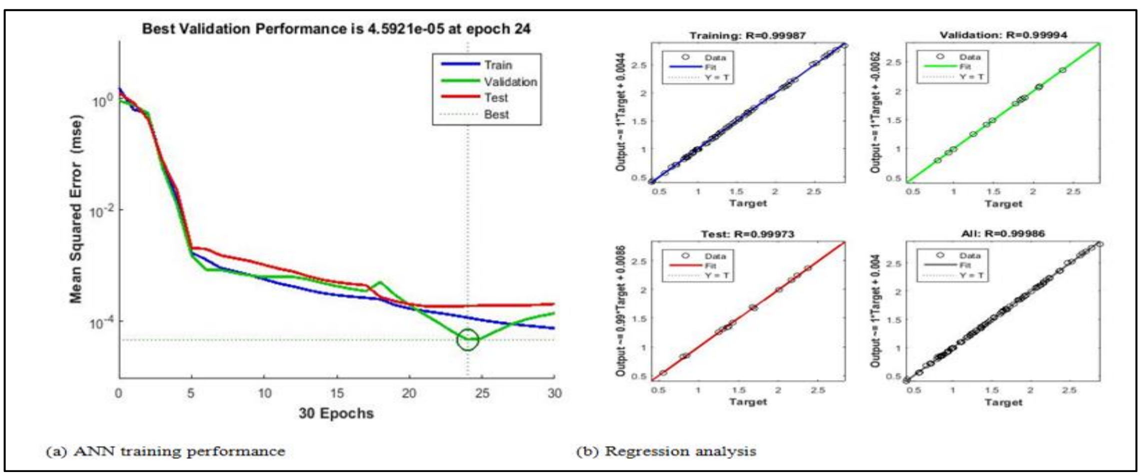
The ANN model was simulated to find the best architecture. This was based on getting a low mean squared error (MSE) and a high correlation coefficient (R). Figure 2 displays the ANN's performance during training and the regression analysis results for both the training and validation datasets concerning drying time. The training ceased after 37 epochs, as illustrated in Figure 2a, with the most appropriate ANN network identified at 31 epochs post-training. As shown in Figure 2b, the regression analysis of the ANN model's performance showed that its predictions were very good. The R values were 0.99979 for training, 0.99968 for validation, 0.99843 for testing, and 0.99943 for the overall dataset.

Furthermore, the MSE value, a measure of the model's accuracy, was exceptionally low at 31 epochs, with a value of 0.00019, affirming the effectiveness and precision of the chosen optimal architecture in predicting drying time. These results suggest that the ANN model performed exceptionally well in predicting drying time, achieving a high level of accuracy and reliability in its forecasts, both during training and when applied to unseen data.



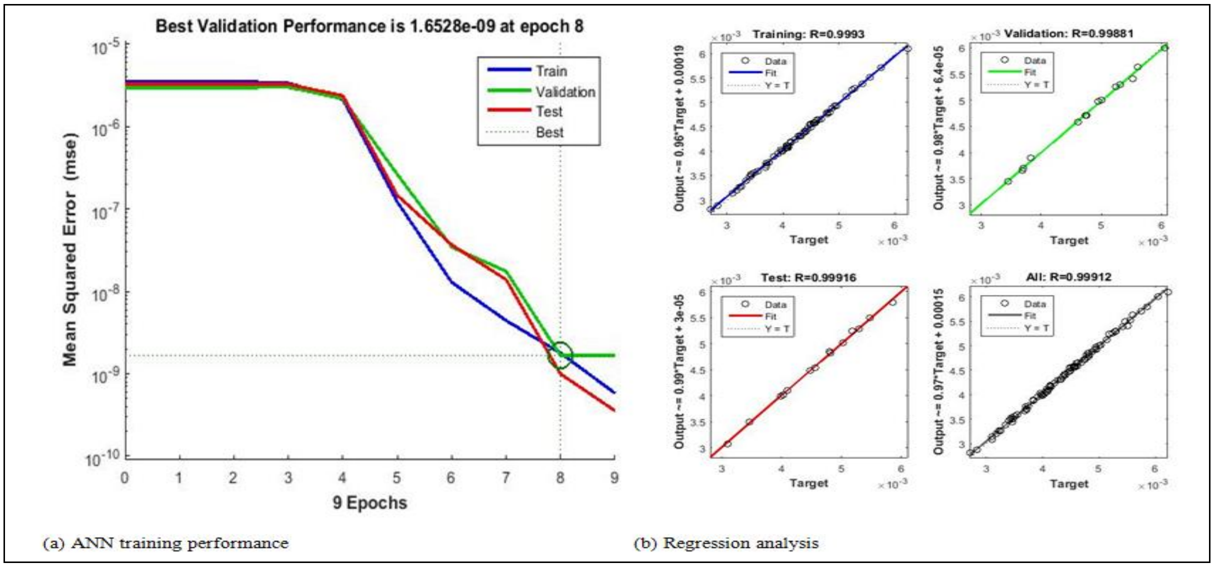
Figures 2. The performance of ANN training and regression analysis for both training and validation datasets for drying time.

