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CLASSIFICATION OF THE ENERGY AND EXERGY OF MICROWAVE DRYERS IN DRYING KIWI USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This investigation uses the artificial neural network model to classify the energy and exergy of the kiwi drying process in a microwave dryer. In this experiment, classification was carried out separately for various pre-treatments and microwave powers using three pretreatments (oven, ohmic, and control treatments) and microwave power values (360, 600, and 900W), and the artificial neural network model. Classification was done using 5 different input data groups. The first group included the overall data (energy efficiency, special energy loss, exergy efficiency, and exergy loss), while the second to fifth groups included the data on the exergy efficiency, special energy loss, energy efficiency and special exergy loss in the order mentioned, which served as the classification inputs. Considering the results, the best R and Percent Correct values for the oven (Percent Correct=90 – R=0.709) and ohmic (Percent Correct=83.33– R=0.846) pretreatments were obtained. The values of this parameters were also calculated for the control (Percent Correct=71.43 – R=0.843), the 360W power (Percent Correct=92.86 – R=0.9975), the 600W power (Percent Correct=100 – R=0.9124), and the 900W power (Percent Correct=100 – R=0.9685). The overall data was used in the classification phase. In addition, the maximum correctly detected data for the oven, ohmic, and pretreatment was 18 (20 items), 15 (18 items), and 5 (7 items), respectively. The maximum correctly detected data for the 360W power, 600W power, and 900W power levels was 13 (14 items), 15 (15 items), and 16 (16 items), respectively. In sum, the neural network using the overall data input displayed acceptable efficiency in classifying the energy and exergy data of the kiwi drying process in microwave dryers

1. Introduction

Artificial neural networks (ANNs) have been widely used in different fields of agriculture like economic, energy and environmental modeling as well as to extend the field of statistical methods, in the Last few decades. A big advantage of ANNs over statistical methods is that they require no assumptions about the form of a fitting function. Instead, the network is trained with experimental data to find the relationship; so they are becoming very popular estimating tools and are known to be efficient and less time-consuming in modeling of complex systems compared to other mathematical models such as regression(B. Khoshnevisan, Sh. Rafiee, M. Omid 2013) The concept of Artificial Neural Networks (ANN) was developed about fifty years ago, but it has been used for practical applications for approximately the last twenty years. Artificial Neural Networks are one of the two major fields of Artificial Intelligence (AI) with the other one being Expert Systems. ANN try to mimic the human brain learning process and are able to learn key information patterns in a multidimensional information domain (Mavromatidis et al. 2013). Artificial Neural Network (ANN) models are developed for each system to provide the energy baseline, which is modelled as a dependency between the energy consumption and suitable explanatory variables. The tool has two diagnostic levels. The first level broadly evaluates the systems performance, in terms of energy consumption, while the second level applies more rigorous criteria for fault detection of supermarket subsystem(Mavromatidis et al. 2013). Neural networks have become ubiquitous in applications ranging from computer vision to speech recognition and natural language processing. While these large neural networks are very powerful, their size consumes considerable storage, memory bandwidth, and computational resources (Han et al. 2015).

The classification problem is the problem of assigning an object into one of predefined classes based on a number of features or attributes extracted from the object. In machine learning, classification is categorized as a supervised learning method. A classifier is constructed based on a training set with known class labels(Siswantoro et al. 2016). A well trained network learns from the pre-seen experimental dataset (training data) and generalizes this learning beyond to the unseen data which is called ‘prediction’. Furthermore, artificial neural networks (ANNs) are able to model non-linear behaviors and complex processes. This is highly important considering the drying applications in which the nature is seriously non-linear and simple modeling methods fail. Although ANN methods are frequently reported on drying fruits and vegetables (Nazghelichi et al. 2011, Nikbakht et al. 2014). Artificial neural networks have been used in the past years for modeling many processes in food engineering. Behroozi Khazaeia et al. (2013) used neural networks to 9 model and control the drying process of grapes(Behroozi Khazaei et al. 2013). Aghbashlo et al. (2012) used artificial neural networks to predict exergetic performance of the spray drying process for fish oil and skimmed milk powder(Aghbashlo et al. 2012). Kerdpiboon et al. (2006) used artificial neural network analysis to predict shrinkage and rehydration of dried carrots(Kerdpiboon et al. 2006). Hernández-Pérez et al. (2004) proposed a predictive model for heat and mass transfer using artificial neural networks to obtain on-line prediction of temperature and moisture kinetics during the drying of cassava and mango(Hernández-Pérez et al. 2004)(Guiné et al. 2015).The purpose of this investigation was to classify the amount of energy and exergy of the microwave dryer for the input of the grid with different potentials and pretreatment (ohmic, oven, and control samples) using the neural network, And is artificial neural network able to detect the amount of energy and extrusion for pre-treated and unprocessed products?. Also The sensitivity coefficient of the data was also analyzed using the neural network to determine which network the input was most sensitive to classification.

2. Materials and methods

2.1. Sample preparation

Newly-harvested kiwi fruit were purchased from the local store in Gorgan city of Iran, and were kept in the laboratory at 10 ° C. At the beginning of each experiment, the kiwi was washed and the slices were cut in circular in a thickness of 5 mm and they were weighted. Then, samples were placed in an oven with Temperature at 100 ° C for 3, 5 and 7 min to be pretreated. Also samples were placed in an ohmic heating with voltage 80 for 3, 5 and 7 min to be pretreated. Drying process was performed in a microwave dryer in the Bio System Mechanics Department of Gorgan University of Agricultural Sciences and Natural Resources Figure 1.

