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Exergy and Energy Analyses of Microwave Dryer for Cantaloupe Slice and Prediction of Thermodynamic Parameters Using ANN and ANFIS Algorithms

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Abstract: The study targeted towards drying of cantaloupe slices with various thicknesses in a microwave dryer. The experiments were carried out at three microwave powers of 180, 360, and 540 W and three thicknesses of 2, 4, and 6 mm for cantaloupe drying, and the weight variations were determined. Artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) were exploited to investigate energy and exergy indices of cantaloupe drying using various afore-mentioned input parameters. The results indicated that a rise in microwave power and a decline in sample thickness can significantly decrease the specific energy consumption (SEC), energy loss, exergy loss, and improvement potential (probability level of 5%). The mean SEC, energy efficiency, energy loss, thermal efficiency, dryer efficiency, exergy efficiency, exergy loss, improvement potential, and sustainability index ranged in 10.48–25.92 MJ/kg water, 16.11–47.24%, 2.65–11.24 MJ/kg water, 7.02–36.46%, 12.36–42.70%, 11.25–38.89%, 3–12.2 MJ/kg water, 1.88–10.83 MJ/kg water, and 1.12–1.63, respectively. Based on the results, the use of higher microwave powers for drying thinner samples can improve the thermodynamic performance of the process. The ANFIS model offers a more accurate forecast of energy and exergy indices of cantaloupe drying compare to ANN model.

Keywords: cantaloupe; improvement potential; energy efficiency; exergy; ANN; ANFIS

1. Introduction

Cantaloupe (Cucumis melo) belongs to the family of Cucurbitaceous. Cantaloupe is one of the important agricultural crops of Iran, having the fifth rank after tomato, cucumber, watermelon, and Persian melon. It is more cultivated in the Khorasan Razavi, Khuzestan, and Semnan provinces. Based on FAO reports in 2018, Iran was rated third in the production of various types of cantaloupes [1,2]. Moreover, the agricultural product of cantaloupe possesses medicinal value. In this regard, there is a need to minimize crop loss after harvesting [3].

However, the structure and moisture content of the agricultural products play a decisive role in their life length. In this context, researchers have tried to use various methods to increase the durability of these products while maintaining their quality [4]. Drying with the sun is one of the most primitive methods of keep agricultural products. This method, however, suffers from several drawbacks such as the need for large spaces, environmental pollution, sudden climate change, long drying times, and so on [5]. Various industries have emerged to facilitate the production and processing of crops. Drying is one of these industries which can prolong the life of products, hence enhancing their use in a better and simpler way [6]. The high latent heat of water evaporation and the low efficiency of industrial dryers have led to high energy consumptions. Therefore, attempts have been focused on declining the energy consumption and drying time while enhancing the efficiency of industrial dryers.

To include the mentioned points in the design of industrial dryers, thermodynamic science should be exploited. The first and second laws of thermodynamics analyze energy efficiency [7]. The first law of thermodynamics states that energy is not lost but rather converts from one form to another. The second law of thermodynamics indicates the quality and image of this energy conversion. As this energy conversion is accompanied by a decline in quality, a parameter called exergy is introduced which is defined as the maximum useful work obtained from the energy flow from one system at equilibrium with the environment [7,8].

Drying by microwave (MW) power is one of the drying methods with optimal energy consumption which helps in saving the longevity and quality of products [9]. In this method, products are exposed to electromagnetic waves focused on the products. These waves have a high frequency and can penetrate into the product texture and vibrate the polar molecules such as water and salts. The vibrations of these molecules can lead to heat which will result in the transfer of humidity to the surface and finally its evaporation [10]. Owing to the energy concentration on the product, moisture elimination occurs at higher paces. The use of MW can decline the drying time up to 50% depending on the product type and drying conditions [11]. The drying time and MW power are two important factors in the drying of products by MW method which can influence the drying parameters such as drying time, drying efficiency, and quality of the final product.

Exergy and energy analyses of an assorted dryer for different agricultural produce appears in the literature. For instance, Jafari et al. [11] investigated exergy analyses and mathematical modelling of a rice barn in a semi-industrial MW dryer. Their results showed that the energy and exergy efficiency increased by enhancing the thickness of the seeds. The researchers further highlighted that at constant power, the energy and exergy efficiency increased by enhancing the thickness of the seeds. For the same layers, the rise in MW power declined the energy and exergy efficiencies.

Surendhar et al. [5] examined the kinetics of drying, energy, and exergy parameters for curcumin drying in a microwave dryer. Their results indicated that a rise in the MW power can accelerate the drying process and decline drying time. Energy and exergy values were reported to be enhanced by increasing the MW power.

In another study, Azadbakht et al. [12] studied the energy and exergy of drying in orange slices using an MW dryer with ohmic pretreatment. Their results indicated that the amount of the absorbed energy exceeded the lost energy at higher powers. The exergy efficiency was reported to improve with an increase in MW power and ohmic time.

Darvishi et al. [6] and Al-Harahsheh at al. [13] hinted that modelling of drying equipment enables designers to select suitable operating conditions and ensures effective drying operation. Among high-level optimization methods, a hybrid of an Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) has been the chosen option. The choice of the hybrid is motivated by the amalgamation having mathematical recompenses, emphasized elsewhere [14,15]. The ANFIS is a governing data-driven and adaptive computational means having the fitness of plotting non-linear and multifaceted data [16]. Conversely, the constraint of ANN is its black box which flops to relation input parameters with the response. Jang and Sun [17] related the fiasco of the black box method of the ANN model to the incapacity of the model to accommodate linguistic information unswervingly. On the other hand, Yaghoobi et al. [18] ascribed the preeminence of the ANFIS model to its capacity to handle lapses in the ANN model.

Presently, the use of ANN and ANFIS techniques have boosted modelling and simulating food processing. These nonlinear modelling methods have been extensively employed for the evaluation of energy, exergy, and quality of the food industry due to their accuracy, robustness, and high speed [19]. ANNs are powerful computational methods to predict the responses of complex systems. The main idea of these types of networks originates from the biological nervous system performance for processing the data and information to learn and create knowledge [8].

ANFIS has recently drawn a considerable deal of attention. This method is a combination of the fuzzy structures with ANN to identify the systems and predict time series. This model has several advantages, among which the ability to simulate nonlinear systems, high precision, and shorter time of model development can be mentioned [20].

Several researchers have presented various models using ANN and ANFIS to predict the energy and exergy parameters of different dryers for drying various products. Abbaspour-Gilandeh et al. [21] used ANFIS and ANN to predict the energy and exergy of the fruits dried by a convective dryer. Kariman et al. [22] applied ANN to predict the energy and exergy of dried kiwi using MW dryer. Azadbakht et al. [4] optimized and predicted the energy and exergy of drying potato slices by fluid substrate dryer, and Nikbakht et al. [8] modelled the drying of pomegranate in the convective drier with MW pretreatment using ANN and a surface response method at the industrial scale. Kaveh et al. [23] used the ANFIS system for the prediction of the energy and exergy of drying green peas using a convective-rotary dryer.