Figure 3 presents the training performance and regression analysis of the ANN concerning moisture diffusivity. Training ceased after 30 epochs, as depicted in Figure 3a, with the optimal ANN architecture emerging after 24 epochs. The regression analysis evaluated the correlation between the ANN's forecasts and the actual experimental data, showcasing the ANN model's remarkably precise predictive ability. The R was notably high, registering values of 0.99987 for training, 0.99994 for validation, 0.99973 for testing, and 0.99986 for all data, as shown in Figure 3b. Moreover, the MSE was determined to be 0.00005 at the 24th epoch for the chosen architecture. These results show that the ANN model is very good at predicting moisture diffusivity, showing that it is accurate and reliable across both training and validation data sets.



Figures 3. The performance of ANN training and regression analysis for training and validation datasets for the effective moisture diffusivity

Figure 4 illustrates the training performance and regression analysis of the ANN for SEC. The training was halted after nine epochs to avert overfitting, as shown in Figure 4a. Following this, the optimal ANN architecture was determined at the eighth epoch, prior to ceasing training. The regression analysis assessed the correlation between the ANN's predictions and the actual experimental data, confirming the model's accuracy and efficacy. The R remained impressively high, with values of 0.99930 for training, 0.99881 for validation, 0.99916 for testing, and 0.99912 for all data, as depicted in Figure 4b. Furthermore, the MSE was exceptionally low, with a value of 1.6528 x 10^{-9}, corresponding to the 8th training epoch for the optimal ANN architecture. These findings indicate that the ANN model performed exceptionally well in predicting specific energy consumption, delivering highly accurate and reliable results for both the training and validation datasets, while also avoiding overfitting issues.

