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Original Article

Thermodynamic and intelligent modeling of a fluidized bed dryer for eggplant drying: A combined energy–exergy–artificial neural network Study

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ABSTRACT

The influences of the air temperature (40, 50, and 60 °C), air velocity (3, 5, and 7 m/s), sample size (0.5, 1.0 and 1.3 cm) on thermodynamic performance of a fluidized-bed dryer were studied in the drying of eggplant cubes (*Solanum melongena* L.). New samples of the eggplant were sliced into cubes and dried in the controlled laboratory conditions. The first and the second law of thermodynamics were used in calculating energy utilization, energy utilization ratio, exergy loss, and exergy efficiency. Findings showed that the utilization of energy and exergy loss rose with the higher drying temperatures and air velocities and reduced with the increased sample size. The results showed the highest exergy efficiency (0.72) at 60 °C, 5 m/s and a sample size of 1.3 cm, while the lowest efficiency (0.017) at 40 °C, 3 m/s and 0.5 cm sample size. The highest energy utilization (3.64 kJ/s) was achieved at 60 °C, 7 m/s, and 0.5 cm, while the lowest (1.08 kJ/s) was observed at 40 °C, 3 m/s, and 1.3 cm. An artificial neural network (ANN) model was created to forecast the energy and exergy variables and the trained model showed good consistency with the experimental data ($R^2 > 0.99$), which supports its effectiveness in prediction of thermodynamics. Finally, higher air temperature and velocity increased the drying performance but decreased the exergy efficiency, especially with smaller samples. ANN modelling provides a significant instrument of maximizing energy and exergy behavior in fluidized-bed dryers utilized in the food industry.

Nomenclature

Symbol	Description (unit)
M	Moisture content (%)
m	Weight of product (kg)
Eu	Energy utilization (kJ/s)
Ex	Exergy (kJ/kg)
$\dot{m}$	Mass flow rate (kg/s)
h	Specific enthalpy (kJ/kg)
ρ	Air density (kg/m^3)
v	Air velocity in dryer (m/s)
A	Cross-sectional area through which air passes (m^2)
T	Temperature (K)
h_{fg}	Latent heat of vaporization of water (kJ/kg)
C_p	Specific heat capacity (kJ/kg.K)
w	Moisture content ratio (kg water/kg dry air)
φ	Relative humidity (%)
P	Air pressure (Pa)

Subscripts

Symbol	Description
1	Initial
2	Secondary
d	Dry
a	Air
i	Inlet
o	Outlet
∞	Ambient
l	Losses
v	Vapor
s	Saturated

1. Introduction

Drying is the process of removing moisture from solid materials and is an essential step in many food industries. Among various drying technologies, the fluidized bed dryer is widely used due to its high heat and mass transfer rates, short drying time, and uniform temperature distribution. Due to the high latent heat of moisture and the generally low thermal efficiency of conventional dryers, improving the energy utilization and efficiency of the drying process remains a crucial research objective (Azadbakht, Vahedi Torshizi, & Jafari, 2020; Vahedi Torshizi et al., 2024). Drying is a complex process that involves transferring heat and mass between the product surface and its surrounding environment. Drying has been one of the oldest methods for preserving various agricultural and food products. One of the primary purposes of drying agrarian products is to transport water from the solid texture to the surface of the products to a certain level, so that microbial damages and routine chemical reactions would basically reach the least amount possible (Azadbakht et al., 2022; Azadbakht, Vahedi Torshizi, Noshad, et al., 2020; Ramezani et al., 2020).

There is a wide range of eggplants with various shapes and colors, including oval or ovoid shapes and colors that range from white to nearly black, as well as yellow, green, and purple. The eggplant is of great economic value in Asia, Africa, and the tropics (India, Central America); it is also cultivated in some hot and moderate regions of the Mediterranean Sea and South America (Sihachakr et al., 1993). Eggplant is a fruit that is known for being

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low in calories and for having a mineral composition that is beneficial to human health. It is a rich source of potassium, magnesium, calcium, and iron (Azadbakht, Ziaratban, et al., 2017). Considering the thermal efficiency of the drying process, fluidized bed dryers—with their high heat and mass transfer and drying rates—are widely utilized in food drying. Moreover, fluidized bed dryers have many applications in the chemistry, metallurgy, and pharmaceutical industries (Azadbakht, Torshizi, et al., 2017; Kariman et al., 2019; M. V Torshizi et al., 2020).

Several studies have been conducted on the energy analysis and exergy of dryers; some of these are mentioned below. Erbay et al. (2011) surveyed the drying process of olive leaves in a tray dryer and concluded that the most energy was used for drying olive leaves, at 0.756 kW, with a maximum exergy loss of 0.027 kW (Erbay & Icier, 2011). Aviara et al (2014) In the energy and exergy analysis of drying native cassava starch in a tray dryer, it was concluded that for starch with contents of 0.76% ash, 0.85% crude protein, 0.16% crude fat, negligible amounts of fiber, an average granule size of 14.1 mm, pH of 5.88, 23.45% amylose content, and a degree of crystallinity of 22.34%, energy utilization and its ratio increased from 1.93 to 5.51 J/s and 0.65 to 0.6 as the drying temperature was increased from 40 to 60 ℃ (Aviara et al., 2014). Other researchers found that the energy utilization and energy consumption ratio increased with increments in drying temperature and bed depth. At the same time, the decrease was offset by increasing the size of the carrot pieces. The maximum energy consumption and energy consumption ratio occurred at a temperature of 70°C, a bed depth of 90 mm, and a particle size of 4 mm. At the same time, the minimum values were observed at a temperature of 50 °C, a bed depth of 30 mm, and a particle size of 10 mm.

