EXERGY PARAMETRIC ANALYSIS AND PREDICTION OF TURMERIC RHIZOME SLICES DRYING USING NEURO-FUZZY, NEURAL-NETWORK AND REGRESSION TECHNIQUES

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ABSTRACT

This study presents exergy parametric analysis and prediction of turmeric rhizome drying using first and second law of thermodynamics as well as soft-computing techniques. The drying experiments were conducted at inlet drying temperature: (40-65^{0}C), air velocity (1.5-3m/s), drying time: (30-240 minutes) and sample thickness: (2-5mm). The Neuro-Fuzzy Exhaustive Search (NFES) parametric analysis results revealed that drying time (RMSE=0.0031), temperature (RMSE=0.096), temperature (RMSE=0.046) and sample thickness (RMSE=0.748) are the most single relevant parameters for Exergy Loss (EL), Exergy Efficiency (EE), Exergetic Improvement Potential (EIP) and Sustainability Index (SI) respectively. Whereas temperature-time (RMSE=0.0031), temperature-velocity (RMSE=0.0945), temperature-time (RMSE=0.046) and time-thickness (RMSE=0.7534) are the most important two-input combinations for EL, EE, EIP and SI correspondingly. NFES also revealed that time-temperature-velocity (RMSE=0.004), temperature-velocity-thickness (RMSE=0.082), time-temperature-velocity (RMSE=0.0436) and time-temperature-thickness (RMSE=0.758) are the three-input significant combination for EL, EE, EIP and SI respectively. The ANN results show that two-input combination architectures gave the highest R^2 with minimum RMSE for the exergy-sustainability indicators. Therefore, this study shows that NFES and ANN are reliable tools for the analyses of turmeric rhizome drying thermo-sustainability indicators.

Keywords: exergy-sustainability, exergy efficiency, exhaustive-search and drying.

1 INTRODUCTION

Thermodynamic analysis is a significant engineering tool for evaluating the energy efficiency of thermal operations in the processing industry. It is used for the design, assessment and optimization of thermal processes or systems (Castro et al, 2018). Energy analysis of thermal engineering system facilitates the understanding of the dynamics of energy conversion and its utilization. The information obtained from energy analysis is limited to conservation of energy which implies that energy is indestructible by the process. However, upon transformation of energy form to another, part of its initial quality is irreversibly lost, leading to a degraded quality (Zisopoulous et al, 2017). Thus, only energy analysis is not adequate for the assessment of thermal engineering system, as the quality of energy changes during the operation of thermal systems.

The paradigm of energy quality has been described as the possibility of energy exchange between a donating and an accepting stream (Baccarelli et al, 2016). Dincer and Acar 2015 defined the possibility as the “maximum work potential of a material or a form of energy in relation to its environment,” This thermodynamic property generally assesses energy quality of thermal processes and also determines the useful work potential or available energy at some specific states (Castro et al, 2018; Aviara et al, 2014). Exergy similarly estimates the maximum work that can be obtained from a stream of matter or energy as it comes to equilibrium with an ambient environment. Analysis of exergy is based on the second law of thermodynamics which states that noticeable changes are irreversible and irreversibility of the thermal process is detrimental to its efficiency due to entropy generation during the process. Therefore, exergy is consumed or destroyed due to process irreversibility and entropy is always generated in real processes such as drying operation.

The drying process is used to decrease the moisture content of the products to a particular value in order to improve the shelf life; and also provides safe storage of agricultural produce. Furthermore, dehydration preserves the quality of appearance and nutritional value during postharvest life, as well as reduces the cost of packing. Drying operation is a solid-liquid separation process which involves transport of heat and mass. The solid is exposed to thermal drying; two processes occur concurrently; firstly, transfer of heat energy from the surrounding to evaporate the moisture from the surface and removal of internal moisture to the surface of the solid (Castro et al, 2018; Aviara et al, 2014; Beigi et al, 2017). Owing to the amount of heat required to vaporize moisture from the food matrix, the drying process thus requires a high energy input (Baccarelli et al, 2016). According to Aviara et al, 2014, ten per cent of the overall energy consumption in food process industries is connected to the drying of food; therefore, food drying is one of the most thermal and energy-consuming operations in food production.

Quite a lot of investigations have been conducted on exergy analyses of food drying in recent times (Beigi et al 2017; Aghbashlo 2016; Chen et al, 2017; Tiwari et al, 2016; Karim and Hawlader 2005; Kumar et al, 2017). Castro et al, 2018 investigated energy and exergy analyses of the convective drying of onion. Samimi et al, 2018 reported the study of energy and exergy of tomatoes slices in a mixed mode natural convection solar dryer. Darvishi et al, 2016 conducted the energetic and exergetic performance analysis of kiwi slices. Azadbakht et al, 2017 also performed energy and exergy analyses during eggplant drying in a fluidized bed dryer. Yogendrasasidhar and Setty (2018) researched on drying kinetics, exergy and energy analyses of Kodo millet grains and fenugreek seeds using wall heated fluidized bed dryer. Karthikeyan and Murugavelh, 2018 investigated the effect of dryer exergy efficiency on only drying time during thin layer drying of turmeric (Curcuma longa) in a mixed mode forced convection solar tunnel dryer. Beigi et al, 2017 studied exergetic analysis of deep-bed drying of rough rice in a convective dryer.

Soft-computing techniques such as Adaptive neuro-fuzzy inference system, artificial neural network, genetic programming have been used in solid-liquid separation processes and other related engineering endeavours (Oke et al 2018a; Oke et al 2018b; Prakash et al 2017; Mashaly and Alazba, 2017; Al-Mahasneh et al, 2016; Bhattarai et al, 2017;Golafshani and Behnood, 2018; Prakash and Kumar, 2014; Rego et al, 2018). Most of the above said studies explored the Artificial Neural network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multi-Linear Regression techniques for variable combinations selection and sensitivity analyses for the prediction of the process systems. The result showed that the methods are reliable tools for selecting the best input variable combination for the process. Mohammadi et al, 2016 used the neuro-fuzzy technique to identify the most and least significant variables, among five input variables, for dew point temperature estimation. Determination of the most and least relevant parameters of weather input parameters on evapotranspiration was also investigated by ANFIS exhaustive search algorithm (Petkovic et al, 2015). The results revealed the appropriate selection of input variables was successfully investigated by soft-computing technique, and the selection also has a notable effect on the prediction.