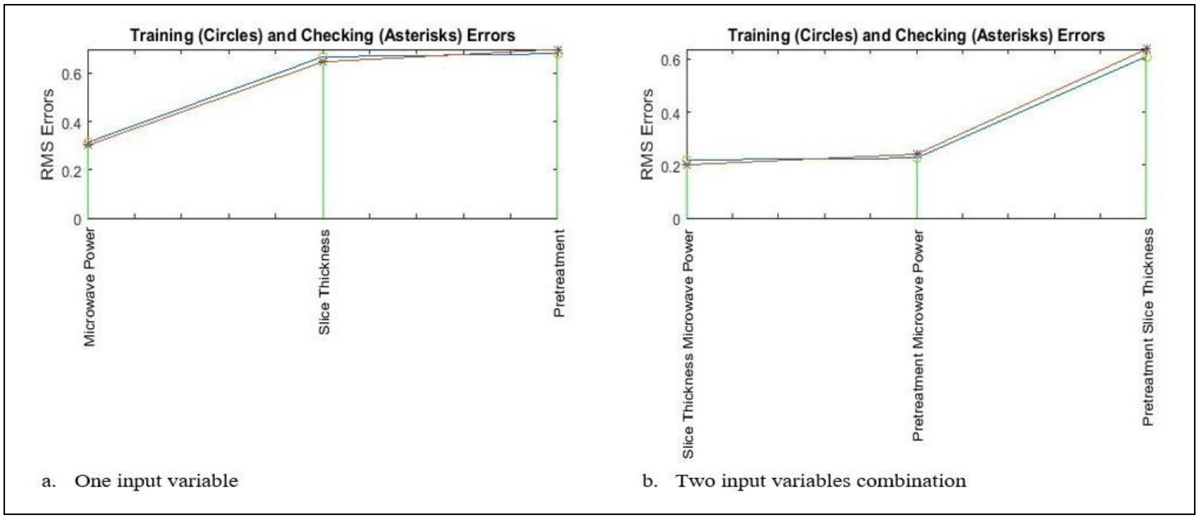


Figures 4. The performance of ANN training and regression analysis for training and validation datasets for the specific energy consumption.

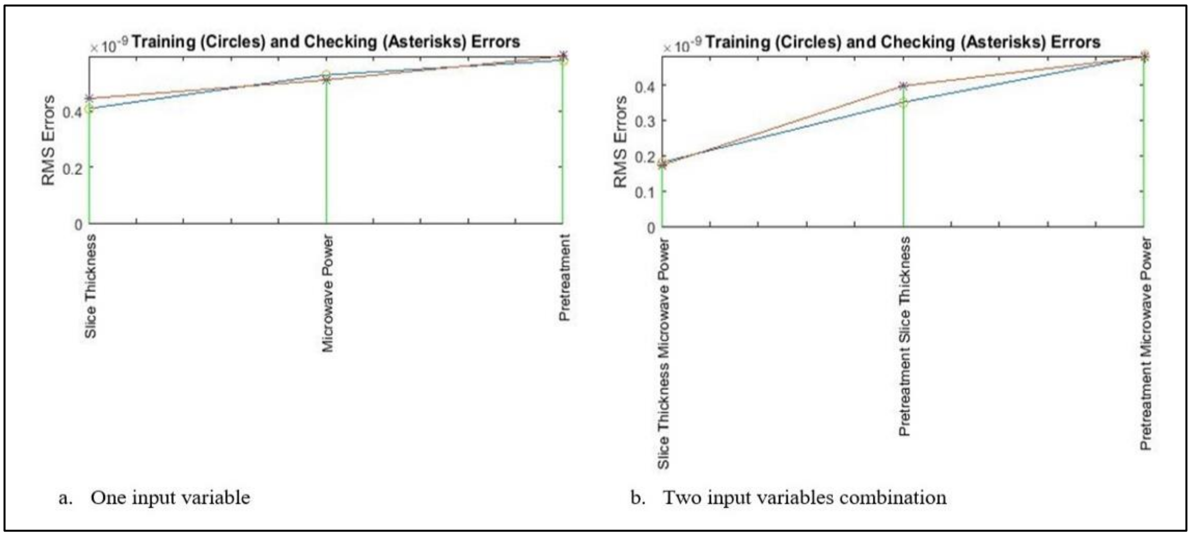
3.5. Modelling the effect of drying conditions on the drying kinetic of microwave dried tomato slices using ANFIS

An exhaustive analysis of experimental data was performed to determine the optimal combination of input variables influencing the drying kinetics of microwave-dried tomato slices using ANFIS. Analysing one input variable at a time for drying time, microwave power was found to have the lowest training error of 0.3127 and checking error of 0.3012 (Figure 5a), indicating its significant role in determining the drying time of pretreated tomato slices in microwave oven drying. Conversely, considering two input variables, the combination of slice thickness and microwave power yielded the smallest training error of 0.2194 and checking error of 0.2008 (Figure 5b), establishing their importance in affecting the drying time. These observations align with Horuz et al. (2017), who observed that microwave power penetrates the tomato slices, generating internal heat and vapour pressure that expels moisture to the surface for vaporation. Likewise, research by Kulanthaisami et al. (2010) and Hussein et al. (2019) supports that increased microwave power for a set thickness leads to reduced drying times.