Nazghelichi et al. (2011) optimized the final ANN model using the Response surface method and Genetic algorithm, obtaining a successful relationship between input and output parameters. An integrated GA and RSM approach in their research demonstrated that these tools are valuable for finding the optimal topology of an artificial neural network to predict energy and exergy through fluidized bed drying (Nazghelichi et al., 2011). Kashaninejad et al. (2009) used a Multilayer Perceptron (MLP) neural network and radial basis function (RBF) to estimate grain moisture during soaking. Artificial neural networks were used to model the soaking of wheat seeds at different temperatures, and a comparison with the results obtained from the model page was created. Soaking temperature and time were used as input parameters, and relative humidity was used as the output parameter. The MLP neural network model is used to describe the features found in wheat seed soaking (Kashaninejad et al., 2009). Nazghelichi et al (2010), in anticipation of energy and exergy carrot pieces in fluid bed dryers, concluded that the energy and exergy of carrot cubes during fluid bed drying, a dynamic system, was a nonlinear system, and an ANN recurrent model was more accurate than a static model (Nazghelichi et al., 2010).

The primary purpose of this Research was thermodynamic analysis for drying of eggplant cubes in fluidized bed dryer under different conditions such as sample size, air speeds and different temperature for energy and exergy analysis to obtain the best conditions for industrial uses and helping to produce intelligent control devices using artificial neural networks in the use of this type of dryers and determining the best conditions for drying of products.

2. Materials and Methods

2.1. Material preparation

Freshly harvested eggplant was purchased from a local market and stored in a laboratory refrigerator at 5°C. At the beginning of each test, eggplants were washed, peeled, and manually cut using a cubic device with dimensions of 0.5 cm, 1 cm, 1.3 cm, and a height of 0.5 cm. The drying experiment was conducted using a laboratory fluidized bed dryer made in the Department of Mechanical Bio-systems of the University of Agricultural Sciences and Natural Resources of Gorgan, Iran.

2.2. Experimental procedure

To supply the required air flow, a centrifugal blower with a 3hp CDF90L_2 three-phase electric motor (KAIJIELI) was used. For outlet temperature measurement, an ST-941 standard multimeter with an accuracy of ±0.1 °C was employed. To measure dryer wind speed, an anemometer (LUTRON, AM-2416) with an accuracy of 0.1 m/s was utilized. The dryer was equipped with an automated temperature controller, which had an accuracy of ±1°C (Fig. 1). Samples were weighed every 5 minutes using a DJ 2000A weigh scale (Shinko Electric Scale), with an accuracy of 0.01 g. During drying, the outlet air temperature of the dryer and the airflow ratio were recorded at 5-minute intervals.

Samples were weighed at the beginning, and after the dryer reached the desired temperature, eggplant was placed inside the drying cabinet. The experiment was performed at temperatures of 40, 50, and 60 °C and air velocities of 3, 5, and 7 m/s. The eggplant samples were cut into cubes with three different sizes: 0.5 × 0.5 × 0.5 cm, 1.0 × 1.0 × 0.5 cm, and 1.3 × 1.3 × 0.5 cm (length × width × height). Each treatment was repeated three times under controlled conditions at a room temperature of 30 °C and a relative humidity of approximately 50 %.

2.3. Determination of moisture content

To determine the moisture content of the samples, they were placed inside an oven at a temperature of 105°C; the final weights were measured after 24 h. Having determined the initial and final weights, and using Eq. (1), the initial moisture content could be obtained (Martynenko & Zheng, 2016).

$$M = \frac{m_1 - m_2}{m_1} \times 100 \quad (1)$$

The initial moisture content of the eggplant was 87.12 %.

2.4. Analysis of energy utilization

In this research, energy utilization was expressed using the first law of thermodynamics, as follows (Vahedi Torshizi et al., 2025)

$$\mathrm{Eu} = \dot{m}_{da} \times (h_{dai} - h_{dao}) \quad (2)$$

where Eu is consumed energy, is dry air mass flow rate, and h_{dai} is inlet air enthalpy, and h_{dao} is outlet air enthalpy. The air mass flow rate was obtained using Eq. (3) (Azadbakht, Aghili, et al., 2017)

$$\dot{m}_{da} = \rho_a \times v_a \times A_{dc} \quad (3)$$

where ρ_a is air density, v_a is air speed inside the dryer, and A_{dc} is the cross-section that air crosses. Dryer air enthalpy was obtained using Eq. (4) (Nazghelichi et al., 2010)

$$h_{da} = C_{pda} \times (T - T_\infty) + h_{fg} \quad (4)$$

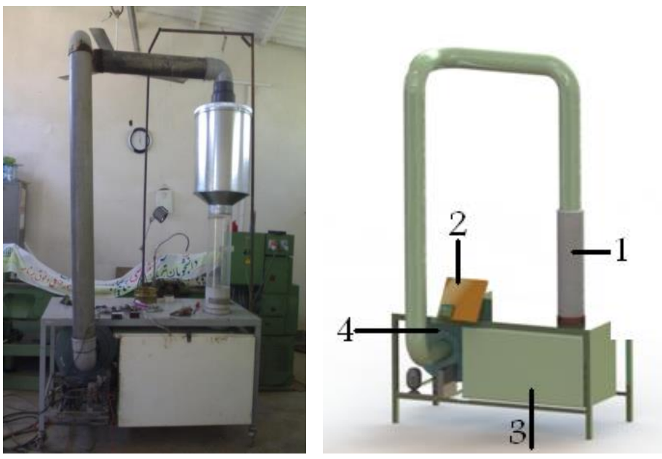

Figure 1. Schematic illustration of the testing apparatus. 1- Fluidizing chamber 2- heater control 3- heaters 4- fan