However, information about the selection of drying input variables for the prediction of thermo-sustainability indicators of turmeric rhizome drying in a tray dryer is rarely found in the literature. Fundamentally, the adequate identification of more significant input drying variables for thermo-sustainability indicators prediction would be of great scientific importance and, moreover provide more precision and less complexity predictive model. Mohammadi et al, 2016 reported that the inclusion of many input variables could cause drawbacks and difficulties in the model interpretation and elucidation. These factors may also consequently deteriorate the generalization and predictability degree capacity of the model. Owing to the thorough literature search, no detailed study found on the investigation of the selection and prediction of pertinent drying input variables that influence thermo-sustainability indicators of turmeric rhizome drying. The uniqueness of this study is to select the most relevant drying variables for exergy loss, exergy improvement potential, exergy efficiency and sustainability index for prediction, which has not been conducted so far.

2 Materials and Method

2.1 Sample Preparation

The fresh turmeric (*Curcuma longa*) rhizome samples were obtained from National Root Crops Research Institute Umudike, South-East of Nigeria. The rhizomes were washed to remove soil and dirt adhered to it. The surface water was removed by wiping with tissue paper. The selected samples were carefully dimensioned using Vernier callipers into desired thickness for drying experiment.

2.2 Drying Procedure

Convective hot air laboratory tray dryer (Heratherm Oven CP 210997), as schematically shown in Figure 1, was used for drying the rhizome. The dimensions of the drying compartment were 360 × 620 × 460 mm. Heating elements were fitted at the interior back of the dryer. The temperature inside the dryer was controlled with a thermostatic temperature controller imbedded into the tray dryer. Air was circulated inside the dryer with a fan fixed at the back of the dryer. The pattern of air flow was cross-circulated type as depicted in Figure. 1. The air velocity inside the chamber was measured with a digital anemometer (Model PM6252A) with accuracy of ± 0.1 and was varied from 1.5m/s to 3m/s. The dryer was allowed to preheat to the desired temperature, and 27g of the cut rhizome of *Curcuma longa* were spread onto the trays in single layer for a specified time. The ambient, inlet and outlet temperature and relative humidity of the dry air were measured with a squared multi-thermometer (Model TA298) with an accuracy of $\pm 0.1^0$C. The components of diagrammatic dryer in figure 1 are: (1) Outdoor door (2) Door latch cut out (3) Door latch and handle (4) Door hinge lower (5) Levelling foot (6) Nameplate (7) Air battle top piece (8) Support rail for wire mesh shelf (9) Shelf support (10) Fan cover, integrated into air baffle (11) Door hook catch (12) Air baffle (13) Door seal (14) Stacking pad (15) Spring for air baffle (16) Temperature sensor (17) Exhaust air tube.

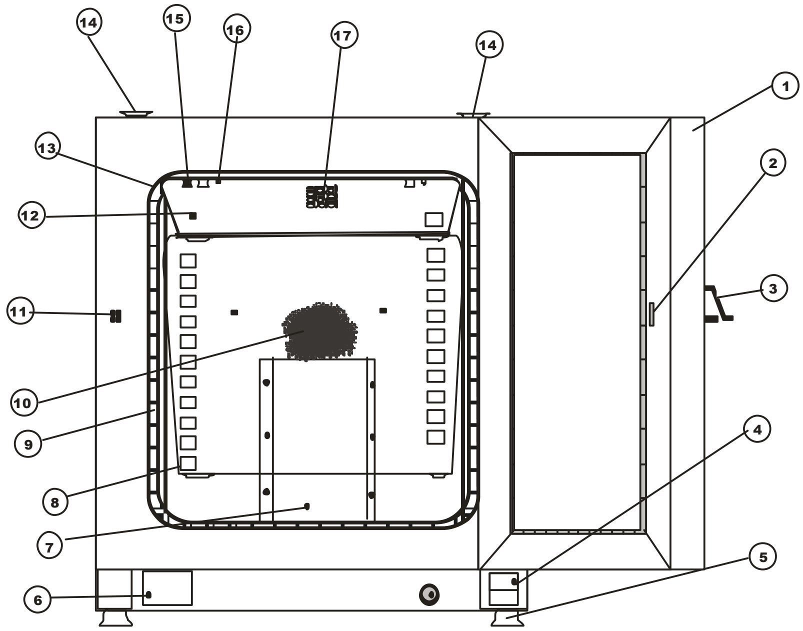


Figure 1: Schematic diagram of the dryer

2.3 Thermodynamic Analyses

2.3.1 Energy Analysis

The dryer energy utilization was calculated using the conservation energy law of thermodynamics (Aviara et al, 2014):

Energy Utilization (EU) = $m_{da}(h_{dai} - h_{dao})$ 1

EU = Energy Utilization (kJ/s); m_{da} = mass flow of dry air (kg/s), h_{dai} = inlet dry air enthalpy (kJ/kg) and h_{dao} = outlet dry air enthalpy (kJ/kg).

The air mass flow rate was obtained using Equation (2):

$$m_{da} = \rho_a \, v_a A d_c \quad 2$$

where, ρa is air density; va is air speed inside dryer and Ad_c is the cross section that air crosses it.

The ratio of energy utilization to the provided energy in the dryer chamber is defined as the energy utilization ratio[28] and is calculated using equation (3):

$$\text{EUR} = \frac{m_{da}(h_{dai} - h_{dao})}{m_{da}(h_{dai} - h_{d\infty})} \quad 3$$

Values of the inlet and outlet air enthalpy are equal to the sum of dry air enthalpy and water vapor enthalpy. Therefore, equation (4) is frequently used to determine air enthalpy (Aviara et al, 2014; Azadbakht et al, 2017):

$$h_{da} = C_{pda}T + h_{fg}w \quad (4)$$

Where h_{da}, is the inlet or outlet dry air enthalpy (kJ/kg); C_{pda} = specific heat of inlet or outlet dry air (kJ/kg^{0}C); T = inlet or outlet air temperature (^{0}C); h_{fg} = the latent heat of vaporization of water (kJ/kg) and w = the humidity ratio of air (kg water =/kg dry air).