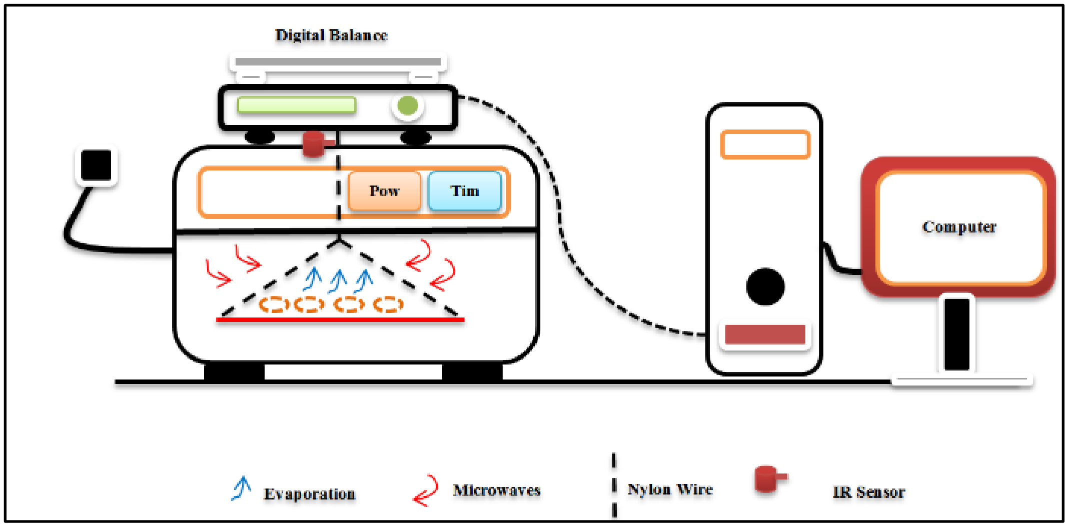

Figure 1. Diagram of microwave drying system

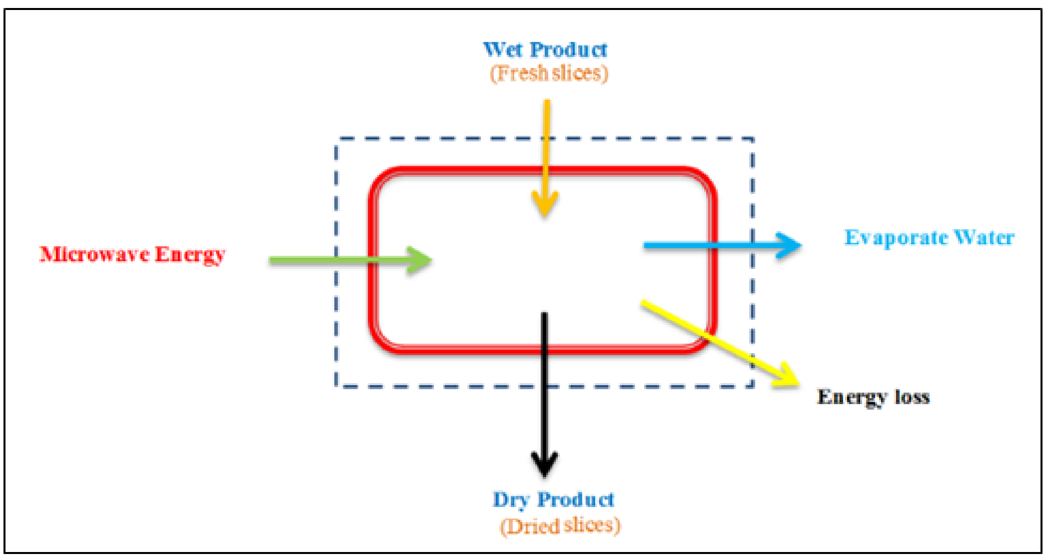

Figure 2. Volume control of microwave system

2.2. Experiment method

Slices were pretreated and placed in containers and dried at three powers of 360, 600 and 900 W. The weight of kiwi was measured using a 0.01 mg precision scale. The weight of each sample was measured and recorded at a time interval of 1 minute to reach constant moisture. For each of the treatments, the experiments were repeated three times. The experiment was conducted at a temperature of 20 ° C and relative humidity of 79%. The moisture content of kiwi was also calculated using equation (1) (Yogendrasasidhar & Pydi Setty 2018).

$$MC = \frac{W - We}{W} \quad (1)$$

2.3. Energy analysis

The mass and energy survival in the microwave dryers' chamber is shown in Figure

According to Equation 3, the initial mass of the sample is equal to the amount of water vapor removed and the rate of dried sample mass.

$$m_o = m_{ew} + m_p \quad \textbf{(3)}$$

The mass of evaporated water is obtained using Equation 4 (Darvishi et al. 2014).

$$m_{wt} = m_d(M_0 - M_t) \quad \textbf{(4)}$$

The protected energy of the sensible heat, latent heat, and the thermal source of the microwave were calculated using Equation 5 and the input energy of the dryer was calculated using Equation 6 (Jindarat et al. 2011). In equation 5, the lost energy is $P_{ref} + P_{tra}$. Equation 6 shows the amount of input energy of the microwave. This formula is composed of three parts, including absorbed energy, reflected energy, and passed energy. In equation (6) equals to the absorbed energy of product.

$$P_{in} = P_{abs} + P_{ref} + P_{tra} \quad \textbf{(5)}$$

$$\mathrm{P_{in}} \times \mathrm{t} = \left((\mathrm{mC_pT})_{\mathrm{dp}} - (\mathrm{mC_pT})_{\mathrm{wp}} \right) + \lambda_K m_w + E_{ref} + E_{tra} \quad (6)$$

The latent heat of the kiwi samples is calculated using Equation 7 (Abdelmotaleb et al. 2009).