where C_{pda} is the specific heat capacity of air, T is the outlet temperature, T_∞ is the ambient temperature, and h_{fg} is indicative of the latent heat of vaporization of water. Inlet and outlet air-specific heat capacities were calculated with Eq. (5) (Nazghelichi et al., 2010)

$$C_{pda} = 1.004 + 1.88 \times w \quad (5)$$

where w is the air moisture content ratio, and Cp is the specific heat capacity of air. During energy and exergy analysis of the eggplant drying process, Eq. (6) was used for the transformation of relative moisture content to the air moisture content ratio (kg water/kg dry air) (Azadbakht, Ziaratban, et al., 2017)

$$w = 0.622 \times \frac{\varphi \times P_{vs}}{P - P_{vs}} \quad (6)$$

where φ is the relative moisture content, P_{vs} is the saturated vapor pressure, and P is the air pressure. The inlet and outlet air moisture content ratio was obtained using Eq. (7) (E. Akpinar, 2004)

$$w_{dao} = w_{dai} + \frac{\dot{m}_v}{\dot{m}_{da}} \quad (7)$$

where, w_{dao} is outlet air moisture content ratio; w_{dai} is inlet air moisture content ratio, and $\dot{m}_v$ is drying rate. Moreover, $\dot{m}_v$ was calculated using the following equation (Azadbakht, Vahedi Torshizi, Noshad, et al., 2020):

$$\dot{m}_v = \frac{w_t - w_{t+\Delta t}}{\Delta t} \quad (8)$$

where, $\dot{m}_v$ is drying rate; Δt is drying time interval; w_t is initial weight and $w_{t+\Delta t}$ is secondary weight. The energy utilization ratio was obtained from Eq. (9) (Corzo et al., 2008).

$$EUR = \frac{\dot{m}da\,(h_{dai} - h_{dao})}{(h_{dai} - h_{dae})} \quad (9)$$

2.5. Analysis of exergy

Eq. (10) was employed to calculate exergy, representing a functional exergy equation with a steady flow (Ranjbaran & Zare, 2013)

$$Ex = \dot{m}_{da} \times C_{pda} \times [(T - T_\infty) - T_\infty \times Ln\frac{T}{T_\infty}] \quad (10)$$

where C_{pda} is air specific heat capacity, T_∞ is ambient air temperature, and $\dot{m}_{da}$ is air mass flow rate. Exergy loss in the drying chamber was obtained using Eq. (11) (E. K. Akpinar, 2007)

$$Ex_l = Ex_i - Ex_o \quad (11)$$

where Ex_i is the inlet exergy and Ex_o is the outlet exergy. Exergy efficiency can be defined as the exergy consumed for drying products compared to the exergy of the drying air in the drying system, as obtained using Eq. (12) (Saidur et al., 2012).

$$\eta_{ex} = \frac{Ex_i - Ex_l}{Ex_i} = 1 - \frac{Ex_l}{Ex_i} \quad (12)$$

2.6. Artificial Neural Network

The Neural Network Toolbox of MATLAB R2014a (8.3.0.532) software was used to predict the parameters of energy and exergy analysis for the drying of eggplant. The network was a two-layer feedforward network with 15 neurons in the hidden layer, utilizing the Levenberg-Marquardt algorithm with a hyperbolic tangent sigmoid transfer function (Eq. 13). The number of neurons in the input and output layers depends on the number of independent and dependent variables. In this paper, 80% of the data was used for training, and 20% of the data was used for testing the network. In addition to speed, temperature, and size of the bed in dryers, these parameters were used as input. At the same time, exergy efficiency, exergy loss, energy utilization, and the ratio of energy consumption were considered as outputs. Finally, the statistical parameters calculated, including R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), have been presented. Related functions are given in Eqs. (13) to (15).

$$\text{Tan-sigm} = \frac{2}{(1+e^{-2x})} - 1 \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2} \quad (14)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}} \quad (15)$$

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \quad (16)$$

where P_i is the predicted value and O_i is actual value (Azadbakht, Torshizi, et al., 2018; Azadbakht, Vehedi Torshizi, et al., 2018).

3. Results and Discussion

3.1. Exergy loss

Figure 2 shows the amount of exergy loss in the three parameters of temperature, speed, and size. The most exergy loss was about 0.74 kJ/s, at the temperature of 60 °C, speed of 7 m/s, and size of 0.5 cm, and the least amount of exergy loss was 0.16kJ/S at 40°C, speed of 3 m/s, and a size of 1.3 cm.

According to Figure 2, the exergy loss increased due to the increase in temperature. This can be explained as follows: the difference between the input and output temperatures of the chamber in the dryer initially increases, leading to more evaporation of water from the product, and resulting in greater exergy loss as more exergy is consumed. Then the difference reduces, resulting in less evaporation and, consequently, less consumption of exergy and lower exergy loss. These results are similar to findings of Corzo et al. (2008) on a coroba slices dryer and Erbay et al. (2011) in drying the olive leaves in a tray dryer, and Aghbashlu et al (2008) on the potatoes in a semi-industrial dryer (Aghbashlo et al., 2008; Corzo et al., 2008; Erbay & Icier, 2011).