Air specific heat is calculated from equation (5).

$$C_{pda} = 0.0001T + 0.967 \quad 5$$

Humidity ratio was calculated[2, 29] using equation (6):

$$w = 0.622 \frac{P_v}{P-P_v}$$

6

Where w = humidity ratio; P = air pressure (kPa) and P_v = vapor pressure (kPa).

2.3.2 Exergy analysis

Exergy analysis of the drying process was carried out on the basis of the second law of thermodynamics. For this purpose, the mathematical formulations used for the exergy balance [5] are as shown in Equation (7):

$$Ex = C_{pda}\left[(T - T_\infty) - T_\infty \ln\left(\frac{T}{T_\infty}\right)\right]$$

7

Air specific heat C_{pda} in equation (5) substituted and equation 7 becomes:

$$Ex = 0.0001T + 0.967\left[(T - T_\infty) - T_\infty \ln\left(\frac{T}{T_\infty}\right)\right]$$

8

Where Ex is the exergy of air (kJ/s), T = the temperature of inlet/outlet air (^{0}C) and T_∞ = the ambient temperature (^{0}C). Equation 8 was used to calculate the exergy inflow and outflow at the inlet and outlet temperatures of the drying chamber, respectively.

2.3.2.1 Calculation of Exergy Loss (EL)

Exergy loss was determined by equation (9):

$$Ex_{loss} = Ex_{inflow} - Ex_{outflow}$$

(9)

Where E_l is the exergy loss

E_{in} = exergy inflow

2.3.2.2 Calculation of Exergy Efficiency (EE)

Exergetic efficiency has been defined as the ratio of exergy outflow in the drying of the product to exergy of the drying air supplied to the system (Castro et al, 2018). The exergy efficiency was calculated using the expression below- (Castro et al, 2018; Aviara et al, 2014) :

$$Ex_{eff} = \frac{exergy\ inflow - exergy\ loss}{exergy\ inflow}$$

(10)

Or $$Ex_{eff} = 1 - \frac{exergy\ loss}{exergy\ inflow}$$

(11)

Equation (11) can be stated as

$$\eta_{EX} = 1 - \frac{EX_l}{EX_{in}}$$

(12)

η_{EX} = exergy efficiency.

2.3.2.3 Calculation of Exergy Improvement Potential (EIP)

The exergetic improvement potential was calculated using the expression below:

$$EIP = (1 - Ex_{eff})(Ex_{inflow} - Ex_{outflow})$$

(13)

Where EIP = Exergetic improvement potential

2.3.2.3 Calculation of Exergy Sustainable Index (SI)

The sustainability index of the system was calculated (Castro et al, 2014) :

$$S.I = \frac{1}{1-Ex_{eff}}$$

(14)

2.4 Soft-Computing Modelling Technique

2.4.1 Neuro-fuzzy Exhaustive Search Parametric Technique

ANFIS exhaustive search programming codes were written in MATLAB 8.4 (R2014b) environment and implemented for the selection of the set of one, two and three variable inputs combination that has the most and least influence on the EL, EE, EIP and SI. The Root Mean Squared Error (RMSE) was used as a performance indicator for the exhaustive search technique. The architecture of ANFIS consists of 5 layers as shown in figure 2. In Figure 2, square nodes (adaptive nodes) show adjustable parameters that are to be learned, whereas the circle nodes (fixed nodes) are fixed parameters. A common rule set with two fuzzy if-then rules is as follows (Oke et al 2018a; Oke et al, 2018b; Prakash and Kumar, 2014):

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1$ x + q_1x+r_1 15a

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2$x +q_2x+r_2 15b

Where A, B are linguistic terms that are user defined and representing a range of values. The sequence and functions of the layers is as follows:

Layer 1: Square node equipped with node function

$$O_i^L = \mu_{Ai}(x)$$
15c

Assuming x and y be the two typical input values fed at the two input nodes, which then transforms those values to the membership functions such as triangle, generalised bell-shaped, Gaussian membership etc. Where, O_i^L is the membership function of A_i and x is the input parameter to the node. A_i is the linguistic label connected with the node function.

Layer 2: This node multiplies the incoming signal and sends the product out. Each node output is the firing strength of a rule.

$$w_i = \mu_{Ai}(x) \times \mu_{Ai}(y), \; i = 1,2$$
16a

Layer 3: circle node. Node calculates the ratio of i-th rule's firing strength to the sum of all rules' firing strengths:

$$w_i' = \frac{w_i}{w_1 + w_2}\;, i = 1, 2$$
16b

Layer 4: Square node with node function:

$$O_i^4 = \; w_i' f_i = w_i'(p_i\, x + q_i y + r_i)$$
17a

p, q, r – parameter set (consequent, linear, parameters)

Layer 5: circle node. This node computes the overall output as summation of all incoming signals.

$$O_i^5 = overall\ output = \sum_i w_i' \, f = \frac{\sum_i w_i f_i}{\sum_i w_i}$$
17b

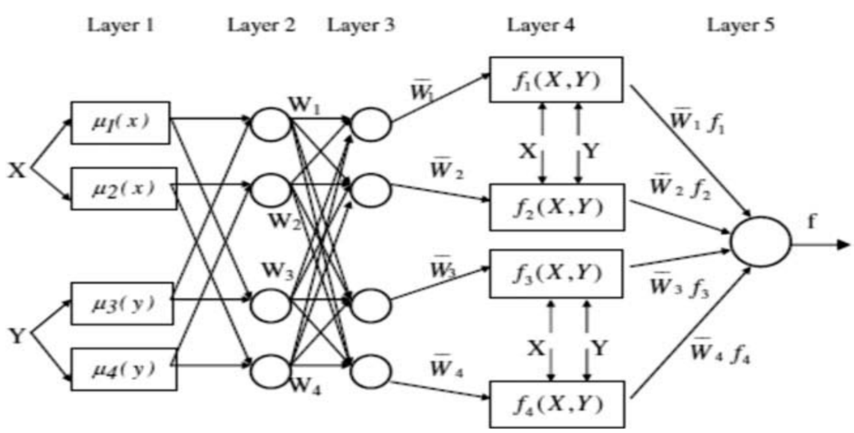


Figure 2: A basic structure of the ANFIS[30].