2. The general relation of mass moisture survival is calculated using Equation (2) (Darvishi et al. 2016).

$$\sum m_{in} = \sum m_{out} \quad \textbf{(2)}$$

$$\frac{\lambda_K}{\lambda_{wf}} = 1 + 23\exp(-40M_t) \quad \textbf{(7)}$$

The latent heat of free water evaporation has been calculated by Broker et al and using Equation 8 (Darvishi 2017).

$$\lambda_{wf} = 2503 - 2.386(T - 273) \quad \textbf{(8)}$$

The thermal capacity is a function of the moisture content and can be calculated through Equation 9 (Brooker et al. 1992).

$$C_P = 840 + 3350 \times \left(\frac{M_t}{1 + M_t}\right) \quad \textbf{(9)}$$

The thermal efficiency of the dryer is calculated using Equation 10 (Soysal et al. 2006).

$$\eta_{en} = \frac{energy\ absorption}{P_{in} \times t} \quad \textbf{(10)}$$

The specific energy loss was measured using Equation 11 (Darvishi et al. 2014)

$$E_{loss} = \frac{E_{in} - E_{abs}}{m_w} \ or \ E_{loss} = (1 - \eta_{en}) \times \frac{P_{in} \times t}{m_w} \quad \textbf{(11)}$$

2.4. Exergy analysis

The general exergy equilibrium in the microwave chamber was stated as follows (Darvishi et al. 2016)

$$EX_{in} = EX_{abs} + \underbrace{EX_{ref} + EX_{tra}}_{\text{Exergy loss}} \quad \textbf{(12)}$$

$$P_{in} \times t = \overbrace{((m \times ex)_{dp} - (m \times ex)_{wp}) + ex'_{exap} \times t)} + E_{ref} + E_{tra} \quad \textbf{(13)}$$

:

The amount of exergy transmitted due to evaporation in the drying chamber was calculated using Equation 14 (Sarker et al. 2015)

$$ex'_{exap} = (1 - \frac{T_0}{T_p}) \times m_{wv}\lambda_{wp} \quad \textbf{(14)}$$

In formula 14, mwv is calculated using formula 15 (Darvishi et al. 2016)

$$m_{wv} = \frac{m_{t+\Delta t} + m_{wv}\lambda_{wp}}{\Delta t} \quad \textbf{(15)}$$

Specific exergy loss was calculated using formula 16 (Darvishi et al. 2014):

$$ex = C_p[(T - T_0) - T_0 \ln(\frac{T}{T_0})] \quad \textbf{(16)}$$

Exergy efficiency for each dryer system as the exergy rate used in drying the product to the exergy of drying source supplied to the system is calculated by the Equation 17 (Dincer & Sahin 2004)

$$\eta_{en} = \frac{exergy\ absorption}{P_{in} \times t} \times 100 \quad \textbf{(17)}$$

The specific exergy loss was calculated using Equation 18 (Darvishi 2017).

$$EX_{loss} = \frac{EX_{in} - EX_{abs}}{m_w} \quad \textbf{(18)}$$

In this research, the source of temperature and pressure in the environment was 20 ° C and 101325 Pascal, respectively. After calculating the energy and exergy, all the data is sorted in Excel.

2.5. Artificial Neural Network Modeling

In this research, the artificial multilayer perceptron (MLP) neural network was used for systematization energy and exergy of the microwave dryer to classification pre-treatment (oven and ohmic) and power microwave by one hidden layer and 5 neurons using the NeuroSolution 6 software. Hyperbolic tangent linear activation functions (Equation 19), which are the most common type of activation functions, were used in the in hidden input and output layer. In this paper, the Levenberg-Marquardt algorithm was used to learn the network. Additionally, 70% of the data were used for training, 15% of them were used for network evaluation (Validating Data), and 15% of the data were used for testing the network (Testing data) (Table 2). Five repetitions were considered to achieve the minimum error rate and maximum network stability as a mean of 4000 Epoch for the network. Error was estimated using algorithm with back propagation error.

The inputs for the neural network are divided into the following modes:

1. Energy efficiency, Specific energy loss, Exergy efficiency, Specific exergy loss (total data) were considered as network inputs
2. Energy efficiency was considered as network inputs
3. Specific energy loss was considered as network inputs
4. Exergy efficiency was considered as network inputs
5. Specific exergy loss was considered as network inputs

The classification for data pre-treatment (Oven, Ohmic and control) and power microwave (360 , 600 and 900 W) were based on the inputs above. Five repetitions were considered to achieve the minimum error rate and maximum network stability as a mean of 4000 Epoch for the network. Error was estimated using algorithm with back propagation error. Statistical parameters including RMS, Root Mean Square Error (RMSE), R2, and Mean Absolute Error (MAE), NMSE were calculated for inputs and relationships were calculated using the formulas shown in Table 1.

Table 1. Neural Network Relationships

Formula	Formula Number	Reference
Tanh = $\frac{e^x - e^{-x}}{e^x + e^{-x}}$	(19)	(B. Khoshnevisan, Sh. Rafiee, M. Omid 2013)
$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}$	(20)	(Azadbakht et al. 2016)
$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}}$	(21)	
$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}}$	(22)	(B. Khoshnevisan, Sh. Rafiee, M. Omid 2013)
$MAE = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{n}$	(23)	(Azadbakht et al. 2017)

Table 2. Optimization values for artificial neural network parameters

Input	Number of hidden layers	Learning rule	Type of activation function	The number of One hidden layer neurons	Testing data %	Training data %	Cross Validation%
total data	1	Levenberg Marquardt	Hyperbolic tangent	5	15%	70%	15%
Energy efficiency	1	Levenberg Marquardt	Hyperbolic tangent	5	15%	70%	15%
Specific energy loss	1	Levenberg Marquardt	Hyperbolic tangent	5	15%	70%	15%
Exergy efficiency	1	Levenberg Marquardt	Hyperbolic tangent	5	15%	70%	15%
Specific exergy loss	1	Levenberg Marquardt	Hyperbolic tangent	5	15%	70%	15%