As shown in Figure 2, considering the exergy loss is a function of drying air temperature and air speed within drying time, exergy loss increased with increasing the speed, which was in line with the results of Akipinar et al. (2004) on the strawberry crop by thermodynamic analysis in a silicon dryer and Abdullah AKbulat et al. (2010) on the berry in a thin layer solar dryer (Akbulut & Durmuş, 2010; E. Akpinar, 2004).

Figure 2 illustrates the exergy loss at different sizes, where the exergy loss is reduced by increasing the size. From the graph, it is clear that wasted energy is more affected by temperature than anything else, and it increases with rising temperature. Exergy is a constant that is spent drying samples As a result, the higher the inlet air temperature, inlet air Exergy rises sharply And because air temperature is directly related to the amount of exergy going up the exhaust air temperature rises And leads to exergy loss rise The results were consistent with the researches of CEYLAN (2009) on a dryer with heat pump control on three kiwi, avocados and bananas (CEYLAN, 2009).

3.2. Exergy efficiency

Figure 3 illustrates the exergy efficiency in three key parameters: temperature, speed, and size. The highest exergy efficiency of 0.72 was achieved at a size of 1.3 cm, a speed of 5, and a temperature of 60°C. The lowest amount of 0.017 was observed at a size of 0.5 cm, a speed of 3, and a temperature of 40°C.

As shown in Figure 3, exergy efficiency increased with increasing temperature. Exergy efficiency is directly related to temperature. Dryer enthalpy rises with increasing temperature. This was the reason for the increase in efficiency. Exergy. The results were consistent with the research by ICIER et al. (2008) on two dryers and CEYLAN (2009) on a dryer with heat pump control, which examined three kiwi, avocado, and banana samples. Colak and colleagues (2007) analyzed the performance of drying green olives in the drying trays (CEYLAN, 2009; Colak & Hepbasli, 2007; İçier et al., 2008).

As shown in Figure 3, by increasing the inlet air speed, the entropy and enthalpy of the air dryer increase, resulting in a faster drying speed. This is leading to increased efficiency in exergy, which was in line with the results of Saidura al (2012) on analysis of a solar energy program and Inaba (2007), in which heat and mass transfer analysis and fluid bed dry seeds, Akpinar (2006) in a dryer on the product silicone Strawberry(E. K. Akpinar, 2007; Inaba et al., 2007; Saidur et al., 2012).