Taghinezhad et al. [24] investigated the application of ANN and ANFIS in energy and exergy analysis of an infrared-convective dryer with ultrasonic pretreatment for drying blackberry samples. To predict the energy and exergy parameters of the blackberry drying process, the ANN (with one or two hidden layers and two Lonberg-Marquardt algorithms and Bayesian regulation) and the ANFIS model (membership function for each input: trimf and Gaussian, membership function for each output: linear and hybrid algorithm) were explored. Drying time, inlet air temperature, and ultrasonic time in the dryer were considered as inputs, while exergy efficiency, exergy loss, energy consumption, and energy consumption ratio were selected as outputs. The statistical parameters showed that the ANFIS network was more successful than ANN in predicting the energy and exergy of the drying blackberry. The prediction of energy efficiency, exergy efficiency, energy consumption ratio and energy consumption at any time were successfully accomplished with the aid of ANFIS approach. The high speed of obtaining the answer makes this method suitable for modelling and controlling the processes.

Azadbakht et al. [10] employed ANN method to predict osmotic pretreatment based on energy and exergy analysis in drying orange slices using a microwave dryer. An increase in MW power enhanced energy and exergy efficiency and reduced drying time. Moreover, a multilayer perceptron (MLP) neural network model was utilized to predict energy efficiency, specific energy loss, exergy efficiency, and specific exergy loss. MW power and osmotic time were considered as inputs, while energy efficiency, specific energy loss, exergy efficiency, and specific exergy loss were regarded as outputs. The studied artificial neural network in osmotic times and microwave power with 6 neurons in the hidden layer was employed to predict the regression coefficient (R^2) for energy efficiency and specific exergy loss as 0.999 and 0.871, respectively.

Liu et al. [7] adopted a multilayer feed-forward neural network to predict the energy and exergy of a convective dryer to dry mushroom slices. Their study entailed four input variables (drying time, air temperature, air velocity, and thickness of the samples) and four responses (energy consumption, energy consumption ratio, exergy loss, and exergy efficiency). The researchers further adopted the sigmoid tangent activator function as a transfer function and the Levenberg−Marquardt algorithm for network training. The researchers attributed the capability of the ANN model in predicting energy and exergy parameters of convective dryers due to that maximum R^2 (0.966) and the lowest value of MSE (0.001261) and MAE (0.02208).

The drying process is an important operation and observing the technical and scientific principles in the cantaloupe drying process will increase its quality and efficiency. The evaluation of energy and exergy parameters of cantaloupe drying and its modelling in different modes leads to further understanding of how the product dries. Such information can be used in designing and optimizing the drying process. In this study, the effect of MW power and sample thickness on the drying kinetics of cantaloupe slices, effective moisture diffusion coefficient, and energy and exergy parameters are investigated. Then, to model the drying behavior of cantaloupe pieces under different powers and thicknesses in an MW dryer, the ANN and ANFIS models were are used. Finally, the performances of these two models in predicting the energy and exergy parameters of cantaloupe drying in a microwave dryer were evaluated. Likewise, integrating ANN and ANFIS models has been very interesting among researchers since it reinforces the performance of the model and aids robust modelling for actual productivity and sustainability [24–27]. Inopportunely, the scrutiny of the survey disclosed that there are (1) no recognized ANN models for the prediction of thermodynamic parameters of a microwave dryer (MD) for cantaloupe slices and (2) comparison capacity of hybrid models such as ANN and ANFIS models for the exergetic parameters of a microwave dryer for cantaloupe slices in the literature is scarce. Henceforth, there is a need to trim the lapses in the knowledge of such reports and launch robust models capable of improving thermodynamic performance and decreasing the environmental penalties of the drying process.

Based on the above mentioned descriptions and the targets of the study, the hypotheses of the study are as follows: (1) higher microwave power increases energy and exergy efficiencies, and (2) higher microwave power and the lower slice thickness reduces drying time, exergy improvement potential, and specific energy consumption.

2. Materials and Methods

2.1. Sample Preparation

Cantaloupe was purchased from a local market in Sardasht (West Azerbaijan, Sardasht, Iran). To prevent initial moisture loss, the product was stored at 4 ± 1 in the refrigerator. To perform the experiments, the product was removed from the refrigerator 2 h before cutting to reach ambient temperature. Cantaloupes were cut to 2, 4, and 6 mm thickness using a cutter. To determine the initial moisture content of the samples, the product was placed in an oven (Memmert, UFB 500, Schwabach, Germany) at 70 °C for 24 h [2]. Finally, the initial moisture content of cantaloupe pieces was obtained at 17.94% on a wet basis.

2.2. Dryer Conditions

In the present research, a programmable domestic microwave oven (Sharp R-I96T, Bangkok, Thailand) was used to perform the experiments that were capable of generating microwave waves in the range of 100 to 900 W. The oven has an internal compartment with dimensions of 350 × 350 × 220 mm^3 and a rotating plate with a diameter of 180 mm. For experiments, sliced cantaloupe samples with similar thicknesses were weighed and placed on the rotating plate of the machine. The proposed method was performed in such a way that the samples with three thicknesses of 2, 4, and 6 mm were subjected to MW powers of 360, 180, and 540 W. The drying of 60 g cantaloupe slices (ca. 14 samples) continued until the relative humidity of the samples approached about 0.2 on a wet basis. The temperature of the samples was measured by IR temperature sensor (accuracy of ±1.5 °C). The reference dead state conditions were considered as T_0 = 22 °C and P_0 = 101.325 kPa. Each experiment was performed in three replications.

2.3. Drying Kinetics

The moisture ratio of cantaloupe was determined using Equation (1) [10].

$$MR = \frac{M_t - M_e}{M_o - M_e} \quad (1)$$

The moisture propagation coefficient was assumed to the same at all directions (isotropic material) with negligible shrinkage. Under such conditions, the moisture transfer from the solid phase in the descending period of the rate can be estimated by Equation (2) as described by Fick law [28].

$$\frac{\partial M}{\partial t} = -D_{eff}\frac{\partial^2 M}{\partial r^2} \quad (2)$$

Assuming constant effective moisture diffusion coefficient and by the analytical solution of Fick's second law, the effective moisture diffusion coefficient can be determined using Equation (3) [21].

$$MR = \frac{M_t - M_e}{M_o - M_e} = \frac{8}{\pi^2}\sum_{n=1}^{\infty}\frac{1}{(2n+1)}\exp\left(\frac{-D_{eff}(2n+1)^2\pi^2 t}{4L^2}\right) \quad (3)$$

By increasing t, all the terms will tend to zero except the first one. The effective moisture diffusion coefficient (D_{eff}) can be obtained from the slope (k) of Ln (MR) vs. t using Equation (4) [20].

$$k = \left(\frac{D_{eff}\pi^2}{4L^2}\right) \quad (4)$$

2.4. Energy Analysis

2.4.1. Specific Energy Consumption, Dryer Efficiency, and Thermal Efficiency

SEC refers to the ratio of the total energy consumption during the drying of cantaloupe slices to the water loss during the drying process. The SEC of cantaloupe slices by microwave method can be determined by Equation (5) [29].

$$SEC = \left(\frac{P.t}{M_w}\right) \quad (5)$$

Dryer and thermal efficiencies, as well as the vaporization latent heat, can be determined by Equations (6)–(9), respectively [23,30].