2.4.2 Neural network modelling

A three layer feed-forward back propagation neural network structure consists of input, output, and intermediate hidden layers with tangent sigmoid transfer function at the hidden layer and a linear transfer function at the output layer was constructed in Matlab 8.4 (2014a) software environment (MathWorks, Inc., Natick, MA). The structure was used for modelling and prediction of exergy-sustainability indicators of turmeric drying. The input layer corresponds to the four experimental parameters including the drying air temperature, air velocity, sample thickness and drying time. The output layer for each network was exergy-sustainability index. All data derived from the drying experiments were divided into training, validation, and test sets with a ratio of 50, 25, and 25%, respectively.

Results and Discussion

3.1 Descriptive statistics of Experimental data

Table 1 shows statistical summary of drying experimental data and thermo-sustainability indicators (drying time, temperature, air velocity, sample thickness, exergy loss, exergy efficiency, exergy improvement potential and sustainability index), including mean, minimum, maximum, standard error, median, standard deviation, skewness, kurtosis for each variable. Skewness of drying temperature, time and exergy efficiency lies between -2.43 to -0.25 , while air velocity, sample thickness, exergy loss, exergy improvement potential and sustainability index skewness ranges from 1..54 to 5.48 as indicated in table 1. Kurtosis of drying temperature, time air velocity, sample thickness, exergy loss, exergy efficiency exergy improvement and sustainability index gave 4.17, -0.75, 14.68, 31.06, 2.22, .36, 9.80 and 16.3 respectively. Skewness and kurtosis are used as indicators for measuring the degree of normality and non-normality of data distributions (D'Agostino 2017; Reise et al, 2018). The distribution curve for drying time is platykurtic; because the value for kurtosis is less than 3 as shown in table 1. However, the distribution curves for other process variables are greater than 3 as indicated in table 1, therefore, the curves are leptokurtic. Table 1 shows the distributions for air velocity, thickness, exergy efficiency, exergy improvement and SI are highly skewed due to the fact that the values are far from one. However, the distributions for temperature, time and exergy loss are slightly skewed because their values are not far from one. The present descriptive statistics results are similar and consistent with prior reports (Harrell, 2015; Snijders et al, 2017).

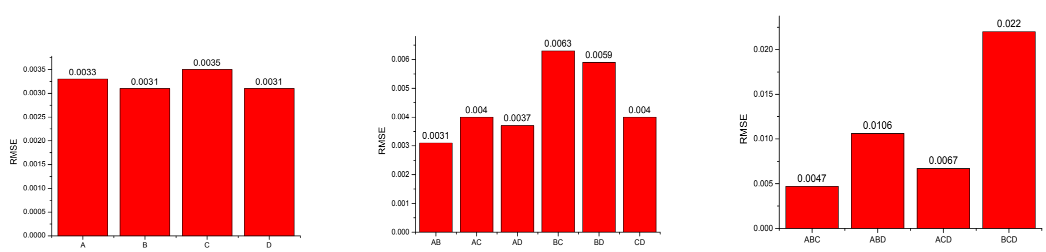
Table 1: Statistics of experimental data

Statistical index	Temp (^{0}C)	time (min)	Air Vel(m/s)	Thick (mm)	Ex Loss	Ex Eff.	EIP	SI
Mean	61.30	210.90	1.61	2.09	0.87	0.89	0.16	29.75
Minimum	40	10	1.5	2	0.03	0.37	0.00	1.60
Maximum	65	420	3.0	5	3.58	0.98	1.48	320.26
Standard error	0.63	14.23	0.03	0.06	0.10	0.01	0.03	6.47
Median	63	240	1.5	2	0.61	0.93	0.04	13.75
Standard deviation	5.18	116.46	0.25	0.45	0.80	0.11	0.27	52.98
Kurtosis	4.17	-0.75	14.68	31.06	2.22	7.36	9.80	16.73
Skewness	-1.86	-0.25	3.47	5.48	1.54	-2.43	2.96	3.91

3.2 Exhaustive-search parametric analysis

Four parameters were considered for analyzing the input parameters (drying temperature, air velocity, thickness and drying time) and EL, EE, EIP and SI as output parameters. A comprehensive search was conducted within the input parameters in order to select the set of the most optimum combination of the input variables that best influence the output parameters (EL, EE, EIP and SI). Neuro-fuzzy exhaustive search codes were written in Matlab 8.4(2014a) environment for developing the model with one epoch number and consequently reported the performance of input variable combinations. NFES results used the Root Mean Square Error (RMSE) as the parameter for quantifying the effect of each or combined drying variables on the output of the process (Azad et al, 2016) .

Figure 3 shows the input selection combination error level for exergy loss. The exhaustive search program was executed for input selection for exergy loss; and drying time is found to be the most influential variable that affects the exergy loss, as shown in figure3a. It was observed that there was no over-fitting between training and checking RMSE for one-variable input selection as claimed by previous researches (Ramasamy et al, 2015; Li et al 2016). This suggests that further analysis can be performed on more than one input variable; therefore, new NFES architecture was developed with one epoch for higher input variable combinations. Similar computer program was used for identifying two and three relevant inputs for exergy loss by replacing 1 with 2 and 3 in exhsrch command arguments. Time-temperature and time-temperature-air velocity are the most significant input combinations, influencing EL, for two and three input combination respectively as observed in figure 3b and 3c. Generally, the orders of variable influence for the EL are as follows: drying time> drying temperature> air velocity> thickness. The order of variable relevance is based on the value of RMSE; that is, the lowest RMSE gave the most relevant variable, while highest RMSE value gave the least relevant variable[18, 38]. The influence order of two and three variable input combination is shown in figure 3b and 3c.