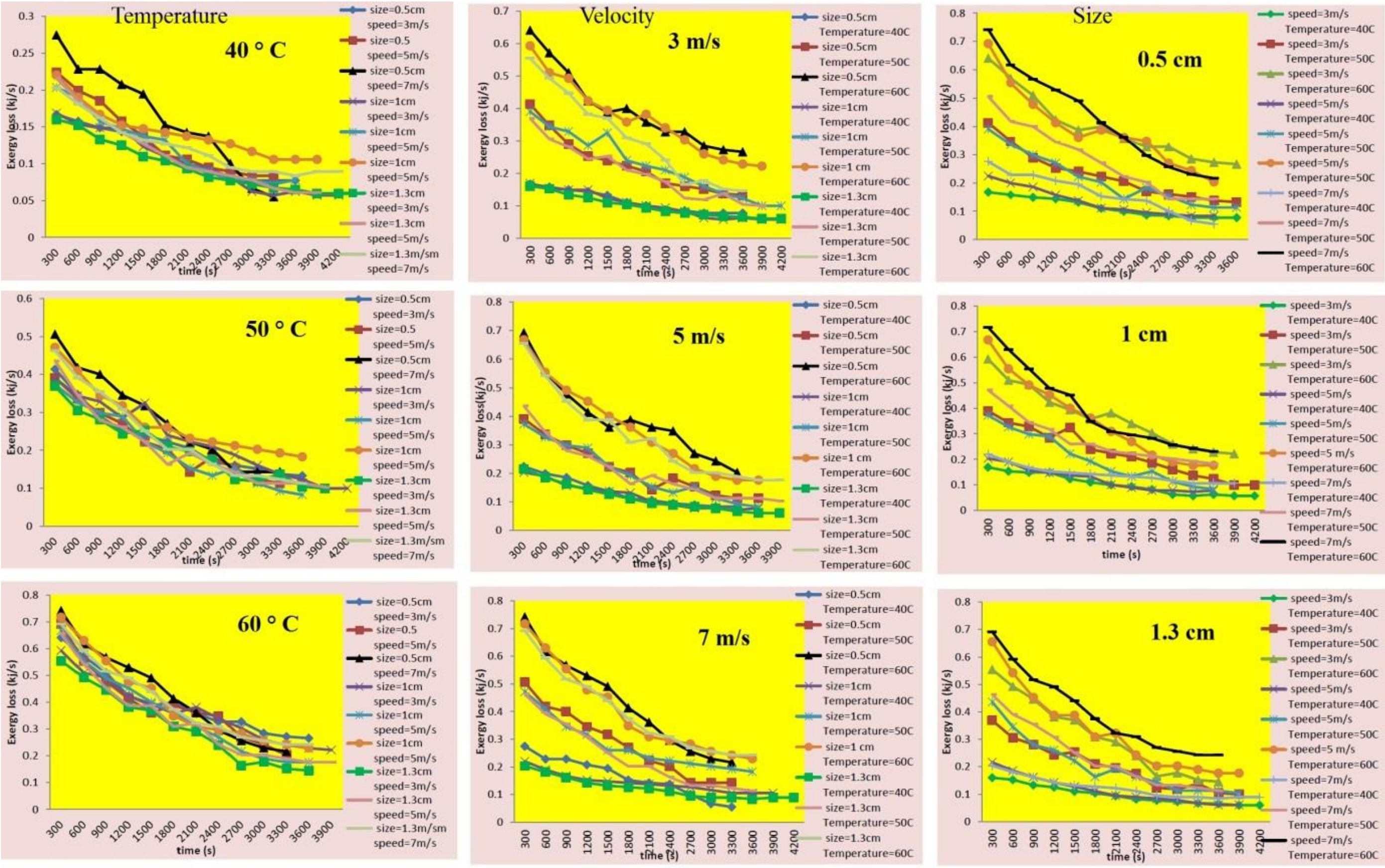

Figure 2. The effects of temperature, speed, and size parameters on the amount of exergy loss

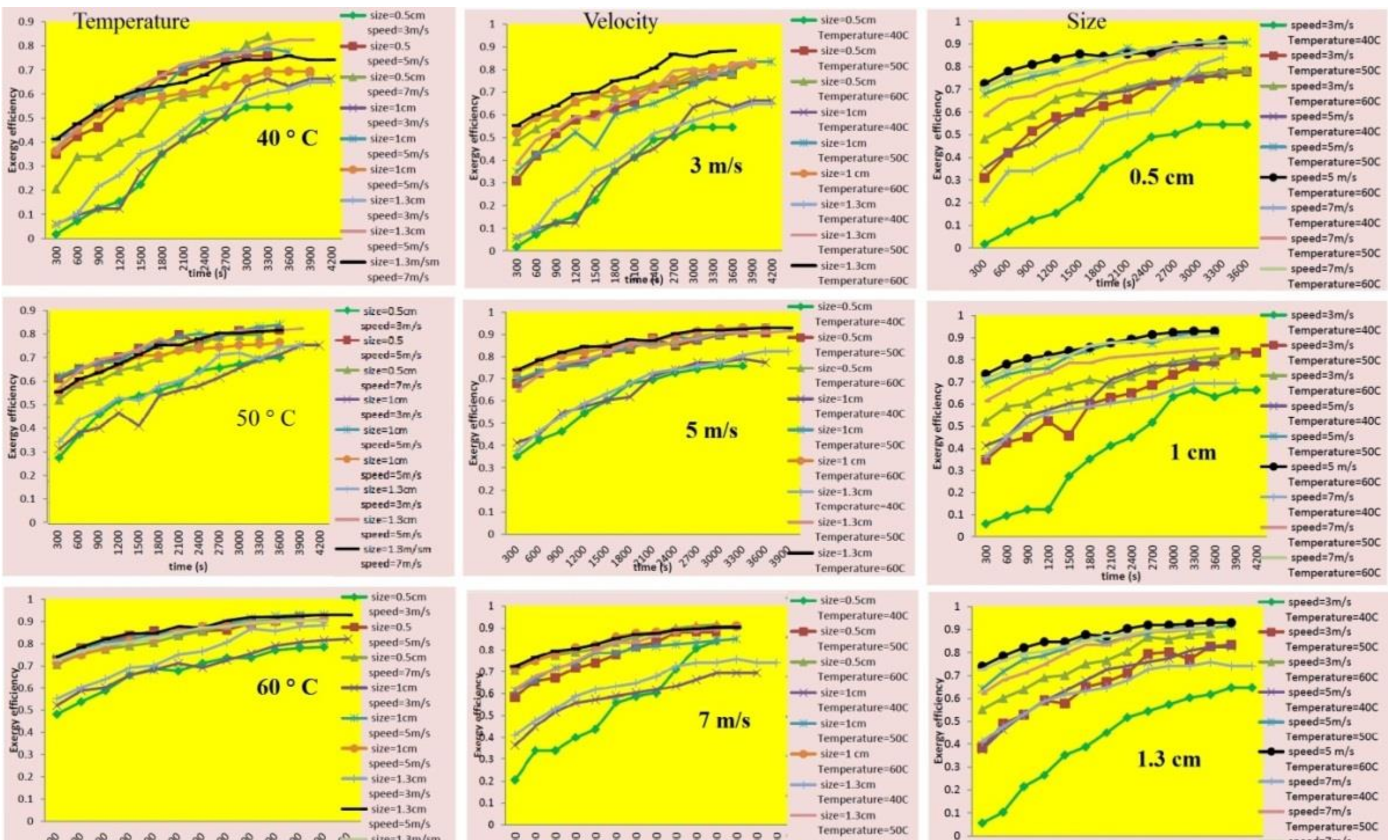

Figure 3. The effects of temperature, speed, and size parameters on exergy efficiency

Given that the exergy efficiency increased with increasing size. According to Eq. (12), by increasing the wasted energy, larger deficits and reduced efficiency exergy, that like the study conducted by Mohsen Ranjbar et al (2013) on soybeans in simulation exergy efficiency and energy of a fluid bed dryers and microwave, Nazghelichi et al (2010) on the product carrots in a fluid bed dryers (Nazghelichi et al., 2010; Ranjbaran & Zare, 2013).