$$D_e = \left(\frac{E_{evap} + E_{heating}}{SEC}\right) \quad (6)$$

$$TE = \frac{D.A.h_{fg}.(M_i - M_o)}{3600.Z.t.(100 - M_o)} \quad (7)$$

$$E_{eva} = h_{fg}.M_w \quad (8)$$

$$\begin{gathered} h_{f.g} = 2.503 \times 10^3 - 2.386(T_{abs} - 273.16) \\ h_{f.g} = (7.33 \times 10^6 - 16T_{abs}^2)^{0.5} \end{gathered} \quad (9)$$

2.4.2. Energy Efficiency and Energy Loss

A thermodynamic analysis is essential for the optimization and design of thermal systems. Based on the first law of thermodynamics, the general mass conservation equation can be expressed by Equation (10) [31].

$$\sum m_{in} = \sum m_{out} \quad (10)$$

Energy equilibrium can be expressed by Equation (11), which states that the input energy is equal to the output energy [32].

$$\sum E_{in} = \sum E_{out} \tag{11}$$

The dryer chamber is considered as the control volume, and the mass conservation energy can be determined by Equation (12) [33].

$$m_{wp} = m_{dp} + m_{wt} \tag{12}$$

The mass of the evaporated water can be calculated by Equation (13) [10].

$$m_{wt} = m_{dp}(M_o - M_t) \tag{13}$$

The energy conservation for the tangible heat, latent heat, and heat source of the microwave can be determined by Equation (14) for the cantaloupe slices [34].

$$P_{in} = P_{abs} + P_{ref} + P_{tra} \tag{14}$$

In the above equation, $E_{loss} = P_{ref} + P_{tra}$ is the lost energy.

The input energy to the microwave can be determined by Equation (15) [35].

$$P_{in} \times t = \left((mC_pT)_{out} - (mC_pT)_{in}\right) + \lambda_k m_w + (E_{ref} + E_{tra}) \tag{15}$$

Equation (15) contains three terms including the absorbed energy, reflected energy, and transmitted energy. Equation (16) shows the energy absorbed by the product [33].

$$\left((mC_pT)_{out} - (mC_pT)_{in}\right) + \lambda_k m_w) \tag{16}$$

The latent heat of the cantaloupe slices can be also determined by Equation (17) [6].

$$\lambda_k = \lambda_{wf}(1 + 23\exp(-0.4M_t)) \tag{17}$$

The latent heat of evaporation was determined by Darvishi et al. [35] based on Equation (18) [10]:

$$\lambda_{wf} = 2503 - 2.386(T - 273) \tag{18}$$

According to Brooker et al. [36], the heat capacity is a function of the moisture content and can be described by Equation (19).

$$C_p = 840 + 3350 \times \left(\frac{M_t}{1 + M_t}\right) \tag{19}$$

Based on Darvishi et al. [6] and Jafari et al. [33], the energy efficiency in the MW dryer can be calculated by Equation (20).

$$\eta_{en} = \frac{(m.C_p.T)_{out} + m_{ew} + \gamma_{wp}}{(m.C_p.T)_{in} + P.t} \tag{20}$$

The specific energy loss for drying cantaloupe slices can be determined by either Equations (21) or (22) [9].

$$E_{loss} = (1 - \eta_{en}.\frac{P.t}{m_w}) \tag{21}$$

$$E_{loss} = \frac{E_{in} - E_{abs}}{m_w} \tag{22}$$

The total input and output energy and exergy loss were determined according to the second law of thermodynamics. The main method to analyze the exergy of the dryer chamber relied on the calculation of the exergy values in stable points and the determination of the reason for the changes in the exergy of the process. Generally, Equation (23) shows the exergy balance for an MW dryer [12].

$$EX_{in} = EX_{abs} + \overbrace{EX_{ref} + EX_{tra}}^{\cong EX_{loss}} \tag{23}$$

The input exergy of the MW dryer can be determined by Equation (24) [35].

$$\overbrace{P_{in} \times t}^{exergy\ input} = \overbrace{\left(\overbrace{(m \times ex)_{dp}}^{exergy\ of\ dry\ poduct} - \overbrace{(m \times ex)_{wp}}^{exergy\ of\ wetproduct} \right) + \overbrace{ex'_{exap} \times t}^{exergy\ evaporation}}^{exergy\ absorption} + \overbrace{EX_{ref} + EX_{tra}}^{\cong EX_{loss}} \tag{24}$$

The exergy rate (J/s) of the evaporation in the dryer chamber can be determined by [5]:

$$ex'_{exap} = \left(1 - \frac{T_O}{T_p}\right) \times \dot{m}_{wv} \lambda_{wp} \tag{25}$$

$$\dot{m}_{wv} = \frac{m_{t+\Delta t} - m_t}{\Delta t} \tag{26}$$

The specific exergy (J/s) can be calculated by Equation (27) [19].

$$Ex = C_p \left[(T - T_\infty) - T_\infty \ln\left(\frac{T}{T_\infty}\right) \right] \tag{27}$$

The exergy efficiency of the MW dryer can be estimated by Equation (28) [5].

$$\eta_{ex} = \frac{EX_{abs}}{P_{in}} \tag{28}$$

The specific exergy loss can be also expressed by Equation (29) as reported by Kariman et al. [22].

$$EX_{loss} = \frac{EX_{in} - EX_{abs}}{m_{wv}} \tag{29}$$

The exergetic sustainability index is defined to express the performance of the exergy. The use of the improvement potential can also be helpful in the evaluation of economic activities [37]. The exergy improvement potential and the exergetic sustainability index can be expressed by Equations (30) and (31), respectively [32].

$$IP = (1 - \eta_{ex}) \times EX_{in} - EX_{out} \tag{30}$$

$$SI = \frac{1}{(1 - \eta_{ex})} \tag{31}$$

2.5. Statistical Analysis

SPSS (V.19) and the Duncan test (at the probability level of 5%) were used to investigate the effect of Mw power and thickness of cantaloupe slices on the studied indices.

2.6. Experimental Uncertainty Analysis

Experimental uncertainty was calculated by Equation (32) [38]:

$$U_R = \left[\left(\frac{\partial R}{\partial x_1} U_1\right)^2 + \left(\frac{\partial R}{\partial x_2} U_2\right)^2 + \ldots + \left(\frac{\partial R}{\partial x_n} U_n\right)^2 \right]^{\frac{1}{2}} \tag{32}$$

All uncertainties are displayed in Table 1.

Table 1. Uncertainties in measurement of parameters during onion drying.

Parameter	Unit	Value
Inlet microwave power	W	±1.5
Slice thickness	mm	±0.02
Uncertainty in the measurement of moisture quantity	G	±0.018
Uncertainty in the measurement of relative humidity of air	RH	±0.65
Drying Rate (DR)	g water/g dry matter min	±0.17
Uncertainty in Moisture Ratio (MR)	Dimensionless	±0.14
Uncertainty in Specific Energy Consumption (SEC)	MJ/kg	±1.01
Uncertainty in energy efficiency	Dimensionless	±1.4
Uncertainty in specific energy loss	MJ/kg	±0.004
Uncertainty in exergy loss	MJ/kg	±0.005
Uncertainty in exergy efficiency	Dimensionless	±1.55

2.7. Artificial Neural Network (ANN)

An artificial neural network is composed of countless artificial neurons operating as interconnected, parallel networks. Each neuron acts as a processor in the network and receives and processes neural signals (input) from other neurons or their surroundings. Similar to the human brain, an artificial neural network can learn everything on its own [39]. Neurons are trained by applying a training algorithm to the network. An artificial neural network consists of 3 layers: the input layer that receives the primary data, the hidden layer that processes the received data, and the output layer. Each layer contains a group of neurons, each of which is connected to all the neurons in the other layers, but the neurons in each layer are not in contact with other neurons in the same layer. In this way, neurons act independently, and a superposition of the neurons' behavior reflects the network behavior [40]. The latent layer may be monolayer (perceptron neural networks) or multilayer (multilayer perceptron (MLP) networks).