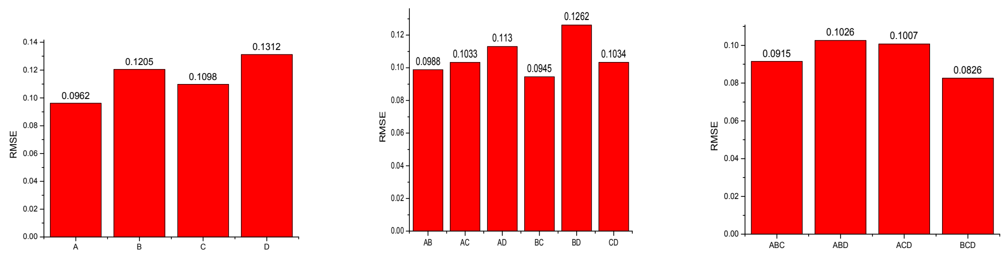


(a) one-input selection (b) two-input selection (c) three-input selection

A = drying time, B = drying temperature, C =air velocity and D= sample thickness

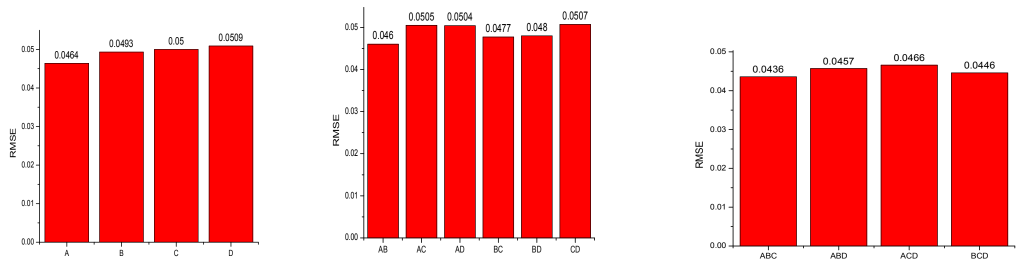
Figure 3: Input Selection Combination Error Level for Exergy Loss

Figure 4 shows the plot of RMSE level against input variable selection combination for exergy efficiency. Drying time is the most important one-input variable for exergy efficiency due to the lowest RMSE value as depicted in figure 4a. However, the least relevant one-input variable for the efficiency is sample thickness as shown in figure 4a. By and large, the orders of one-variable influence for the efficiency are as follows: drying time> air velocity>temperature>thickness as shown in figure 4a. Figure 4b presents the order of two input parameter combinations on EE. The order revealed that Air velocity – drying time > temperature – time>Air velocity–time>thickness–air velocity>time–thickness>temperature–thickness as depicted in figure 4b. Furthermore, temperature-velocity-thickness>time-temperature-velocity>time-velocity-thicness>time-temperature-thicness are the order of three variable influence on exergy efficiency as observed in figure 4c.

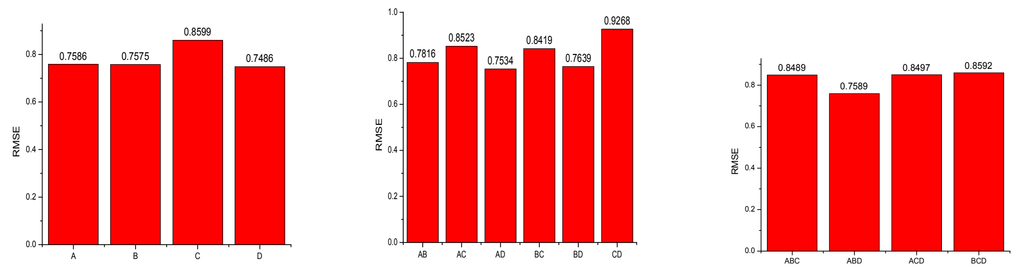


(d) one-input combination (e) two-input combinations (f): three-input combinations
A = drying time, B = drying temperature, C =air velocity and D= sample thickness
Figure 4: Input Selection Combination Error Level for Efficiency

Figure 5 shows input selection combination for exergy improvement potential. Drying time is the most influential variable and sample thickness is the least significant variable as shown in figure 5a. Figure 5b revealed that the lowest RMSE was obtained in the combination of time and temperature; therefore, the combination of temperature-time gave highest influence on exergy improvement potential of the process. Furthermore, three- input variable combination was analysed as shown in figure 5c. Three variable input combination of time-temperature-velocity is the optimal combination for exergy improvement potential of the drying process. Figure 6 also shows the relevant input variable identification for sustainability index of the rhizome drying. Figure 6a revealed that sample thickness is the most relevant variable while air velocity is the least important variable for SI of the drying. In addition, combination of time-thickness and velocity-thickness are the most significant and least important two variable combinations selected by NFES, respectively, as shown in figure 6b. Combination of time-temperature-thickness is the optimal relevant three input variable combination; while temperature-velocity-thickness is the least three input variable combination found in figure 6c for SI. It was observed that all RMSE obtained from neuro-fuzzy exhaustive search is less than one; and the result obtained from this section is comparable with existing studies in the literature (Petkovic et al, 2015; Azadbakht et al, 2017). The selected combinations were used for further analysis. Since both the single and optimal input variable combination have been identified, large epoch numbers was used to develop grid partitioning ANFIS structure for the prediction of exergy-sustainability indicators.



(g) one-input combination (h) two-input combinations (i): three-input combinations
A = drying time, B = drying temperature, C =air velocity and D= sample thickness
Figure 5: Input Selection Combination Error Level for Exergy Potential Improvement



(j) one-input combination (k) two-input combinations (l): three-input combinations
A = drying time, B = drying temperature, C =air velocity and D= sample thickness
Figure 6: Input Selection Combination Error Level for Exergy sustainability index

3.3 Soft-computing prediction of exergy-sustainability indicators

This section presents application of ANFIS, ANN and Multi-Linear Regression (MLR) models for the prediction of the selected input-output variables. Table 2 shows statistical parameters, RMSE and R^2, which evaluate the degree of predictability of soft-computing models. For ANFIS model, R^2 values ranged from 0.23 to 0.805 and RMSE values from 0.22 to 5.1as observed in table 2. Some of R^2 values were far from one as indicated in table 2. The RMSE values for ANFIS model were not close to zero (Chen et al 2017; Chong et al, 2015; Rezakazemi et al, 2017) therefore, the model results disagree with the experimental results. As it was shown from table 2, MLR model has R^2 values ranging from 0.22 to 4.1 and RMSE values ranging from 0.12 to 0.98. All the statistical indicators found for MLR are not generally close to the acceptable range

For ANN model, R^2 for the indicators lies from 0.83-0.99 and RMSE is ranged from 0.0000038 to 0.17. It was noticed that all the R^2 values were closed to 1 and RMSE values were not far from zero. The obtained results from ANN model were consistent with existing findings from the literature (Chong et al 2015; Deo and Sahin, 2015). Based on the results obtained from this study, it is evidently found that ANN technique provides higher accuracy for the prediction of exergy-sustainability indicators than the ANFIS and MLR. Finally, the ANN results obtained from two and three input variable combinations were compared as shown in table 2; and it is apparently clear that two input variable combination outperforms the three inputs.