With only one input variable, slice thickness had the lowest training error of 0.4082 and the highest checking error of 0.4440 for effective moisture diffusivity (Figure 6a). This shows that slice thickness has a big effect on the moisture diffusivity of microwave-dried tomato slices that have been pretreated. For two input variables, the combination of slice thickness and microwave power achieved the lowest training error of 0.1807 and a checking error of 0.1733 (Figure 6b), underscoring their importance in affecting the output performance. These observations are in line with research by Touil et al. (2014), Afolabi et al. (2014), and Onu et al. (2016), which suggests that the shorter distance moisture travels before evaporating has a significant impact on effective moisture diffusivity. Still, the big difference between the training errors and the checking errors (Figure 6) points to a possible overfitting problem during the exhaustive search. This is similar to what Aremu et al. (2014) and Oke et al. (2018) said about model development and validation.



Figures 5. The ANFIS exhaustive search illustrates the impact of one and two input variables on the drying time

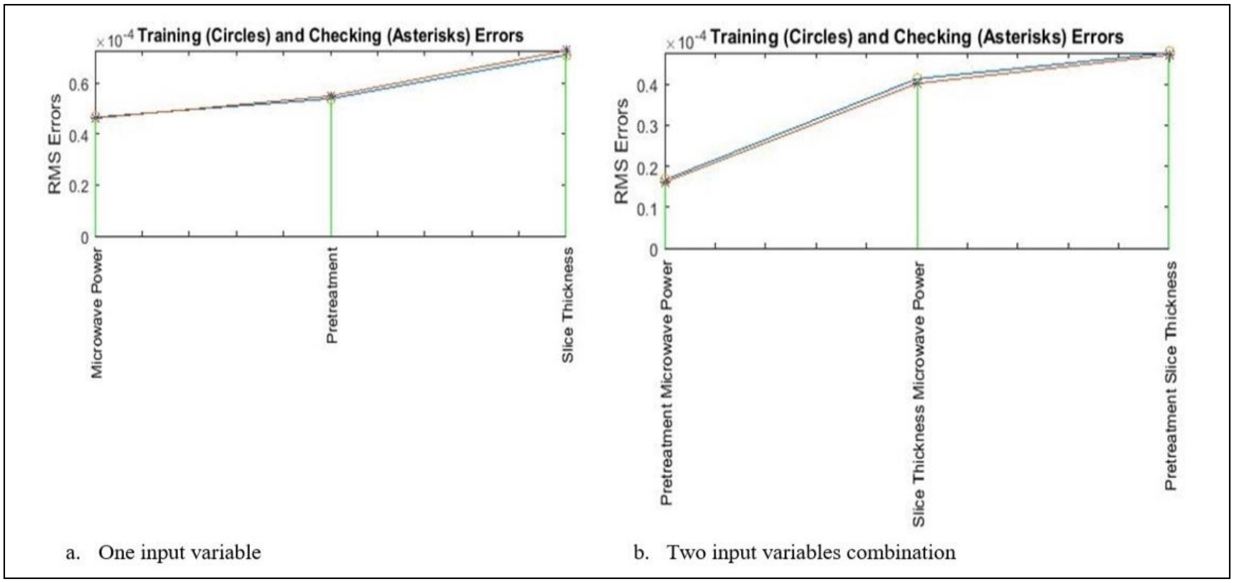


Figures 6. The ANFIS exhaustive search illustrates the impact of one and two input variables on the moisture diffusivity.

For SEC, with a single input variable, microwave power was found to have the lowest training and checking errors, both at 0.0005 (as shown in Figure 7a). This indicates that microwave power is the most significant variable in determining the SEC for pretreated tomato slices dried using a microwave oven. Conversely, with two input variables, the combination of pretreatment and microwave power yielded the lowest training and checking errors, both at 0.0002. Hence, these two variables were determined to be the most critical in influencing the output performance.