3.Results and discussions

3.1. Classification based on pre-treatment of ohmic, oven and control

Table (3) shows the MSE, RMSE, NMSE, R-MAE, and percent correct values. According to this table, the best MSE, NMSE, R-MAE, and percent correct values were associated with the oven and ohmic pretreatments in the classification process. All of the energy efficiency, special energy use, exergy efficiency, and special exergy use values constituted the input. The best oven pretreatment values were MSE $_{Train}$ =0.123, RMSE $_{Train}$ =0.350, NMSE $_{Train}$ =0.497, MAE $_{Train}$=0.248, R $_{Train}$=0.709, and Percent Correct $_{Train}$=90. Moreover, the best ohmic pretreatment values were MSE $_{Train}$=0.068, RMSE $_{Train}$=0.260, NMSE $_{Train}$=0.258, MAE $_{Train}$=0.164, R $_{Train}$=0.846, and Percent Correct $_{Train}$=83.33. Finally, the best Percent Correct $_{Test}$ value was obtained through the network input that was composed of the energy efficiency, exergy efficiency, and exergy loss data. The best MSE $_{Test}$, RMSE $_{Test}$, NMSE $_{Test}$, and MAE $_{Test}$ values were obtained by means of the network that used the overall data as the input. As regards the ohmic pretreatment, the best Percent Correct $_{Test}$ value was obtained through the network that used the exergy loss as the input. The best MSE $_{Test}$, RMSE $_{Test}$, NMSE $_{Test}$, and MAE $_{Test}$ values were also similar to the oven results. The R$_{Train}$ values of the oven pretreatment corresponding to the energy efficiency, special energy loss, exergy efficiency, and special exergy loss were 0.061, 0.31, 0.49, and 0.44, respectively. These values were 0.182, 0.501, 0.567, and 0.501 for the ohmic pretreatment in the order mentioned. These values did not suit the classification. The Percent Correct $_{Train}$ values corresponding to the energy efficiency, special energy loss, exergy efficiency, and special exergy loss were 84.21, 68.42, 82.35, and 50 using the oven pretreatment and 20, 77.78, 47.37, and 81.81 using the ohmic pretreatment in the order mentioned. The best MSE, RMSE, and R-MAE values for testing the network with the oven and ohmic pretreatments were obtained when the network carried out the classification using the overall data as the input. Table (3) shows the “Test” values of this network.

Table 3. Error values in predicting experimental data using optimal artificial neural network

	Total input					
Performance	**Oven**		**Ohmic**		**Control**	
	Train	Test	Train	Test	Train	Test
MSE	0.123	0.187	0.068	0.106	0.038	0.111
RMSE	0.3507	0.4324	0.2608	0.3256	0.1949	0.3332
NMSE	0.497	0.757	0.285	0.476	0.292	0.643
MAE	0.248	0.343	0.164	0.229	0.080	0.170
R	0.709	0.537	0.846	0.738	0.843	0.636
Percent Correct	90	75	83.33	33.33	71.43	50
	Energy efficiency					
MSE	0.271	0.349	0.259	0.237	0.091	0.019
RMSE	0.52058	0.59076	0.50892	0.48683	0.30166	0.13784
NMSE	1.110	1.412	1.050	0.960	0.787	0
MAE	0.480	0.564	0.456	0.452	0.195	0.121
R	0.061	-0.326	0.182	0.305	0.466	0
Percent Correct	84.21	100.00	20.00	0.00	16.67	0
	Specific energy loss					
MSE	0.231	0.272	0.190	0.219	0.114	0.067
RMSE	0.4806	0.5215	0.4359	0.4680	0.3376	0.2588
NMSE	0.949	1.100	0.793	0.887	0.781	0.679
MAE	0.419	0.479	0.322	0.393	0.247	0.157
R	0.310	0.016	0.501	0.479	0.481	0.633
Percent Correct	68.421	25	77.778	100	12.500	0

	Exergy efficiency					
MSE	0.200	0.417	0.168	0.371	0.120	0.011
RMSE	0.4472	0.6458	0.4099	0.6091	0.3464	0.1049
NMSE	0.852	1.689	0.687	1.501	0.748	0
MAE	0.373	0.607	0.322	0.561	0.186	0.079
R	0.490	-0.428	0.565	0.239	0.601	0
Percent Correct	82.35	100	47.37	40	22.22	0
	Specific exergy loss					
MSE	0.199	0.377	0.187	0.177	0.014	0.381
RMSE	0.4461	0.6140	0.4324	0.4207	0.1183	0.6173
NMSE	0.806	2.181	0.749	1.022	0.232	1.545
MAE	0.403	0.574	0.374	0.322	0.057	0.452
R	0.441	-0.083	0.501	0.199	0.878	0.406
Percent Correct	50	100	81.81	50	66.66	20