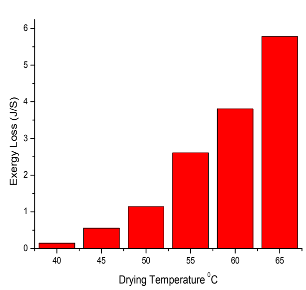
Table 2: Statistical Parameters for Soft-Computing Model Performance

		ANFIS		ANN		MLR	
Indicator	variable number	R^2	RMSE	R^2	RMSE	R^2	RMSE
Exergy Loss	2	0.307	0.963	0.97	0.0000063	0.317	0.98
Exergy Efficiency	2	0.805	0.817	0.99	0.0000038	0.22	0.97
Exergy Improvement	2	0.23	0.37	0.978	0.000048	0.27	0.34
Sustainability Index	2	0.28	5.1	0.954	0.0031	4.1	0.12
Exergy Loss	3	0.46	0.22	0.95	0.0000125	0.217	0.277
Exergy Efficiency	3	0.25	0.43	0.88	0.018	0.6	0.52
Exergy Improvement	3	0.251	0.433	0.902	0.17	0.06	0.5
Sustainability Index	3	0.42	0.32	0.83	0.17	0.32	0.23

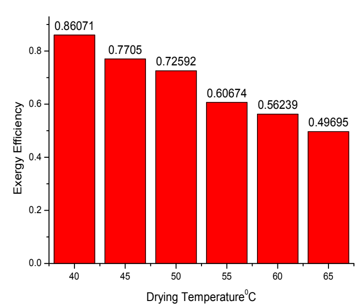
3.4 Effect of turmeric rhizome drying conditions on exergy-sustainability indicators

3.4.1 Effect of drying temperature on exergy-sustainability indicators

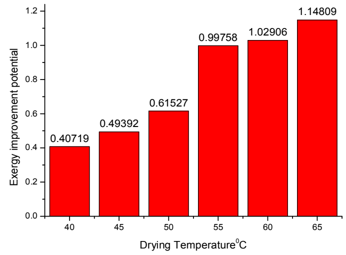
Figure 7 shows the EL, EE, EIP and SI for different drying air temperatures at air velocity1.5m/s, sample thickness 2mm and drying time 240 minutes. The highest and lowest EL was obtained at 65^{0}C and 40^{0}C respectively. It was observed from Figure 7a that as the drying air temperature increases, it results in higher EL. The behaviour is as a result of the higher latent heat of evaporation needed to remove the reasonable amount of moisture from the food material; consequently increased exergy usage. This behaviour is also similar to Lamidi et al, 2019. EE - drying temperature profile, as shown in figure 7b, indicates that EE is decreasing as temperature increases. Figure 7b revealed that the maximum and minimum EE of the system was achieved at 40^{0}C (86.07%) and 65^{0}C (49.69%) respectively. EIP also follows EE - drying temperature as depicted in figure 7c, this shows the dependency of EIP on EE. The peak and lowest of EIP of the system was observed at 40^{0}C (0.407J/s) and 650C (1.148J/s) respectively. The pattern found in EE and EIP of the drying system in this study is consistent with previous studies (Castro et al, 2018; Beigi et al, 2017). SI of turmeric drying process varies from 1.98 to 7.17. It was observed that at higher efficiency drying temperature, the SI increases and consequently, the environmental impact becomes lower. The SI values obtained in this study are similar to Beigi et al, 2017.



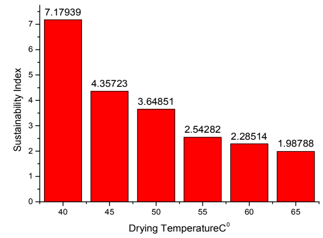
(a)



(b)



(c)

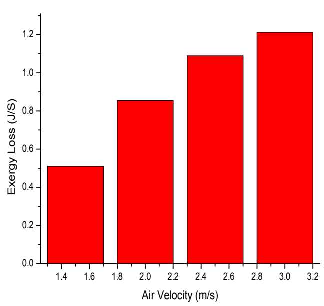


(d)

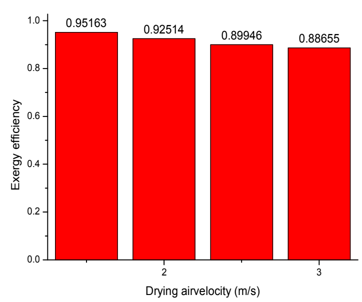
Figure 7: Effect of drying air temperature on thermo-sustainability indicators

3.4.2 Effect of drying air velocity on exergy-sustainability

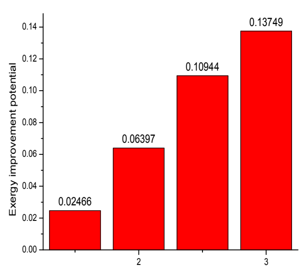
Figure 8 shows the variation of drying air velocity on (EL), (EE), (EIP) and (SI) of turmeric drying. It was observed from figure 8a that exergy loss rate increases as air velocity is increased. The highest loss was reached at 3m/s, while the lowest loss was observed at 1.5m/s. The possible explanation for this occurrence is as a result of the higher influx of air in the drying chamber against the food material moisture content. The finding obtained from this study is similar to Azadbakht et al, 2017. Maximum EE was obtained at air velocity of 1.5 m/s (95%). The improvement potential needed for the drying system at lower air velocity relatively small as compared with higher air velocity as observed in figure 8c. The highest value (0.137J/s) of EIP was obtained at air velocity 3m/s as seen in figure 8c. Figure 8d shows the effect of drying air on SI of drying system; the figure revealed that the lowest SI value was obtained at air velocity 3m/s (8.81).