3.6. The ANN and ANFIS model's performance indices

Table 2 presents the performance metrics of the ANN and ANFIS models in predicting drying kinetics. It's evident that the ANN regression plot achieved an R^2 value greater than or equal to 0.9982, with RMSE and MAE values less than or equal to 0.02366 and 0.01496, respectively.



Figures 7. The ANFIS exhaustive search illustrates the impact of one and two input variables on the specific energy consumption.

Table 2. ANN and ANFIS drying kinetics prediction metrics

	Input Membership Function		**Membership Function's Type**		**ANFIS's Regression Coefficient**			**ANFIS's Coefficient of Determination**			**ANN's Coefficient of Determination**		
Quality Characteristics	**Input**	**Epoch**	**Input**	**Output**	**R**	**RMSE training**	**RMSE testing**	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**
Drying Time	2-2-2	1000	gauss	linear	0.9999	0.00309	0.00296	1.0	0.00309	0.00296	0.9989	0.02366	0.01496
Effective Moisture Diffusivity	2-2-2	1000	tri, gbell and gauss	linear	1.0	1.45×10^{-11}	1.57×10^{-11}	1.0	1.45×10^{-11}	1.15×10^{-11}	0.9996	0.01225	0.00615
Specific Energy Consumption	2-2-2	1000	tri, gbell and gauss	linear	1.0	1.36×10^{-6}	1.30×10^{-6}	1.0	1.36×10^{-6}	9.95×10^{-7}	0.9982	0.00004	0.00003

These results demonstrate that the prediction model effectively simulated the experiments. The ANFIS model, employing two types of membership functions (gauss IMF and linear OMF), exhibited the highest predictive accuracy for drying time. Additionally, the ANFIS model with two types of MFs (tri, gbell, and gauss IMF) combined with linear OMF demonstrated superior predictive accuracy for moisture diffusivity and SEC. The correlation coefficients between ANFIS outputs and experimental data were exceptionally high (0.99999, 1.0, and 1.0) for drying time, moisture diffusivity, and SEC, respectively (Figure 8). The data points closely aligned with the ideal trend line in the regression plot indicate the model's suitability for predicting test data. Notably, ANFIS displayed very low RMSE values for both training (≤ 0.00309) and testing (≤ 0.00296), underscoring its ability to capture the fundamental relationships between input and output variables.

These results demonstrate the high accuracy and reliability of the ANFIS model in predicting drying time, moisture diffusivity, and SEC. The low RMSE values indicate that the model can effectively capture the complex interactions between the input and output variables, making it a valuable tool for further analysis and optimisation in this field. The simulation accuracy of the ANFIS model was evaluated to confirm its dependability. The regression plot from the simulation yielded an R^2 value of 0.9999 or higher, with RMSE and MAE values at or below 0.00309 and 0.00296, respectively. As per Hussein et al. (2022), an R^2 value nearing one signifies a more accurate fit of the empirical model to the experimental data. Hence, given the high R^2 value along with minimal RMSE and MAE values, the ANFIS model is anticipated to simulate the drying kinetics of microwave-dried tomato slices effectively.