3.3. Energy utilization

Figure 4 illustrates energy utilization in three parameters of temperature, speed, and size. The most excellent energy utilization was 3.64 kJ/s at 60°C, with a speed of 7 and a size of 0.5 cm, and the lowest value was 1.08 kJ/s at a temperature of 40°C, a speed of 3, and a size of 1.3 cm.

According to Figure 4, the energy utilization increased with increasing temperature. The most significant energy consumption was observed at the beginning of the drying time, and its value decreased over time, because the transfer of moisture from the air was higher at the start of the process. These results are similar to those of Erbay et al. (2011) in drying olive leaves in a tray dryer and Akpinar (2007) in a dryer using silicone product (E. K. Akpinar, 2007; Erbay & Icier, 2011).

According to Figure 4, energy utilization increases with increasing speed. Given that energy consumption depends on the speed of the inlet air, the latent heat of water vapor, the specific heat capacity, and the temperature of the outlet air, the mass flow rate of air increases with speed, causing moisture to evaporate quickly. These results are consistent with the findings of Corzo et al. (in 2008 on a coroba slices dryer and Akipinar et al. (in 2004 on drying the slices of carrot in a silicon dryer (E. Akpinar, 2004; Corzo et al., 2008).

Energy utilization increases with the reduction of the sample size (Figure 4). Given that, by reducing the contact area, hot air transmission is enhanced. As a result of heat and mass transfer, most of the energy produced by the dryer is used to evaporate moisture from the eggplant. Whatever The sample size be larger, In contrast constant input energy, more moisture is remain inside sample's, Because the after a while is decreased moisture evaporation process Input energy, capable of penetrating sample's and removing moisture samples does not have. that like the study conducted by Minaei et al (2014) on energy consumption, thermal utilization efficiency and hyperic in content in drying leaves of St and Aghbashlo et al (2008) on the potatoes in a semi-industrial dryer (Aghbashlo et al., 2008; Minaei et al., 2014).

3.4. The Energy utilization ratio

Figure 5 shows the energy utilization ratio in three parameters: temperature, speed, and size. The most significant ratio of consumed energy was 1.18 at 40 °C, speed of 7 m/s, and a size of 0.5 cm, and the lowest value was 0.14 at 60 °C, speed of 3 m/s, and a size of 1.3 cm.

As shown in Figure 5, the energy utilization ratio decreased over time and with an increase in temperature, resulting in a rise in drying speed. The reason is that by increasing the drying air temperature, a partial pressure difference of water vapor exists between the product and the drying air. As the result increases, the transmission speed of product moisture from the air and the drying rate of the products increase. These results are consistent with the findings of Bennamoun et al. (2003), which focus on the design of a solar dryer for agricultural products, and Midilli (2003) on exergy and energy analysis of a dryer for pistachios (Bennamoun & Belhamri, 2003; Midilli & Kucuk, 2003).

According to Figure 6, the energy utilization ratio increased with increased speed, but over time, it decreased. Because in the early stages there is more moisture to evaporate, which requires more energy, this process is reduced over time. These results are similar to those of Corzo et al. (2008) on a coroba slices dryer and Akpinar (2004) in a dryer on the product silicone Strawberry.