The results from the classification conducted using the neural network, the oven and ohmic pretreatments and the control sample are shown in Table (4). According to the results from the Train classification, when the overall data was used as the input, the network displayed an acceptable capacity to distinguish the classified data pretreated by the oven and ohmic from the control data in the classification process. Moreover, the neural network was more potent in classifying the oven data than the ohmic data, resulting in the accurate classification of 18 data items out of the 20 data items. However, the ohmic results were 15 data items out of the total 18 data items, 5 of the 7 control treatment data items were classified accurately. As seen in Table (4), when only the energy efficiency was used as the classification input, the classification did not succeed. In other words, of the 20 ohmic data items, only 4 data items were identified for classification while 16 data items were wrongly classified for the oven. Concerning the ohmic pretreatment data, of the 19 data items, 16 and 3 data items were classified wrongly for the oven and ohmic pretreatments, respectively. Moreover, concerning the control data, , only 2 of the 7 input data items were classified correctly, reflecting the incapacity of the energy efficiency (as the input) to identify the data for classification purposes. The data was mostly classified for the oven. As regards the special energy loss, 16 and 3 data items of the 19 input data items for the oven were classified correctly and wrongly for the ohmic, respectively. As for the ohmic, 14 and 4 data items of the 18 data items were classified correctly and wrongly for the oven, respectively. Moreover, as for exergy efficiency, of the 17 data items, 14 and 3 data items were classified correctly and wrongly for the oven, respectively. As for the ohmic, 9 and 10 data items of the 19 data items were classified accurately and wrongly, respectively. Out of the 19 data items for the control treatment, only 2 data items were classified correctly. According to these results, the classification of the ohmic and oven data did not match the control data, while not all of the inputs mistook the oven and ohmic data for the control data. Concerning the data classification using the exergy loss as the network input, out of the 19 oven data items, 10 and 9 data items were classified correctly and wrongly, respectively. Moreover, 18 and 4 data items of the 22 ohmic data items were classified accurately and wrongly (for the oven), respectively. Table (2) shows the “Test” data detected and classified for the network of concern.

Table 4. Correct and incorrect values for each network's input data

	Total input train					
Output / Desired	**control**		**ohmic**		**oven**	
	Test	**Train**	**Test**	**Train**	**Test**	**Train**
oven	1	2	2	3	3	18
ohmic	0	0	1	15	1	2
control	1	5	0	0	0	0
	Energy efficiency					
oven	0	5	4	16	5	16
ohmic	0	0	0	4	0	3
control	0	1	0	0	0	0
	Specific energy loss					
oven	1	7	0	4	1	13
ohmic	0	0	4	14	3	6
control	0	1	0	0	0	0
	Exergy efficiency					
oven	0	7	3	10	4	14
ohmic	0	0	2	9	0	3
control	0	2	0	0	0	0
	Specific exergy loss					
oven	4	1	4	4	2	10
ohmic	0	0	0	18	0	9
control	1	2	1	0	0	1

Table (5) shows the learning results of the neural network. According to this table, the best learning results in the training phase were obtained when the classification was carried out using the oveall network inputs, and thus it performed the classification in Run=1 and Epoch=3999. Given the RUN and Epoch values of the neural network with all inputs it could be stated that the neural network classified the data satisfactorily at a good speed when all of the input data was selected. As for cross validation, the best network with energy loss was simulated, which performed classification for RUN=4 and Epoch=76. Based on these values it is concluded that the data was not properly assessed for the classification purposes.

Table 5. Some of the best neural network topologies to predict test values

	Cross Validation		**Training**	
	Run	**Epoch**	**Run**	**Epoch**
Total input data	4	87	1	3999
Energy efficiency	5	2177	2	2000
Specific energy loss	4	76	3	4000
Exergy efficiency	4	234	2	3999
Specific exergy loss	5	38	5	2897

Figures (3) and (4) show the Test and Training sensitivity coefficients of the network. As seen in Figure (3), the highest sensitivity coefficient was obtained in the testing using all inputs. As for the oven pretreatment, ohmic pretreatment, and control treatment the highest sensitivity coefficient was obtained with the overall data of energy efficiency, energy efficiency, and exergy loss, respectively. Figure (4) also suggests that the Training sensitivity coefficients of the oven pretreatment, ohmic pretreatment, and control treatment were obtained using the overall inputs of special exergy loss, energy efficiency, and exergy loss, respectively.

3.2. Classification based on the input power of the microwave

Table (6) shows the MSE, RMSE, NMSE, R-MAE, and percent correct values. According to this table, the best MSE, NMSE, R-MAE, and percent correct values were associated with the microwave power in the classification process, all of the energy efficiency, special energy loss, exergy efficiency, and special exergy loss values constituted the input. The best 360 W power values were Train =0.00243، RMSE Train =0.0493 ، NMSE Train =0.0113 ،0.0458= Train MAE ، 0.9975 = R Train ، =92.86 Train Percent CorrectMoreover, the best 600 W powe values were Train =0.0403 MSE، RMSE Train =0.0.2009 ، NMSE Train =0.1816 ،0.0878= Train MAE ، 0.912 = R Train ، =100 Train Percent Correct, also the best 900 W power values were = 0.0153 MSE Train، RMSE Train =0.124 ، NMSE Train =0.067 ،0.0679= Train MAE ، 0.9685 = R Train ، =100 Train Percent Correct .Finally, the best Percent Correct Test value was obtained through the network input that was composed of the specific exergy loss data. The best MSE Test, RMSE Test, NMSE Test, and MAE Test values were obtained by means of the network that used the exergy efficiencyas the input. As regards the ohmic pretreatment, the best Percent Correct Test value was obtained through the network that used the exergy loss as the input. The best MSE Test, RMSE Test, NMSE Test, and MAE Test values were also similar to the oven results. The RTrain values of the oven pretreatment corresponding to the energy efficiency, special energy loss, exergy efficiency, and special exergy loss were 0.061, 0.31, 0.49, and 0.44, respectively. These values were 0.182, 0.501, 0.567, and 0.501 for the ohmic pretreatment in the order mentioned. These values did not suit the classification. The R Train values corresponding to the energy efficiency, special energy loss, exergy efficiency, and special exergy loss were 0.73, 0.45, 0.71 and 0.53 using the 360 W and 0.52, 0.42, 0.43 and 0.58 using the 600 W in the order mentioned, and for 900 W, best value was 0.69, 0.46, 0.57 and 0.60, That this amount can not be suitable for classification . Table (6) shows the “Test” values of this network.