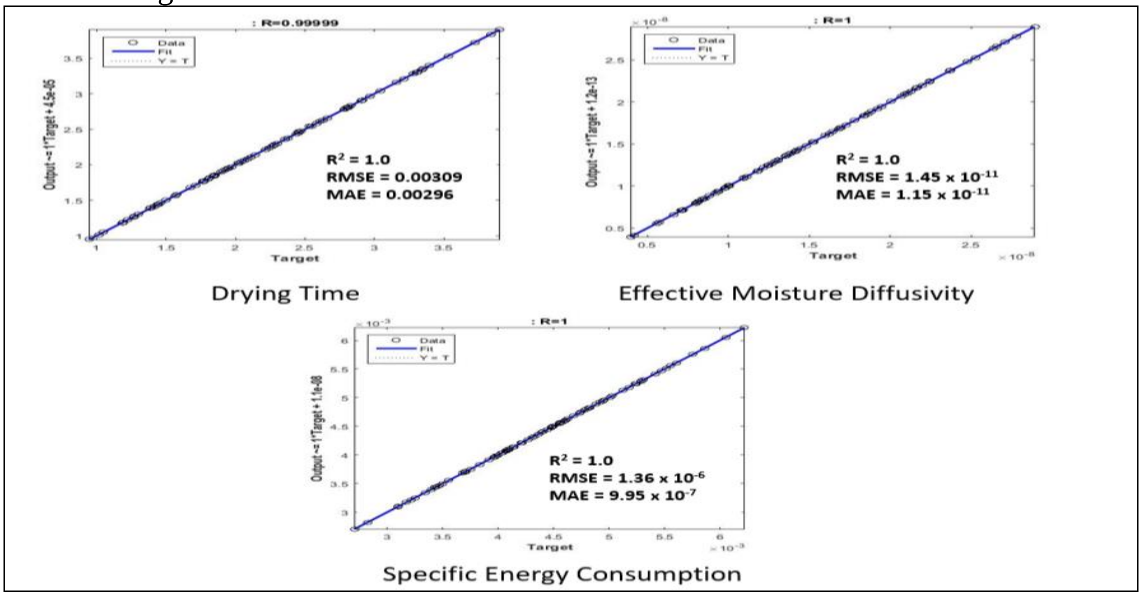


Figure 8. Regression between the experimental and predicted values for the drying kinetics

Figure 9 presents the ANFIS decision surface plot, which demonstrates the effects of pretreatment, thickness, and microwave power on drying time. The plot clearly shows that an increase in microwave power decreases the drying time, whereas a greater slice thickness leads to a longer drying time. Previous studies by Workneh and Oke (2013) and Onu et al. (2016) have indicated that higher microwave power produces more heat energy, which speeds up the movement of water molecules and enhances moisture diffusivity, thus shortening the drying time.

Furthermore, the WBP pretreatment has shown a more pronounced decrease in drying time compared to other methods. According to Kaymak-Ertekin (2002), this is due to the blanching heat's alteration of the cell membrane's physical properties, which shortens the drying time. This highlights the importance of optimising both parameters for efficient drying processes in food industry applications.

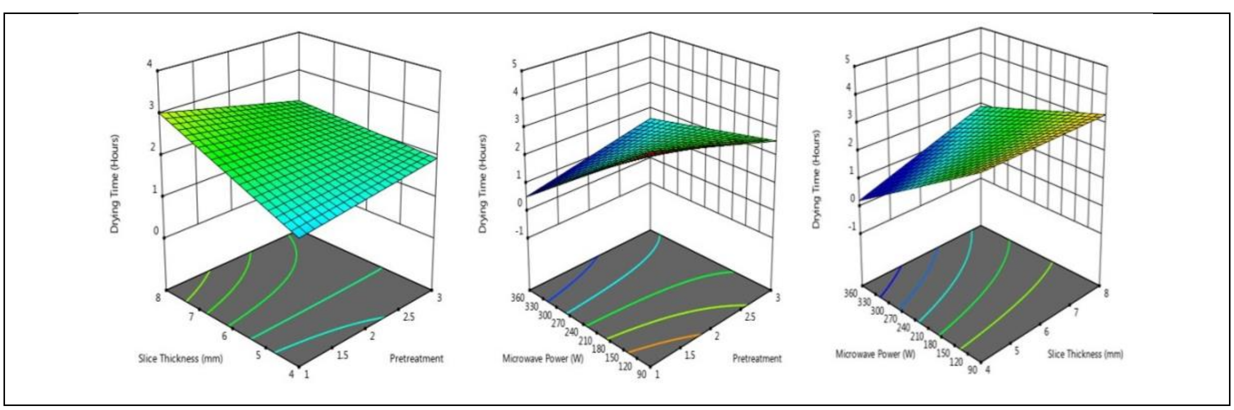


Figure 9. The ANFIS decision surface plot illustrates the impact of pretreatment, slice thickness, and microwave power on the drying time value.