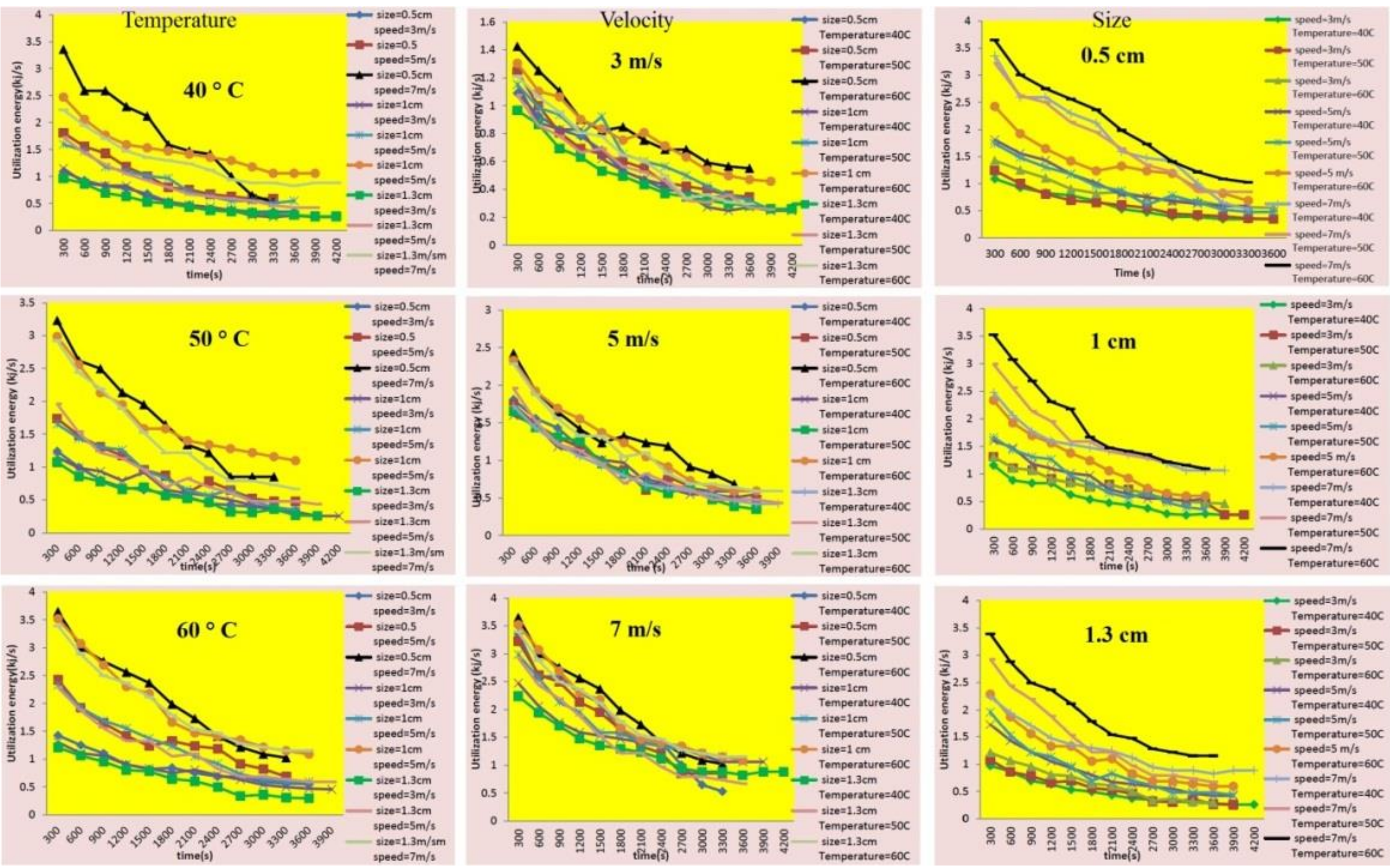

Figure 4. The effects of temperature, speed, and size parameters on energy utilization

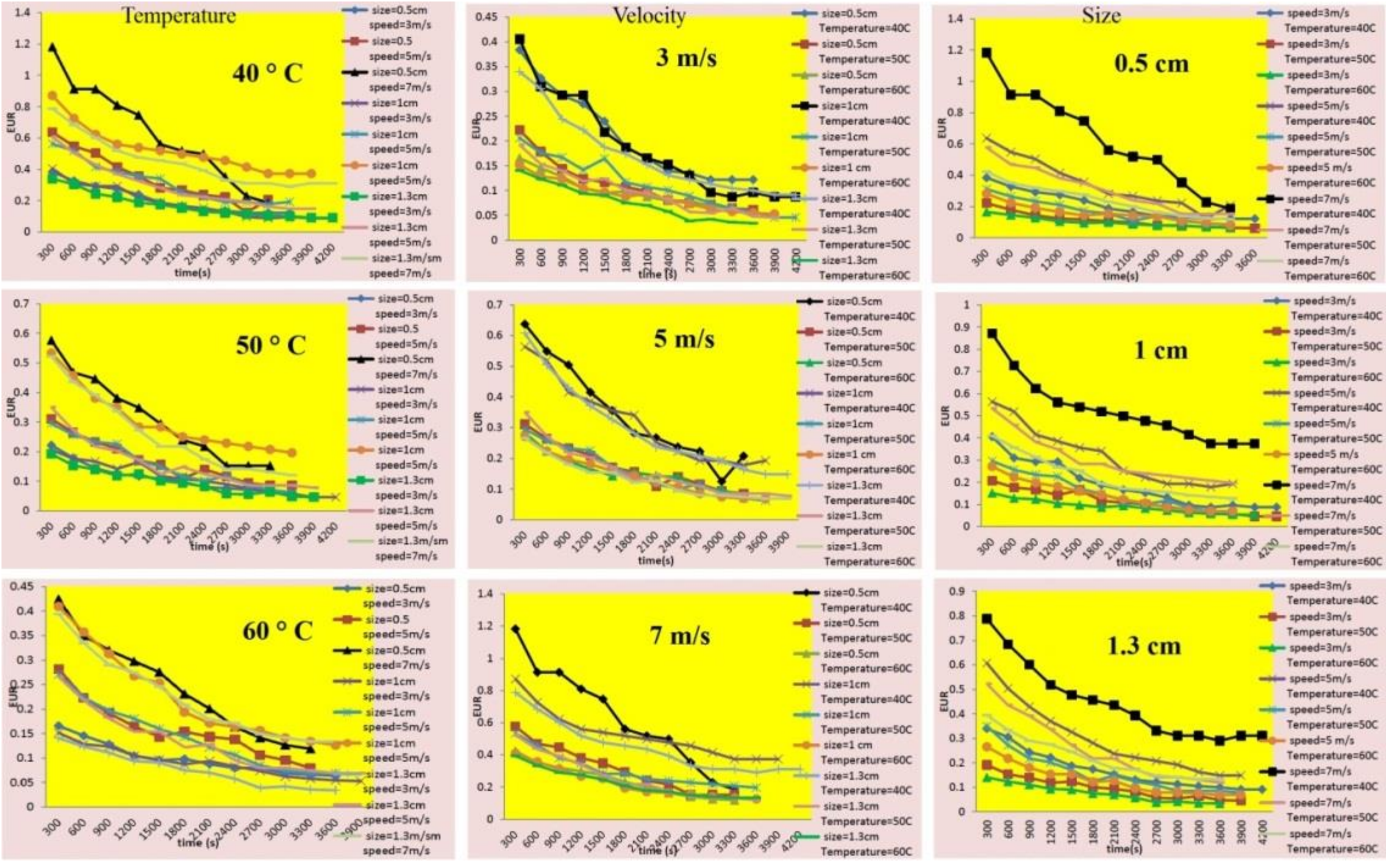

Figure 5. The effects of temperature, speed, and size parameters on the energy utilization ratio

As shown in Figure 5, the energy utilization ratio decreased with increasing size. Because increased speed and temperature led to a faster reduction in particle size and created a larger area for heat and mass transfer, significantly more energy was used in the drying chamber to evaporate at the beginning of the drying process. Nazghelichi et al. (2010) on carrots in a fluidized bed dryer and Sazat Hussain Sarkar et al. (2015) on rice in an industrial dryer (Nazghelichi et al., 2010; Sarker et al., 2015).