In this study, a multilayer perceptron artificial neural network was selected for modelling energy parameters (SEC, energy loss, energy efficiency, dryer efficiency, and thermal efficiency), exergy parameters (exergy drop, exergy efficiency, and exergy recovery potential) and duration of heating and drying cantaloupe by a microwave dryer considering different thicknesses. The perceptron multilayer neural network is a feed-forward network with three inputs, one or two hidden layers, and one output layer. This network was selected by one or two hidden layers for the experiment, in which 2–15 neurons were placed in each layer by trial and error. Moreover, Tansig, Logsig, and Purelin activation functions were used in the hidden input and output layer. In this research, the Levenberg−Marquardt optimization was used to train the network. Three iterations were considered the average of the learning cycle for simulation of artificial neural network data to minimize the error rate and maximize network stability. The error estimation algorithm in the formed networks was performed using the error propagation algorithm.

2.8. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system formulates the behavior of a process using descriptive if-then rules. This system includes 4 main parts: rule base, fuzzification, inference engine, and defuzzification. Each ANFIS model consists of 5 layers which include inputs, membership functions corresponding to inputs, rules, membership functions related to outputs, and outputs [19]. In this study, a hybrid method was used to train ANFIS, which is a combination of the least-squares method and the post-diffusion method. The error limit used to create a training stop criterion was set to zero. To optimize the model, different types and numbers of membership functions were used to determine the optimal number and type. A Sugeno-type fuzzy inference system was employed to find the optimal model; triangular, trapezoidal, and Gaussian membership functions were examined. Regarding the two-variable nature of the model input, 2-2 and 3-3 membership functions were investigated.

30% of the data were used for testing while 70% of them were applied for training. Microwave power, the thickness of samples, and drying time were regarded as inputs of both models (ANN and ANFIS) while SEC, energy loss, energy efficiency, thermal efficiency, dryer efficiency, exergy drop, exergy efficiency, exergy improvement potential, and exergetic sustainability index during microwave drying were the outputs. In this study, Matlab software (Matlab R2019a) was used to model ANN and ANFIS.

To evaluate the network, two criteria of coefficient of determination (R^2) and root mean square error (RMSE) were taken into account. The coefficient of determination determines the degree of correlation between the output data of ANN and ANFIS and the observed data which can be calculated from Equation (34); its ideal value is one. The root mean square of the error determines the difference between the predicted and the actual data and can be calculated by Equation (33) [7]. The goal of a good network is to minimize the amount of this error, and its ideal value is zero.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_p)^2} \tag{33}$$

$$R^2 = \frac{\left[\sum_{i=1}^{N}(X_i - X_{mean})^2\right] - \left[\sum_{i=1}^{N}(X_i - X_p)\right]}{\left[\sum_{i=1}^{N}(X_i - X_{mean})^2\right]} \tag{34}$$

$$MRE = \frac{1}{N}\sum_{p=1}^{N}\left|\frac{X_i - X_p}{X_i}\right| \tag{35}$$

3. Results and Discussions

3.1. Kinetics of Drying

The diagram of moisture reduction in cantaloupe pieces with different thicknesses during drying at various MV powers is depicted in Figure 1. MW drying reduced the moisture content of cantaloupe pieces from 17.99 to 0.20 w.b., and the drying time varied from 55 to 180 min (Figure 1). According to Figure 1, a rise in the microwave power and a decrement in the sample's thickness enhanced the slope of the moisture reduction. The time required to reach the moisture content of 0.2 w.b. showed a significant decline by increasing the microwave power and decreasing the sample thickness (Table 2). This time was decremented from 180 min for the power of 180 W and thickness of 6 mm to 55 min for the case of the power of 540 W and thickness of 2 mm.

The mass and heat transfer are faster in higher MW powers and thinner thicknesses. Higher powers, indeed, enhance the kinetic energy and absorbed energy, giving rise to a higher difference in the vapor pressure between the center and surface of the samples; this will eventually increase the rate of moisture elimination [9]. In a similar study, Darvishi et al. [6] dried white mulberry using an MW dryer and declared that the high humidity of the samples led to elevated friction against the rotation of dipoles, resulting in high heat generation within the white mulberries. This phenomenon accelerated the vapor motion, guiding the water toward the surface of the samples. For constant microwave power, a rise in the sample thickness will increase the path the moisture has to pass to reach the surface which will eventually enhance the drying time [41]. Other researchers also addressed the effect of the MW power and sample thickness on the drying time of the agricultural products, among which the works by Beigi and Torki [29] on onion slices, Çınkır and Süfer [42] on red meat radish, and Darvishi et al. [43] on sweet potato can be mentioned.