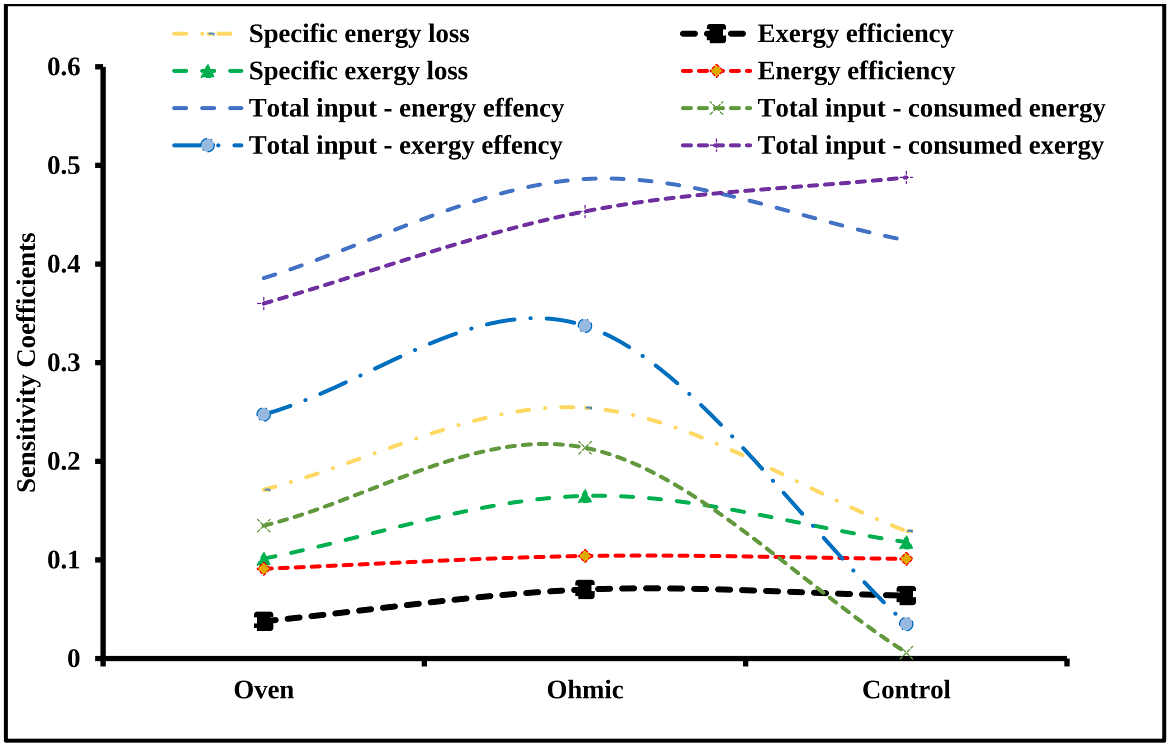

Figure 3. Artificial Neural Network Test sensitivity coefficients

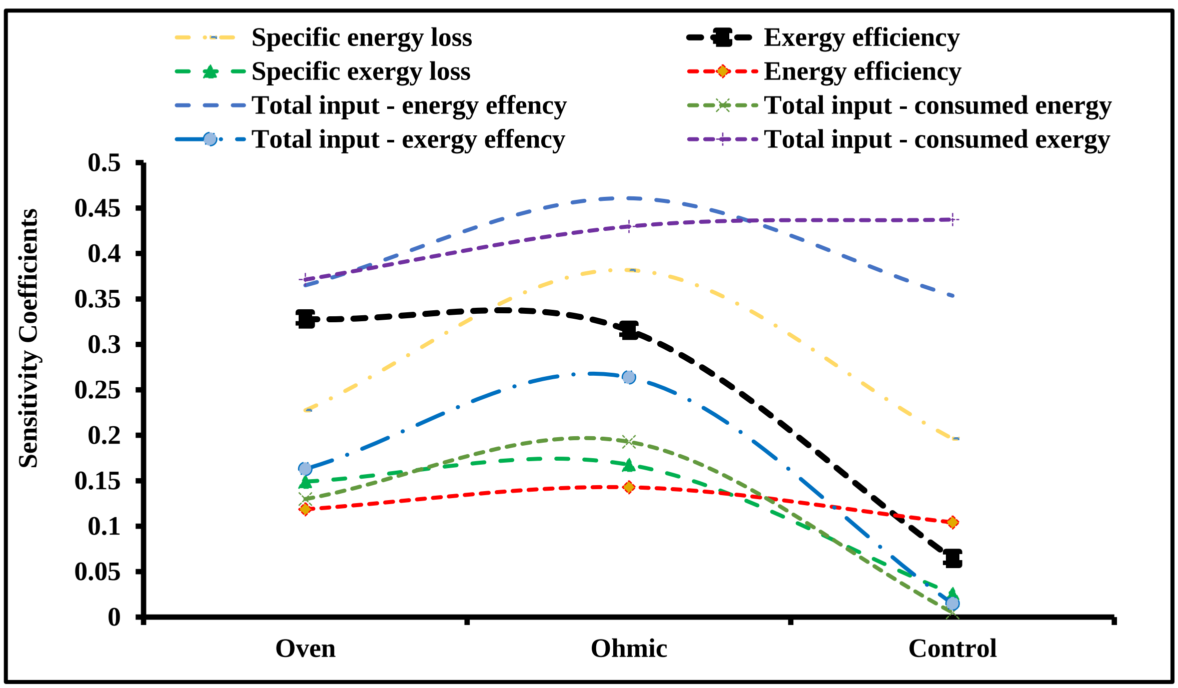

Figure 4. Artificial Neural Network Train sensitivity coefficients

Table 6. Error values in predicting experimental data using optimal artificial neural network