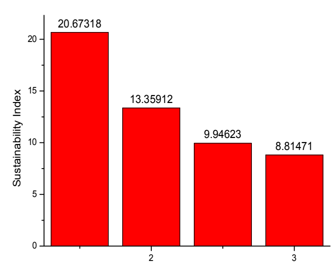
(a)



(b)



(c)



(d)

Figure 8: Effect of air velocity on thermo-sustainability indicators

3.4.3 Effect of sample thickness on exergy-sustainability

Figure 9 shows the plot of EL, EE, EIP and SI against the variation of the sample thickness during turmeric rhizome drying. The maximum EL, EE, EIP and SI were observed at thickness 5mm, 3mm, 5mm and 3mm, respectively, as shown in figure 9. However, the lowest EL, EE, EIP and SI were obtained at thickness 3mm, 5mm, 3mm and 5mm respectively. The pattern of the results in figure 9a and c are similar to (Azadbakht et al, 20177; Beigi et al 2017) which show the increase in the thickness leads to EL and EIP increase and the behaviour in figure 9b and 9d is vice versa to the counterpart figure (9a and c).

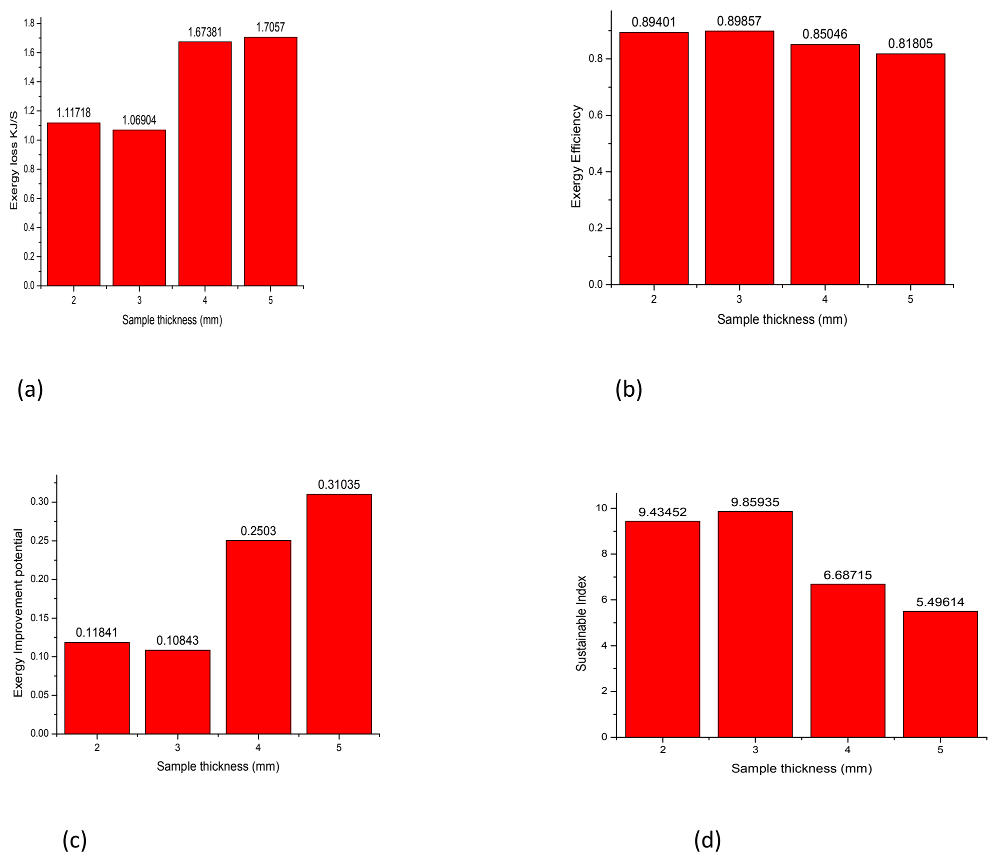


Figure 9: Effect of sample thickness on thermo-sustainability indicators

3.4.4 Effect of drying time on exergy-sustainability

Figure 10 presents the effect of drying time at different drying temperatures (50^{0}C, 55^{0}C, 60^{0}C and 65^{0}C) on thermo-sustainability indicators. Figure 10a shows that EL increases as drying time increases. The lowest EL was obtained at process time 30 minutes for all the studied temperatures. However, the highest EL achieved at drying time 240, 240, 220 and 310 minutes for 65, 60, 55 and 50^{0}C respectively as shown in figure 10a. Figure 10b and c show that as the drying time increases the EE decreases, while EIP increases at different drying temperatures. It was observed that SI of turmeric rhizome drying increased at the beginning of the process as depicted in figure 10d. However, the SI was reducing as drying operation progresses as shown in figure 10d.