The disruption of the cell membrane tissue by blanching heat allows for faster moisture evaporation during the drying process. This phenomenon is further enhanced by the higher microwave power, which intensifies the heat energy and accelerates the migration of water molecules, ultimately reducing the drying time even more significantly.

The ANFIS decision surface plot illustrated in Figure 10 demonstrates how pretreatment, thickness, and air temperature affect moisture diffusivity. The plot indicates that an increase in microwave power reduces moisture diffusivity, while a greater slice thickness also leads to lower diffusivity. Hussein et al. (2016) explain this effect by noting that water must traverse the slice's thickness from inside to the surface to evaporate. Similarly, Beigi (2016) and Torki-Harchegani et al. (2016) observed that higher microwave power enhances mass and heat transfer within the tomato slice, creating a larger vapour pressure gradient between the surface and core of the slice, thus accelerating water vapour diffusion.

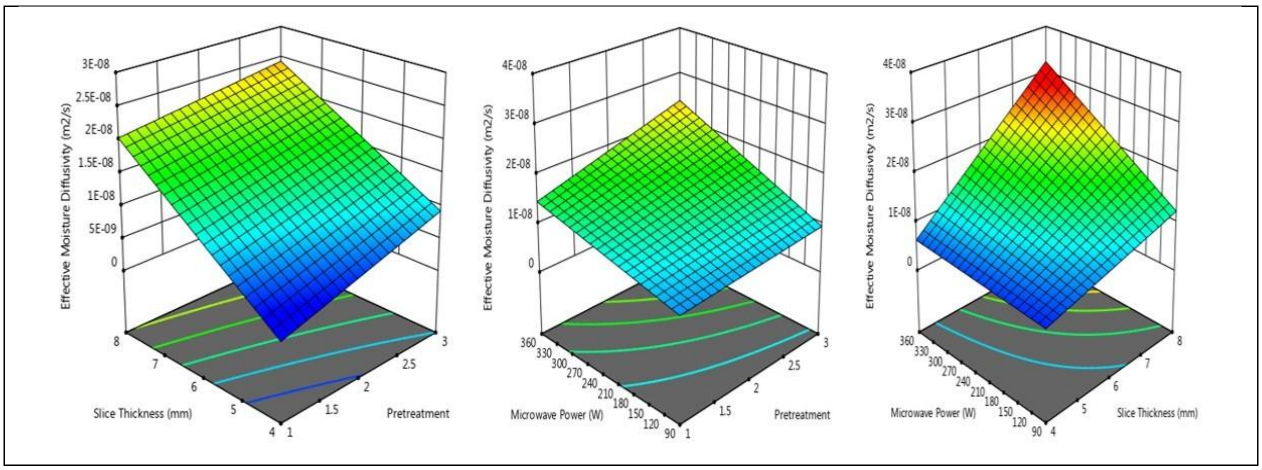


Figure 10. The ANFIS decision surface plot illustrates the impact of pretreatment, slice thickness, and microwave power on the moisture diffusivity value.

Furthermore, the WBP pretreatment exhibited higher moisture diffusivity compared to other pretreatments. According to Kaymak-Ertekin (2002), this improvement results from the blanching heat altering the physical properties of the cell membrane tissue, which shortens the drying time. The increased moisture diffusivity due to the WBP pretreatment can also be attributed to the breakdown of cell walls, which allows for easier movement of water molecules. Additionally, the shorter drying time achieved with WBP pretreatment can lead to improved product quality by preserving more of the tomato's natural colour and flavour.

Figure 11 presents the ANFIS decision surface plot, which shows the effects of pretreatment, thickness, and microwave power on the SEC. The plot indicates that an increase in microwave power correlates with a higher SEC, as does an increase in slice thickness. This is because the water has to move through the thickness of the slice from the inside to the surface to evaporate, requiring more energy. Moreover, samples pretreated with WBP showed the highest SEC, followed by those treated with AAP and SMP. This suggests that SMP pretreatment is effective in reducing the energy needed to dry tomato slices, leading to lower energy use in the drying process, which is beneficial. Similar results were observed by Sharma and Prasad (2006) in their research on microwave drying of garlic cloves and by Kumar et al. (2014) in their study of microwave-assisted hot-air drying of okra. Sharma and Prasad (2006) also found that microwaves' volumetric heating effect could decrease drying time, thus reducing SEC.