	Total input data					
Performance	**360 W**		**600 W**		**900 W**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
MSE	0.002437	0.12654	0.040361	0.17813	0.015376	0.24952
RMSE	0.049366	0.355725	0.2009	0.422054	0.124	0.49952
NMSE	0.011369	0.51247	0.181623	0.80157	0.067106	1.44368
MAE	0.045817	0.16661	0.087845	0.25175	0.067987	0.28026
R	0.9975	0.7905	0.9124	0.6703	0.9685	0.3460
Percent Correct	92.86	75	100.00	100	100	50
	Energy efficiency					
MSE	0.08987	0.1544	0.14406	0.2470	0.12513	0.2727
RMSE	0.299783	0.392938	0.379552	0.496991	0.353737	0.522207
NMSE	0.45955	0.6947	0.67218	1.0002	0.51293	1.5776
MAE	0.18729	0.2175	0.29344	0.3742	0.26264	0.3899
R	0.73613	0.6154	0.57258	0.4120	0.69871	0.3132
Percent Correct	58.33	67	64.29	50	89.47	50
	Specific energy loss					
MSE	0.1542	0.268	0.1853	0.297	0.1835	0.251
RMSE	0.392683	0.517687	0.430465	0.544977	0.428369	0.500999
NMSE	0.7886	1.207	0.8089	1.718	0.7807	1.017
MAE	0.3132	0.414	0.3788	0.480	0.3723	0.464
R	0.4597	-0.106	0.4378	-0.053	0.4686	0.167
Percent Correct	41.67	0	75.00	50	41.18	0
	Exergy efficiency					
MSE	0.1052	0.2934	0.1837	0.2492	0.1523	0.0763
RMSE	0.392683	0.517687	0.430465	0.544977	0.428369	0.500999
NMSE	0.4911	1.1883	0.8265	1.1215	0.6649	0.4415
MAE	0.2175	0.4104	0.3691	0.3964	0.3080	0.1730
R	0.7135	0.2689	0.4166	0.1289	0.5789	0.7497
Percent Correct	64.3	75	80.0	33	37.5	50
	Specific exergy loss					
MSE	0.1576	0.2620	0.1344	0.2956	0.1499	0.2875
RMSE	0.396989	0.511859	0.366606	0.543691	0.387169	0.53619
NMSE	0.7093	1.0610	0.6542	1.7105	0.6377	1.2936
MAE	0.3260	0.3979	0.2766	0.3917	0.3176	0.4012
R	0.5395	0.3503	0.5883	-0.0581	0.6039	0.4255
Percent Correct	40	25	46	0	100	100

The results from the classification conducted using the neural network, the microwave power's 360 W, 600W and 900 w are shown in Table (7). According to the results from the Train classification, when the overall data was used as the input, the network displayed an acceptable capacity to distinguish the classified data, Moreover, the neural network was more potent in classifying the oven600W and 900 W power data than the 360 W power data. Resulting in the accurate classification of 18 data items out of the 20 data items. However, the ohmic results were 15 data items out of the total 18 data items, 5 of the 7 control treatment data items were classified accurately. As seen in Table (7), when only the energy efficiency was used as the classification input, the classification did not succeed, In other words, of the 12 360 W data items, only 7 data items were identified for classification while 5 data items were wrongly classified for the 900 W. the 600 W power data, of the 14 data only 9 data items were identified for classification while 5 data items were wrongly. For 900 W power Classified from 19 data, 17 data are correct and 2 data are wrong.As regards the special energy loss, 5 and 7 data items of the 12 input data items for the 360 W power were classified correctly and wrongly, respectively, As for the 600 W power, 12 and 4 data items of the 16 data items were classified correctly and wrongly for, respectively, Moreover, as for exergy efficiency, of the 14 data items, 9 and 5 data items were classified correctly and wrongly for the 360 W power, respectively. As for the 600 W power, 12 and 3 data items of the 15 data items were classified accurately and wrongly, respectively. For 900 W power Classified from 16 data, 6 data are correct and 10 data are wrong.. Also for the data classification using the special exergy loss as the network input, out of the 15 360 W power data items, 6 and 9 data items were classified correctly and wrongly, respectively. Moreover, 6 and 7 data items of the 13 600 W power data items were classified accurately and wrongly, respectively. Table (7) shows the “Test” data detected and classified for the network of concern. For 900 W power Classified from 17 data, 17 data are correct and 0 data are wrong.

Table 7. Correct and incorrect values for each network's input data

	Total input data					
Output / Desired	**360 W**		**600 W**		**900 W**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
360 W	13	3	0	0	0	0
600 W	1	1	15	3	0	1
900 W	0	0	0	0	16	1
	Energy efficiency					
360 W	7	2	1	0	0	0
600 W	3	0	9	2	2	1
900 W	2	1	4	2	17	1
	Specific energy loss					
360 W	5	0	1	0	1	0
600 W	6	1	12	1	9	4
900 W	1	2	3	1	7	0
	Exergy efficiency					
360 W	9	3	1	2	0	0

600 W	5	1	12	1	10	1
900 W	0	0	2	0	6	1
	Specific exergy loss					
360 W	6	1	0	0	0	0
600 W	1	1	6	0	0	0
900 W	8	2	7	2	17	3

Table 8. Some of the best neural network topologies to predict test values

	Cross Validation		***Training***	
	Run	Epoch	Run	Epoch
Total input data	4	63	2	132
Energy efficiency	3	1	2	339
Specific energy loss	5	22	5	122
Exergy efficiency	4	4	3	133
Specific exergy loss	3	42	5	121