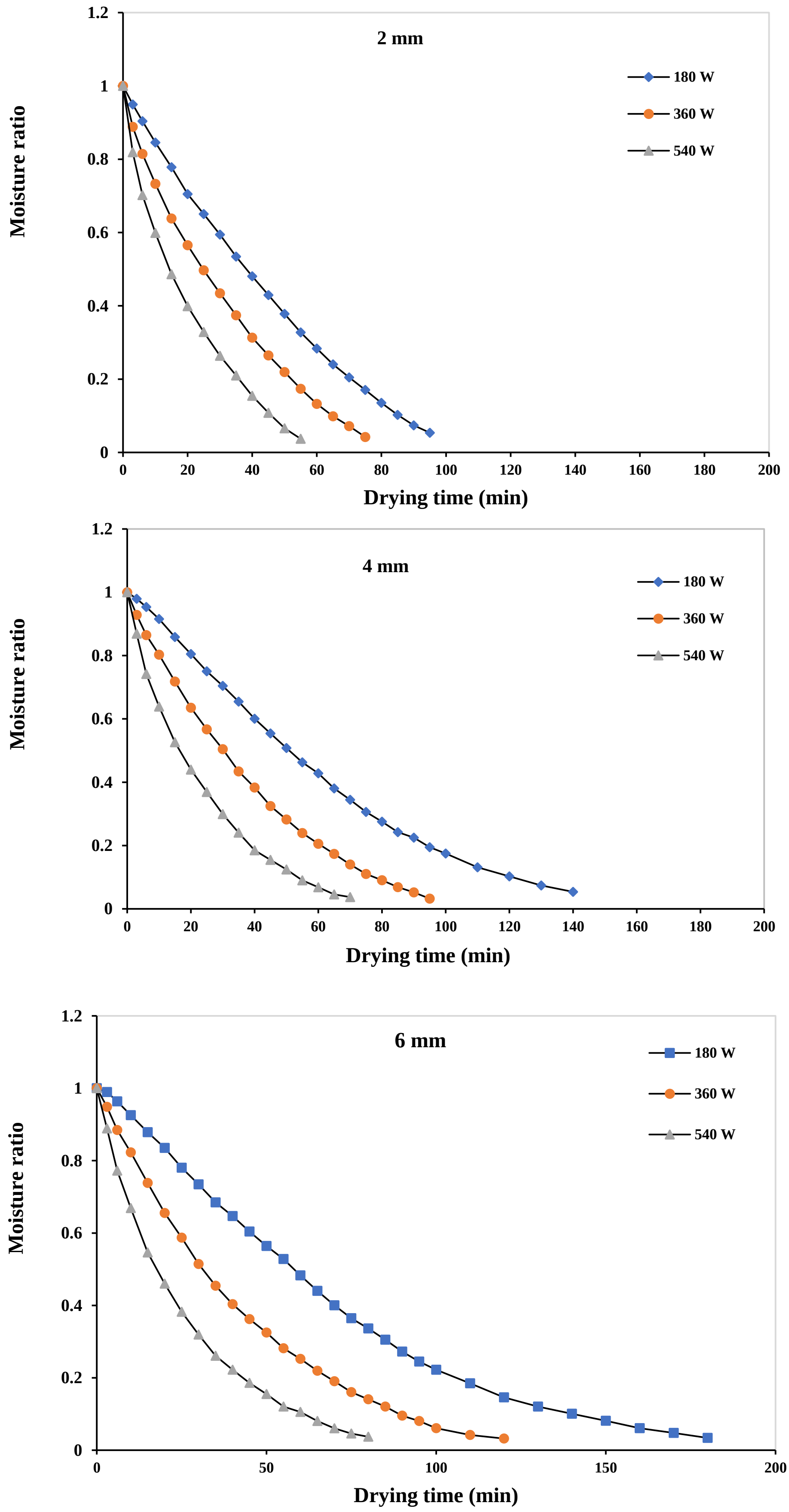

Figure 1. Variation of moisture ratio for different thicknesses and microwave power levels.

Table 2. Variation of drying time, effective moisture diffusivity and specific energy consumption of cantaloupe slices at various slice thickness and microwave power levels.

Microwave Power (W)	Slice Thickness (mm)	Drying Time (min)	D_{eff}	SEC
	2	95 ± 5 [d]	$3.15 \times 10^{-12} \pm 8.04 \times 10^{-13}$ [g]	17.1 ± 1.01 [d]
180	4	140 ± 10 [b]	$9.05 \times 10^{-11} \pm 9.11 \times 10^{-13}$ [e]	23.26 ± 0.92 [b]
	6	180 ± 10 [a]	$1.85 \times 10^{-11} \pm 1.31 \times 10^{-13}$ [c]	25.92 ± 1.14 [a]
	2	75 ± 5 [ef]	$4.22 \times 10^{-12} \pm 7.51 \times 10^{-13}$ [fg]	13.5 ± 0.88 [e]
360	4	95 ± 5 [d]	$1.48 \times 10^{-11} \pm 1.41 \times 10^{-12}$ [d]	17.25 ± 1.21 [d]
	6	120 ± 10 [c]	$2.83 \times 10^{-11} \pm 1.48 \times 10^{-12}$ [b]	21.60 ± 0.80 [c]
	2	55 ± 5 [g]	$6.00 \times 10^{-12} \pm 7.04 \times 10^{-13}$ [f]	10.48 ± 0.57 [f]
540	4	70 ± 5 [f]	$2.05 \times 10^{-11} \pm 1.51 \times 10^{-12}$ [c]	13.34 ± 0.98 [e]
	6	80 ± 5 [e]	$4.04 \times 10^{-11} \pm 1.77 \times 10^{-12}$ [a]	16.20 ± 0.79 [d]

Different letters for the same segment represent statistically significant differences at a confidence level of 95%.

3.2. Effective Moisture Diffusion Coefficient

The D_{eff} of all samples lie within the range reported by Kaveh et al. [44] for the food products (10^{-12}–10^{-7} m^2/s) as indicated in Table 2. The analysis of the D_{eff} values indicated that at a specific thickness, the microwave power has a significant influence ($p < 0.05$) on the moisture diffusion. As observable in Table 2, a rise in the Mw power enhanced the value of D_{eff} which can be assigned to the increment of the heat energy which declined the viscosity of the water present in the samples and hence increased its activity and accelerated the evaporation [29]. Sharabiani et al. [39] and Raj and Dash [45] also reported similar results in drying apple and dragon fruit slices using an MW dryer. Moreover, the statistical analysis indicated that at a given MW power, the sample thickness significantly affected the effective diffusion coefficient ($p < 0.05$); however, the increase in the thickness from 2 to 6 mm elevated the diffusion coefficient, which can be attributed to the surface hardness of the samples as surface hardening occurs more rapidly in thinner samples while the evaporation rate of thinner samples is far higher [46]. The faster surface hardening in the thinner samples can limit the displacement of humidity, hence declining the moisture propagation in the thinner samples [47]. Studied on drying kiwi fruit [19,43] and eggplant slices [48] with various thicknesses also led to similar results.

3.3. Specific Energy Consumption

Table 2 lists the SEC of drying cantaloupe slices using an MW dryer at various thicknesses. The lowest required SEC (10.47 MJ/kg) was achieved at the MW power of 540 W and thickness of 2 mm. The increase in the energy consumption by changing the power from 180 to 540 W was significant at all thicknesses ($p < 0.05$); the results indicated that a rise in the MW power and a decrement in the sample thicknesses can decrement the energy consumption. The reason could be the enhanced destruction of the product thickness and accelerated moisture release [39,41]. Moreover, with increasing MW output power, the thermal gradient inside the sample increased, followed by an increment in evaporation rate and a decrease in drying time. By reducing this time, the energy consumption also decreased [49]. In a study by Azimi-Nejadian and Hoseini [47], a specific energy consumption between 0.68 to 2.59 MJ/kg was obtained for drying potatoes in a microwave dryer at power range of 200–800 W. In another study, Khan et al. [50] reported specific energy consumption for drying fenugreek leaves in various MW powers (30 to 100 W) in the range of 1.86–2.47 MJ/kg.

Furthermore, the energy required to remove one kilogram of water from the cantaloupe pieces during the microwave drying process significantly increased (with a probability level of 5%) by enhancing the thickness of the samples. The rise in energy consumption by increasing the thickness of the sample can be attributed to the processing time. In thicker samples, the water must travel a longer distance inside the product to reach the surface, i.e., it takes longer to remove moisture. Such an increment in drying time led to higher energy consumption [41]. Similar reports were also emphasized by researchers elsewhere [29,43,51] for drying kiwi, apple, and onion by microwave dryer, respectively.

3.4. Dryer Efficiency and Thermal Efficiency

Table 3 depicts the dryer efficiency and the thermal efficiency of the microwave dryer for the cantaloupe slice. As shown, the highest and lowest dryer efficiency and heat efficiency were observed at the power level of 540 and 180 W and thickness of 2 and 6 mm, respectively. Furthermore, by increasing the microwave power and decreasing the sample thickness, both efficiencies (heat and drying) exhibited an increasing trend, which can be due to the high drying rate. Such a high drying rate can be assigned to the difference in thermal gradient between the product and the drying temperature. Moreover, microwave energy penetrates the cantaloupe samples and generates heat by inducing polarity in the water molecules, hence improving drying and uniformity of heat and water distribution in the sample [28]. Similar results have been reported for drying rice paddy [33], chamomile [30], dragon fruit slicess [45], and apple [52].