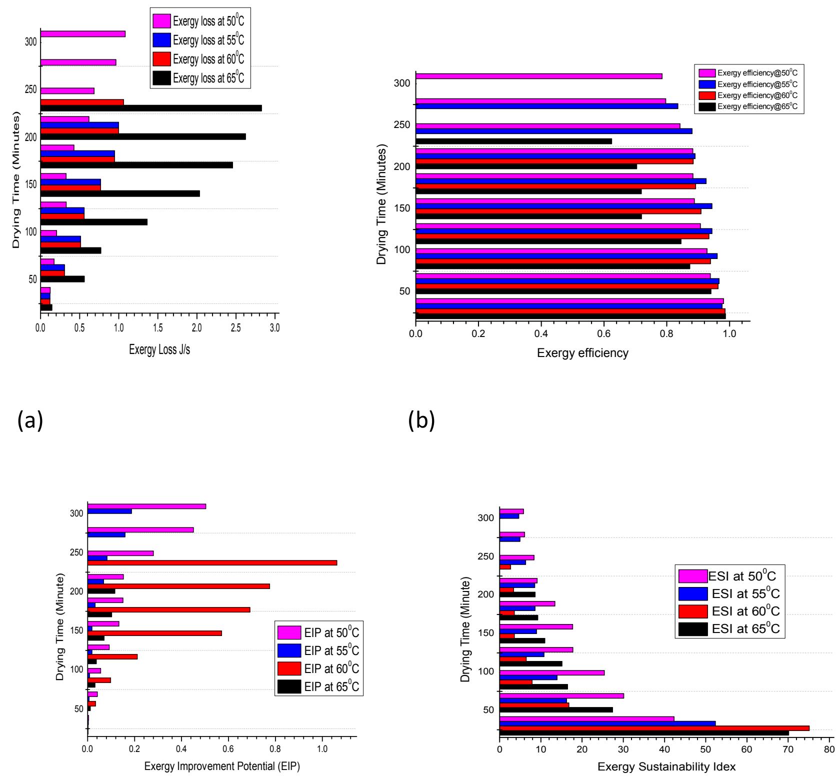


Figure 10: Effect of drying time on thermo-sustainability indicators

3.5 Effect of turmeric rhizome drying conditions on energy utilization

Figure 11a shows that increase in the drying temperature leads to an increase in the energy utilization ratio while figure 11b depicted that energy utilization ratio increases with increase in the inflow of air into the drying system.These results are similar to the findings of Azadbakht et al, 2017 and Bennamoun et al, 2003. on a coroba slices dryer and the design of a solar dryer for agricultural products, respectively. The energy utilization ratio in figure 11c increased simultaneously as the thickness of the turmeric samples was increased. The values for the energy utilization in figure 11d was inconsistent as the drying time increases, with the highest value (0.97979) observed at 220minutes and lowest (0.61054) at 20minutes indicating that increase in the drying time leads to adequate consumption of the energy in the drying system.

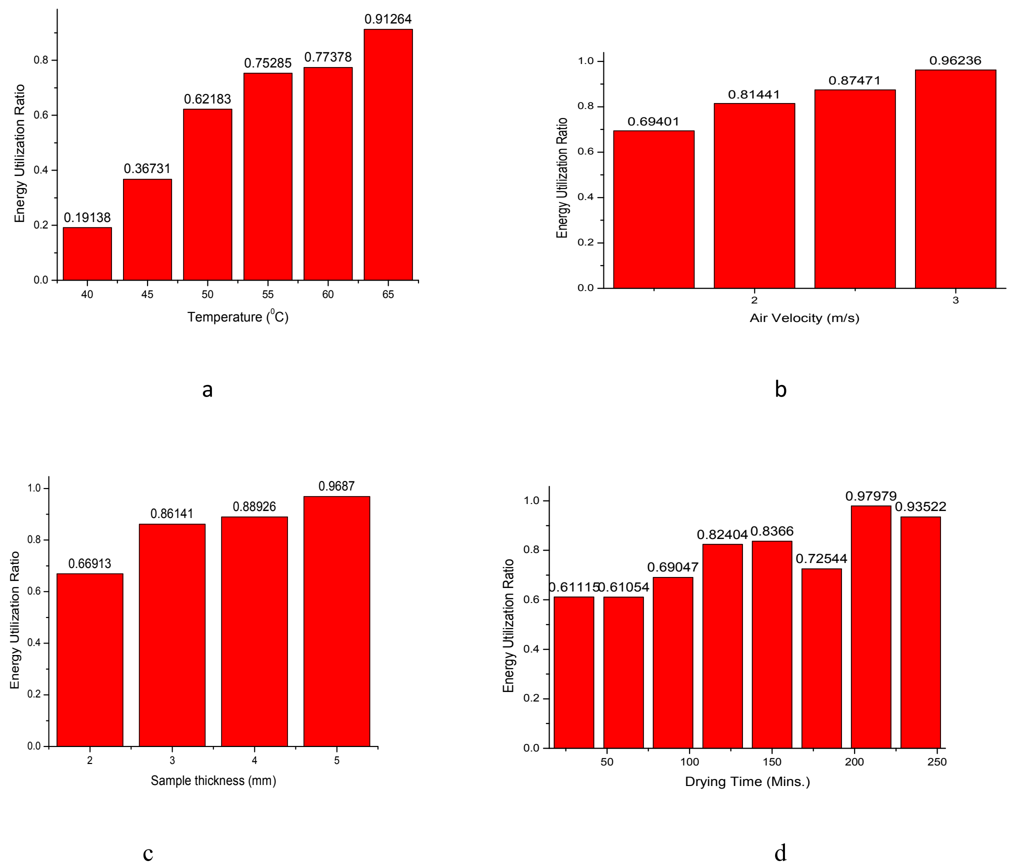


Figure 11: Effect of the drying conditions on energy utilization

Conclusion

Thermo-sustainability indicators such as EL, EE, EIP and SI of turmeric rhizome drying were experimentally determined and soft-computing models were developed for the input variables selection and prediction for indicators of the rhizome drying. Experimentally, the results indicated that highest and lowest EL attained at 65^0C, 3m/s, 5mm, 240minutes and 40^0C, 1.5m/s, 3mm, 30minutes respectively. Moreover, the results showed that the peak and minimum EE occurred at 40^0C, 1.5 m/s, 3mm, 30 minutes and 65^0C, 3 m/s, 5mm and 240 minutes. The highest and lowest EIP obtained at 65^0C, 3m/s, 5mm, 240minutes and 40^0C, 1.5m/s, 3mm, 30minutes respectively. The results also showed that the highest and minimum SI occurred at 40^0C, 1.5 m/s, 3mm, 30 minutes and 65^0C, 3 m/s, 5mm and 240 minutes. Drying time (RMSE=0.0031), temperature (RMSE=0.096), temperature (RMSE=0.046) and sample thickness (RMSE=0.748) are the single relevant parameters for Exergy Loss (EL), Exergy Efficiency (EE), Exergetic Improvement Potential (EIP) and Sustainability Index (SI) respectively. The results showed that temperature-time (RMSE=0.0031), temperature-velocity (RMSE=0.0945), temperature-time (RMSE=0.046) and time-thickness (RMSE=0.7534) are the most important two-input combinations for EL, EE, EIP and SI correspondingly. NFES also revealed that time-temperature-velocity (RMSE=0.004), temperature-velocity-thickness (RMSE=0.082), time-temperature-velocity (RMSE=0.0436) and time-temperature-thickness (RMSE=0.758) are the three-input significant combination for EL, EE, EIP and SI respectively. The ANN results show that two-input combination architectures gave the highest R^2 0.998 with minimum RMSE for the exergy-sustainability indicators.

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