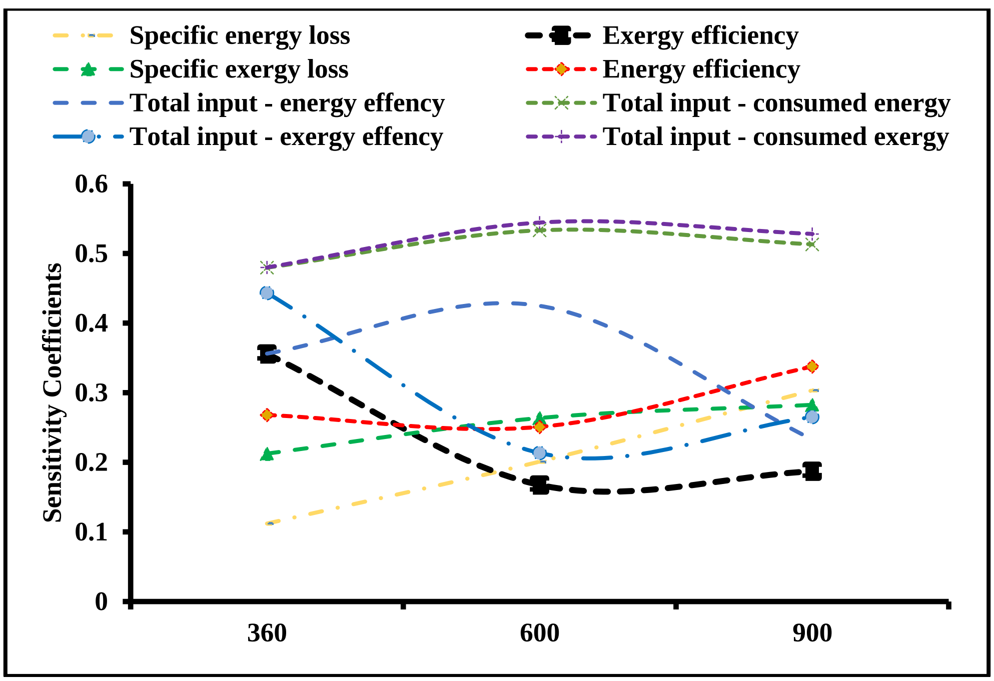

Figure 5. Artificial Neural Network Test sensitivity coefficients

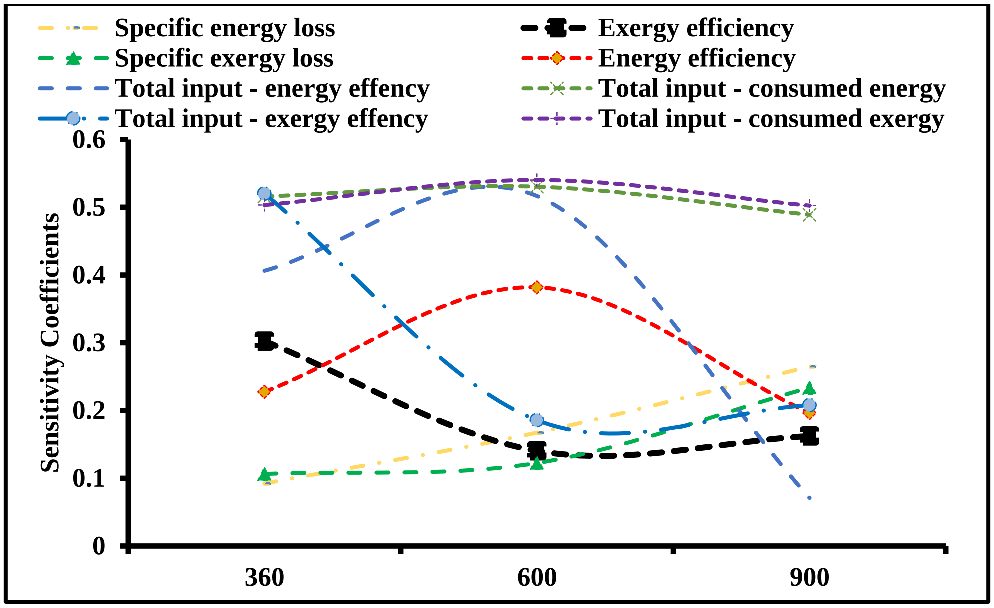

Figure 6. Artificial Neural Network Train sensitivity coefficients

Table (8) shows the learning results of the neural network. According to this table, the best learning results in the training phase were obtained when the classification was carried out using the oveall network inputs, and thus it performed the classification in Run=12 and Epoch=132. Given the RUN and Epoch values of the neural network with all inputs it could be stated that the neural network classified the data satisfactorily at a good speed when all of the input data was selected. As for cross validation, the best network with energy efficiency was simulated, which performed classification for RUN=3 and Epoch=761. Based on these values it is concluded that the data was not properly assessed for the classification purposes.

Figures (5) and (6) show the Test and Training sensitivity coefficients of the network. As seen in Figure (5), the highest sensitivity coefficient was obtained in the testing using all inputs, As for the power 360, 600 and 900 W the highest sensitivity coefficient was obtained with the overall data (Specific exergy loss). Figure (6) also suggests that the Training sensitivity coefficients of the 360 W was obtained using the overall inputs (special energy loss) and for 600 W and 900 W was obtained using the overall inputs (special exergy loss)

4. Conclusions

According to the results, the neural network classifies the energy and exergy more effectively when there are more input items. The best network suiting the energy and exergy data was the network using the energy efficiency, special energy loss, exergy efficiency, and special exergy loss data (i.e. overall data) as the input. In this state, the neural network detected the pretreatment and microwave power data with acceptable precision and using the overall data as the input improved the classification precision. Moreover, when the overall data served as the input, the neural network staged the ability to learn better and faster than the other states, and it trained the network with fewer RUNs than the cases with fewer inputs. The sensitivity coefficient of the classification also indicated that when the neural network was trained using the overall data as the input, the sensitivity coefficient observed in the network testing and training phases was larger. In sum, the neural network displayed an acceptable capacity to classify the pretreatment and microwave power data for the classification of energy and exergy of the kiwi drying process.

5.References

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