Table 3. Variation of drying efficiency, thermal efficiency, energy efficiency, and exergy efficiency of cantaloupe slices at various slice thickness and microwave power levels.

Microwave Power (W)	Slice Thickness (mm)	Drying Efficiency (%)	Thermal Efficiency (%)	Energy Efficiency (%)	Exergy Efficiency (%)
	2	24.64 ± 1.2^{e}	17.40 ± 0.57^{cd}	28.18 ± 1.97^{cd}	24.59 ± 1.77^{c}
180	4	14.64 ± 1.24^{fg}	10.40 ± 0.88^{ef}	19.19 ± 1.36^{ef}	15.22 ± 1.22^{e}
	6	12.36 ± 0.99^{g}	7.02 ± 74^{f}	16.91 ± 1.02^{f}	11.25 ± 1.01^{f}
	2	32.69 ± 1.34^{b}	30.45 ± 0.54^{b}	37.24 ± 2.12^{b}	32.59 ± 2.01^{b}
360	4	21.36 ± 0.88^{e}	17.12 ± 0.77^{d}	25.91 ± 1.15^{d}	22.36 ± 1.54^{c}
	6	17.35 ± 0.91^{a}	12.91 ± 0.88^{e}	21.90 ± 1.22^{e}	18.88 ± 1.08^{d}
	2	42.70 ± 1.44^{c}	36.46 ± 0.90^{a}	47.24 ± 2.31^{a}	38.89 ± 2.04^{a}
540	4	30.14 ± 1.12^{c}	25.90 ± 1.01^{b}	36.69 ± 1.88^{b}	29.99 ± 1.48^{b}
	6	26.31 ± 1.05^{d}	22.40 ± 0.88^{c}	30.86 ± 1.55^{c}	24.66 ± 1.11^{c}

Different letters for the same segment represent statistically significant differences at a confidence level of 95%.

3.5. Energy Efficiency

The energy efficiency of microwave drying of the cantaloupe slices was calculated from the experimental data using Equation (17). The mean energy efficiency obtained in this study (Table 3) varied from 16.91 to 47.24%, which was in line with the reported drying efficiency for various products by microwave as such as chrysanthemum (29.98 to 62.52%), green peas (28.36 to 57.98%), and chamomile (35.83 to 49.99%) reported by Wang et al. [28], Kaveh et al. [31], and Motevali et al. [30], respectively. The experimental results and statistical analysis revealed a significant improvement in the energy efficiency of the process (at a probability level of 5) with increasing microwave power and decreasing the thickness of the samples. Shortening the duration of the drying process at higher MW powers in thinner samples incremented the energy efficiency. This phenomenon may be due to the fact that the moisture content of cantaloupe pieces is generally high, and since the thickness of the samples are low and their surface is higher compared to their mass, they have a high rate of moisture transfer to their surface; thus, a decline in the thickness of the samples will accelerate moisture transfer to the surface. Therefore, reducing the thickness of the samples will increase energy efficiency [53].

Darvishi et al. [43] reported that the energy efficiency of drying kiwifruit slices with different thicknesses (3, 6, and 9 mm) by microwave (at power levels of 200, 300, 400, and 500) were in the range of 15.15 to 32.27%. Their results also established that the increase in the thickness of the samples led to a significant reduction (at a probability level of 5%) in energy efficiency [51].

3.6. Specific Energy Loss

The mean specific energy loss during the MW drying process of cantaloupe slices at different thicknesses and power levels was calculated by Equation (18) as shown in Table 4. Darvishi [35] and Kouhila et al. [9] highlighted that the lost energy for MW-dried soybean and Dosidicus gigas ranged from 8.89–5.04 MJ/kg and 12.9–59.47 MJ/kg, respectively. This implies that the increase in the microwave power of the dryer investigated led to a significant reduction of specific energy loss at the probability level of 5%. Additionally, the lost energy during the drying of thicker samples was significantly higher than the thinner samples at a probability level of 5%. Owing to the governing mechanism of product heating during the MW drying process, the use of higher powers for thinner samples (as much as possible) can decrement the specific energy loss. Since the specific energy loss is inversely related to water discharged from the product, the specific energy loss decreased by enhancing the amount of water discharged from the product [10].

Table 4. Average values of energy and exergy loss of microwave drying process of cantaloupe slices.

Microwave Power (W)	Slice Thickness (mm)	Energy Loss MJ/kg	Exergy Loss MJ/kg
	2	7.44 ± 0.32 [e]	8.14 ± 0.41 [e]
180	4	10.22 ± 0.42 [b]	10.83 ± 0.35 [b]
	6	11.24 ± 0.52 [a]	12.20 ± 0.44 [a]
	2	4.79 ± 0.27 [g]	5.73 ± 0.27 [g]
360	4	8.39 ± 0.39 [d]	8.88 ± 0.39 [d]
	6	9.29 ± 0.44 [c]	10.11 ± 0.29 [c]
	2	2.65 ± 0.31 [h]	3.00 ± 0.24 [h]
540	4	5.24 ± 0.33 [g]	6.26 ± 0.33 [g]
	6	6.67 ± 0.40 [f]	7.41 ± 0.28 [f]

Different letters for the same segment represent statistically significant differences at a confidence level of 95%.

3.7. Specific Exergy Loss

Table 4 summarizes the influence of drying conditions (microwave power and slice thickness) on the specific exergy loss. As noticed, the reduction in the microwave power led to the exergy loss by 3.008 to 12 MJ/kg water. Moreover, the changes in the specific exergy loss with decreasing thickness exhibited a descending trend in various MW powers. This implies that the use of thinner samples reduces the contact time of the product with the microwave power. As the rate of mass and heat transfer increases, the drying time decreases, and less energy is transferred out of the dryer chamber, resulting in reduced specific exergy loss [47]. Additionally, the exergy loss declined with increasing microwave power due to the shorter process time. The lowest exergy loss (3.008 MJ/kg water) was observed at the MW power of 540 W and thickness of 2 mm. Higher microwave powers had lower exergy, and this exergy increased water evaporation or exergy consumption, hence reducing exergy loss [43].

The result is consistent with findings reported elsewhere [10,35]. For instance, Azadbakht et al. [10] reported a reduction in the exergy loss of the MW drying process of orange slices at the power levels of 90 to 900 W, with the osmotic pretreatment ranging from 19.85 to 3.71 MJ/kg water with an increase in microwave power. They stated that the intensity of the process reduction is much greater at higher powers, which reduced the exergy loss.