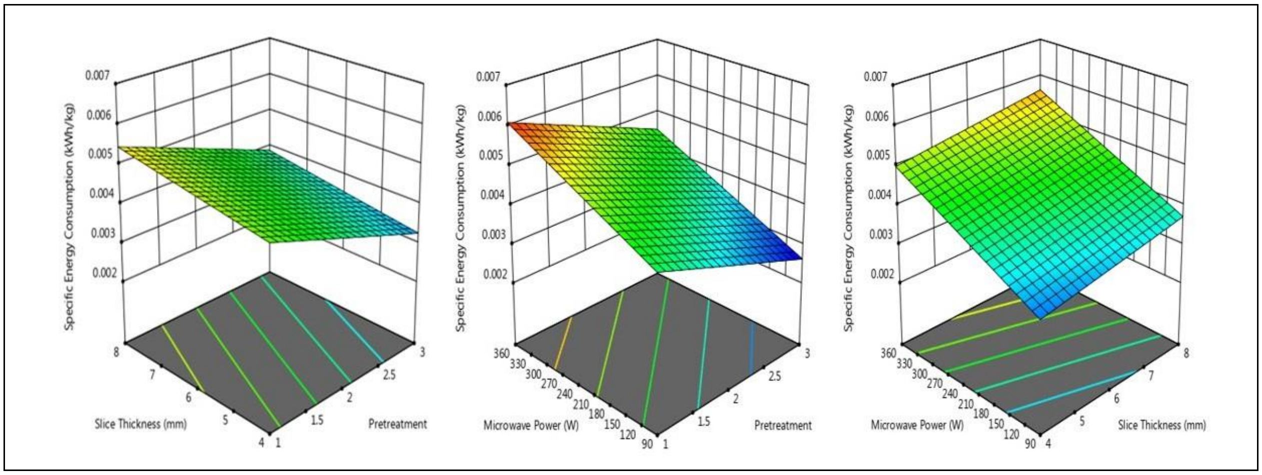


Figure 11. The ANFIS decision surface plot illustrates the impact of pretreatment, slice thickness, and microwave power on the specific energy consumption value.

These findings imply that microwave drying methods can decrease energy use and enhance drying efficiency. Furthermore, the volumetric heating effect of microwaves can shorten drying times, contributing to reduced specific energy consumption.

4. Conclusions

This study evaluated the drying characteristics of pretreated tomato slices in a microwave dryer, focussing on drying time, effective diffusivity (D_{eff}), and specific energy consumption (SEC). The most favourable results were observed under certain conditions: SMP pretreatment, 4 mm slice thickness, and 360 W microwave power resulted in a drying time of 0.92 hours, D_{eff} of 0.28 x 10^{-8} m^2/s, and SEC of 0.0027 kWh/kg. Similarly, WBP pretreatment with 4 mm slice thickness at 90 W and SMP pretreatment with 6 mm slice thickness at 90 W yielded optimal results. The study found that SEC increases with slice thickness and microwave power. Among the pretreatment methods (SMP, AAP, and WBP), SMP significantly reduced SEC. A comparison between the ANN and ANFIS models for parameter prediction showed that ANFIS was superior in modelling and optimising the drying process. The findings provide insights into the drying kinetics and energy efficiency of microwave-dried tomato slices, beneficial for both pilot and industrial-scale processing.

Additionally, these findings have the potential to mitigate postharvest tomato losses that often occur during bumper harvests. This can help reduce food waste and ensure a more sustainable food supply chain. Furthermore, the use of the ANFIS model can also contribute to cost savings and improved efficiency in tomato processing by accurately predicting drying times and optimising energy usage. Implementing this model in the industry can lead to increased productivity and reduced environmental impact, making it a valuable tool for sustainable food production.

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