3.8. Exergy Efficiency

Table 3 shows the mean exergy efficiency. As detected, the exergy efficiency of the cantaloupe slice drying varied from 11.25 to 38.89%. This implies that the adoption of higher powers significantly improved the thickness of the slice samples at the probability level of 5%, implying the lowest exergy efficiency (11.25%) obtained at the power of 180 W and a thickness of 6 mm while the highest exergy efficiency (38.89%) released at the power of 540 W and a thickness of 2 mm. The reduction in the drying process time at higher microwave powers reduced the energy loss and ultimately increased the exergy efficiency of the system [12]. In thinner samples, the drying process occurred faster due to the low internal strength of the specimens, increasing the exergy efficiency [43]. This finding was further corroborated by other researchers [43,51].

3.9. Improvement Potential

Table 5 presents the average exergy improvement rate, as determined from Equation (27). The minimum average value of the exergy improvement ability (1.83 MJ/kg) was obtained with the 2-mm thick samples at the microwave power of 540 W, while the maximum value of the exergy improvement ability (10.83 MJ/kg) was observed with 6-mm-thick samples at the power of 180 W. Furthermore, the increase in the microwave power and decrease in the thickness of the samples enhanced the rate of exergy improvement ability.

Table 5. Average improvement potential and exergetic sustainability index of microwave drying process of cantaloupe slices.

Drying Conditions		IP	SI
	2	6.14 ± 0.44 [e]	1.32 ± 0.05 [c]
180	4	9.18 ± 0.49 [b]	1.17 ± 0.06 [ef]
	6	10.83 ± 0.38 [a]	1.12 ± 0.04 [f]
	2	3.86 ± 0.28 [f]	1.48 ± 0.07 [b]
360	4	6.89 ± 0.33 [d]	1.28 ± 0.05 [cd]
	6	8.20 ± 0.42 [c]	1.23 ± 0.04 [de]
	2	1.83 ± 0.33 [g]	1.63 ± 0.06 [a]
540	4	4.38 ± 0.27 [f]	1.42 ± 0.05 [b]
	6	5.58 ± 0.46 [e]	1.34 ± 0.04 [c]

Different letters for the same segment represent statistically significant differences at a confidence level of 95%.

Microwave power enhancement and the sample's thickness decline, indeed, increased the enthalpy around the dryer chamber. The results are comparable to observations reported elsewhere [35]. For instance, Darvishi et al. [35] reported that the average exergy of soybean ranged from of 1.31 to 5.35 MJ/kg as the microwave power increased from 200 to 600 W. The enhancement is attributed to the increase in the microwave power.

3.10. Exergetic Sustainability Index

Table 5 presents the mean exergetic sustainability index and varied from 1.12 to 1.63. Similar reports were reported by Okunola et al. [54], Arslan and Aktas [37], and Beigi et al. [40] for the exergetic sustainability index range for the drying of okra at 2.14 to 2.77, 1.07 to 1.21, and 1.05 to 1.42, respectively. As the value of the exergetic sustainability index is proportional to the exergy efficiency, the highest exergetic sustainability index values showed a slight impact on the environment, resulting in environmental imbalance and improvement of exergy efficiency.

3.11. Artificial Neural Network

Tables 6 and 7 highlight the data simulated from the predicted values of the ANN and ANFIS models. Table 6 presents the values of R^2, MSE, and MAE as well as network type, network topology, algorithm, and threshold functions for predicting data by ANN to easily understand the consistency between real data and simulation. As noticed, the ANN-obtained values of R^2 for the effective moisture diffusion coefficient, SEC, dryer efficiency, energy efficiency, energy loss, energy efficiency, exergy efficiency, exergy loss, improvement potential, and exergetic sustainability index were 0.8917, 0.9040, 0.9188, 0.9441, 0.8894, 0.9258, 0.9008, 0.9321, 0.8998, and 0.9139, respectively. These results indicated that the points predicted by ANN are less accurate. The statistical indices of ANN obtained from the finding are consistent with those of researchers elsewhere [7,10,22].

Table 6. Performance indices for the ANN models.

Parameters	Network Topology	Training Algorithm	Function	Train			Test			Epoch
				RMSE	MAE	R^2	RMSE	MAE	R^2	
D_{eff}	3-10-10-1	Tansig-Tansig-Tansig	LM	2.77×10^{-24}	3.95×10^{-13}	0.8812	3.57×10^{-24}	5.06×10^{-13}	0.8917	67
SEC	3-10-1	Tansig-Tansig	LM	0.2994	0.1362	0.8892	0.2642	0.1469	0.9040	39
Energy efficiency	3-5-1	Tansig-Logsig	LM	1.0851	0.3311	0.9077	0.7925	0.2839	0.9188	25
Drying efficiency	3.8-8-1	Tansig-Logsig-Tansig	BR	0.7046	0.2669	0.9376	0.7873	0.2827	0.9441	93
Thermal efficiency	3-8-1	Tansig-Tansig	BR	1.2081	0.3605	0.8797	1.1318	0.3464	0.8894	29
Energy loss	3-5-5-1	Tansig-Purelin-Tansig	LM	0.1009	0.0885	0.8978	0.1045	0.0876	0.9258	59
Exergy efficiency	3-10-10-1	Tansig-Logsig-Logsig	LM	1.2561	0.3469	0.8917	0.8423	0.3000	0.9015	55
Exergy loss	3-15-1	Tansig-Logsig-Tansig	LM	0.0995	0.0962	0.9036	0.0749	0.0787	0.9321	38
IP	3-15-10-1	Tansig-Tansig-Tansig	LM	0.1783	0.1236	0.8896	0.0911	0.0909	0.8998	44
SI	3-10-1	Tansig-Tansig	BR	0.0003	0.0060	0.8791	0.0003	0.0056	0.9139	97

Table 7. Performance indices for the ANFIS models.

Parameters	Number of MF		Type of MF		Train			Test		
	Input	Cycle	Input	Output	RMSE	MAE	R^2	RMSE	MAE	R^2
D_{eff}	3-3-3	100	Trimf	Linear	2.62×10^{-24}	3.92×10^{-13}	0.9076	2.08×10^{-24}	3.96×10^{-13}	0.9445
SEC	3-3-3	100	Trimf	Linear	0.1759	0.1296	0.9315	0.1662	0.1230	0.9599
Energy efficiency	3-3-3	100	Trimf	Linear	0.4938	0.2222	0.9702	0.2977	0.1744	0.9763
Drying efficiency	3-3-3	100	Gaussmf	Linear	0.2291	0.1432	0.9775	0.1879	0.1350	0.9811
Thermal efficiency	3-3-3	100	Trimf	Linear	0.4074	0.2098	0.9633	0.4030	0.2106	0.9698
Energy loss	3-3-3	100	Gaussmf	Linear	0.0232	0.0469	0.9804	0.0180	0.0414	0.9830
Exergy efficiency	3-3-3	100	Trimf	Linear	0.0837	0.0938	0.9910	0.0601	0.0777	0.9927
Exergy loss	3-3-3	100	Trimf	Linear	0.0090	0.0283	0.9908	0.0061	0.0225	0.9946
IP	3-3-3	100	Gaussmf	Linear	0.0605	0.0741	0.9390	0.1148	0.0959	0.9507
SI	3-3-3	100	Trimf	Linear	0.00005	0.0019	0.9806	0.00002	0.0016	0.9890

3.12. ANFIS

To obtain the best ANFIS model capable of predicting the kinetics, energy, and exergy indices of cantaloupe drying, different ANFIS structures were tested. Then, the best ANFIS structure with the best results is presented in Table 7. To achieve the best ANFIS structure with the highest precision in predicting kinetics, energy, and exergy indices, changes were applied in various parameters such as number and type of input and output membership functions, optimization methods, and number of epochs. The best ANFIS model had the input and output membership functions, the number of epochs, and the learning algorithm type of Trimmf, linear, 100, and hybrid, respectively. The values of R2, RMSE, and RMSE of the best ANFIS model for predicting kinetic, energy, and exergy indices are shown in Table 7.

As shown in Table 7, R2 values of effective moisture diffusion coefficient, SEC, dryer efficiency, energy efficiency, energy loss, energy efficiency, exergy efficiency, exergy loss, improvement potential, and exergetic sustainability index were 0.9445, 0.9599, 0.9763, 0.9811, 0.9698, 0.9830, 0.9927, 0.9946, 0.9507, and 0.9890, respectively.

3.13. Comparison of ANFIS and ANN Models

The prediction capabilities of the statistical indices for the ANN and ANFIS models of exergy based of microwave dryer for the cantaloupe were compared. Owing to the higher value of R^2 and lower values of other statistical indices of ANN compared to ANFIS, the accuracy of the ANFIS model is better than that of the ANN model. Similar results were observed by [21,24,31] for the ANN-ANFIS based prediction of exergy parameters of onion drying with continuous industrial dryer, quince under hot air dryer, and of blackberry drying by an infrared-convective dryer, respectively. The higher prediction ability of the latter model compared to the former can be attributed to the use of fuzzy inference system.

3.14. Certainty Analysis

For the purpose of certainty, sensitivity tests are often conducted to determine the relative importance of each independent variable in affecting the dependent variables. All independent variables are, in turn, taken into consideration in the analysis of sensitivity. To obtain the sensitivity level of each input variable in the determination of different parameters by ANNs and ANFIS, the omission of each input variable (microwave power, slice thickness, and drying time) was used as a technique [25]. The results of the sensitivity analysis of the input parameters in the drying process of cantaloupe are given in a set of classified data in Table 8. These results indicate that drying time and microwave power had the highest and lowest effects on different parameters of cantaloupe, respectively.

Table 8. Analyzing the effects of indirect independent variables in predicting different parameters in cantaloupe slices.

Parameters	ANN				ANFIS			
	Total	**Without Microwave Power**	**Without Slice Thickness**	**Without Drying Time**	**Total**	**Without Microwave Power**	**Without Slice Thickness**	**Without Drying Time**
Deff	0.8917	0.8898	0.8823	0.8323	0.9445	0.9325	0.9301	0.9090
SEC	0.9040	0.8952	0.8878	0.8657	0.9599	0.9511	0.9421	0.9237
Energy efficiency	0.9188	0.8995	0.8912	0.8804	0.9763	0.9553	0.9432	0.9025
Drying efficiency	0.9441	0.9425	0.9389	0.9025	0.9811	0.9621	0.9425	0.9166
Thermal efficiency	0.8894	0.8599	0.8468	0.8226	0.9698	0.9258	0.9090	0.8882
Energy loss	0.9258	0.9090	0.9053	0.8888	0.9830	0.9632	0.9489	0.9208
Exergy efficiency	0.9015	0.8680	0.8511	0.8258	0.9927	0.9880	0.9733	0.9494
Exergy loss	0.9321	0.9123	0.9089	0.8974	0.9946	0.9911	0.9722	0.9525
IP	0.8998	0.8931	0.8898	0.8529	0.9507	0.9411	0.9212	0.8859
SI	0.9139	0.9045	0.8969	0.8787	0.9890	0.9833	0.9599	0.9489

4. Conclusions

In the present study, cantaloupe pieces were dried under different conditions using a microwave dryer, and energy and exergy indices were explored. According to thermodynamic analysis, an increase in the microwave power declined the SEC, while the enhancement of sample thickness declined SEC. The minimum and maximum SEC were 10.48 and 25.92 MJ/kg water, respectively. Energy efficiency was in the range of 16.91 to 47.24% and was higher at higher powers and lower thicknesses of the samples. Increasing the microwave power and decreasing the thickness of the samples led to a reduction in specific energy and exergy losses and IP. Dryer and thermal efficiencies were recorded between 12.36 to 42.70% and 7.02 to 36.46%, respectively. The mean exergy efficiency of the cantaloupe drying process ranged from 11.25% for microwave power of 540 W and thickness of 2 mm to 38.98% for microwave power of 180 W and thickness of 6 mm. The minimum and maximum mean exergetic sustainability indices were 1.12 and 1.63, respectively. According to the predicted results, energy and exergy parameters predicted by ANFIS models were much more accurate than ANN as the R^2 values of the ANFIS-predicted variables were closer to one and also exhibited more agreement with the real data. Real and predicted results for energy and exergy parameters could be useful for designing and manufacturing modern dryers with maximum exergy and minimum energy consumption. The use of these results can lead to lower environmental consequences.

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Abbreviations

A	Tray area (m^2)	m_{wp}	Mass of wet product [kg]
C_p	Heat capacity [J/kg K]	m_{dp}	Mass of dry product [kg]
D	Weight density (kg/m^2)	M_w	Mass of water evaporated [kg]
D_{eff}	Effective diffusivity coefficient [m^2/s]	Mt	Moisture content of the product at any level and at any time [g water/g dry matter]
D_e	Drying efficiency (%)	Mo	Initial moisture content [g water/g dry matter]
$E_{heating}$	Energy for the material heating (kJ)	m_d	Mass of dry sample [kg]
E_{ref}	Energy reflected [J]	m	Mass [kg]
E_{tre}	Energy transmitted [J]	N	Total the data [-]
E_{in}	Energy input	P_{tra}	Microwave power transmitted (W)
E_{out}	Energy output	P_{in}	Microwave power emitted by the magnetron [W]
E_{loss}	Specific energy loss [J/kg water]	P_{abs}	Microwave power absorbed [W]
EX_{in}	Exergy input [J]	P_{ref}	Microwave power reflected [W]
EX_{abs}	Exergy absorbed [J]	P	Microwave output power (kW)
EX_{ref}	Exergy reflected [J]	SEC	Specific energy consumption [J/kg water]
EX_{tra}	Exergy transmitted [J]	SI	Exergetic sustainability index
ex_{exap}	Exergy of evaporation water [J/kg water]	TE	Thermal efficiencies
EX_{loss}	Specific exergy loss [J/kg water]	T_o	Ambient temperature [K]
Ex	Exergy [J]	T	Temperature [K]
ex	Specific exergy [J/kg water]	t	Drying time [min]
E_{evap}	Energy consumed to evaporate moisture from drying samples (kJ)	Xi	Measured values
$h_{f.g}$	Latent heat of vaporization (kJ/kg)	X_p	Predicted values
IP	Improvement potential [MJ/kg water]	X_{mean}	Average predicted values
L	Product thickness [m]	λ_{wf}	Latent heat of free water [J/kg]
m_{in}	Mass input [kg]	λ_K	Latent heat of sample [J/kg]
m_{out}	Mass output [kg]	η_{ex}	Exergy efficiency [%]
Me	Equilibrium moisture content [g water/g dry matter]	η_e	Energy efficiency [%]
MR	Moisture ratio [-]		

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