3.5. Artificial neural network

Data before entering the network were normalized in the range of -1 to 1. In Figures 7 to 11, the data illustrated with lines and squares are data predicted by the artificial neural network, and the data marked with lines and circles are measured data; measured and predicted data have a largely good overlap. Figure 7 shows the overlap of measured and predicted data for energy efficiency; part (a) is related to +data for network testing, and part (b) is data for the training of the network. It should also be noted that in these figures, the horizontal axis represents the number of data points and the vertical axis represents the values of normalized data.

Figure 6 indicates the overlap of the measured and predicted data for energy utilization. Figure 7 illustrates the overlap of the measured and predicted data for the energy utilization ratio. Figure 8 demonstrates the overlap of the measured and predicted data for exergy efficiency. Figure 9 shows the overlap of the measured and predicted data for exergy loss.

3.6. Statistical analysis using a neural network

The statistical parameters, such as R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), were calculated using an artificial neural network and the software MATLAB R2014a (8.3.0.532). As evident from the statistical parameters, the created ANN is successful in predicting data associated with energy and exergy. These parameters related to energy and exergy change irregularly over time, as fluidized bed dryers are unable to maintain a constant temperature over a prolonged period. ANN can, at all times, predict exergy efficiency, the energy utilization ratio, and energy utilization. Achieving the answer in this way is more than mathematical modeling methods; therefore, it is suitable for modeling processes and the control (Kaminski & Tomczak, 1999; Nazghelichi et al., 2011). On the other hand, errors in input data do not have an adverse impact on data processing due to the distribution of data in artificial neural networks. Artificial neural networks, due to their versatility, are more reliable than statistical models and offer greater interoperability and approximation.

4. Conclusion

– The exergy loss increased with increasing speed and temperature, and decreased with reducing sample size.
– The energy utilization increased with increasing temperature.
– Increased speed, sample size, and time will increase the exergy efficiency.
– The energy utilization increased with increasing the speed and temperature, and decreased with the sample size.
– The energy utilization ratio was reduced with time and increased with the temperature and sample size.
– The energy utilization ratio soared with increasing speed and size of the bed.
– The statistical analysis results showed that neural networks can be used in an intelligent drying process, which has a large share of energy utilization in the food industry.
– Prediction by a trained neural network due to a parallel processing structure is faster than usual mathematical models; it also does not require long calculations to solve differential equations using numerical methods.

In an artificial neural network, results are obtained by multiplying the input matrix by the weight matrix. Additionally, if necessary, the input and output variables in the neural network can be adjusted to reduce or increase their values. Therefore, it is a suitable method for predicting energy and exergy in various dryers.

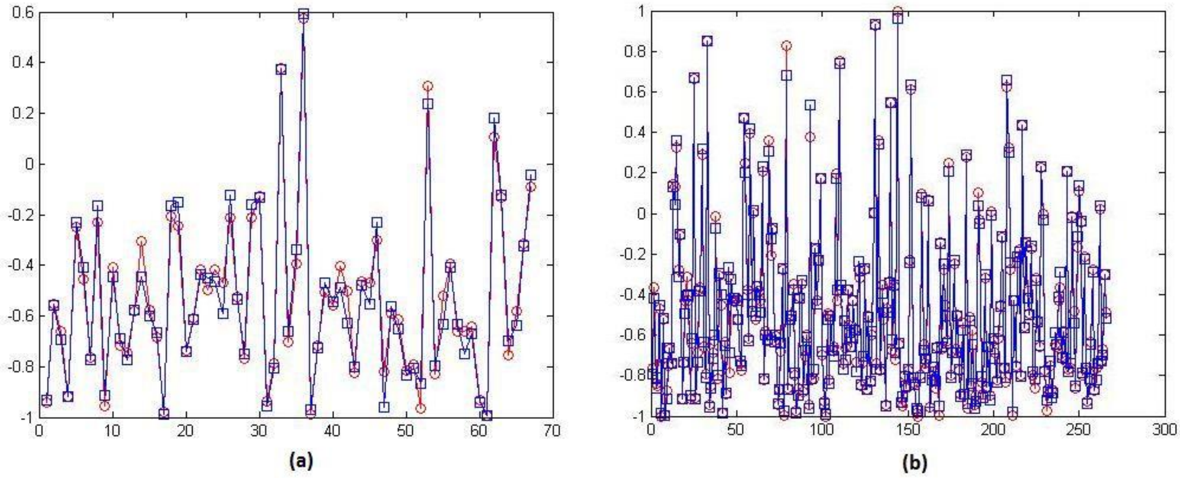

Figure 6. Overlap of predicted and measured data for energy consumption in test (a) and train (b)

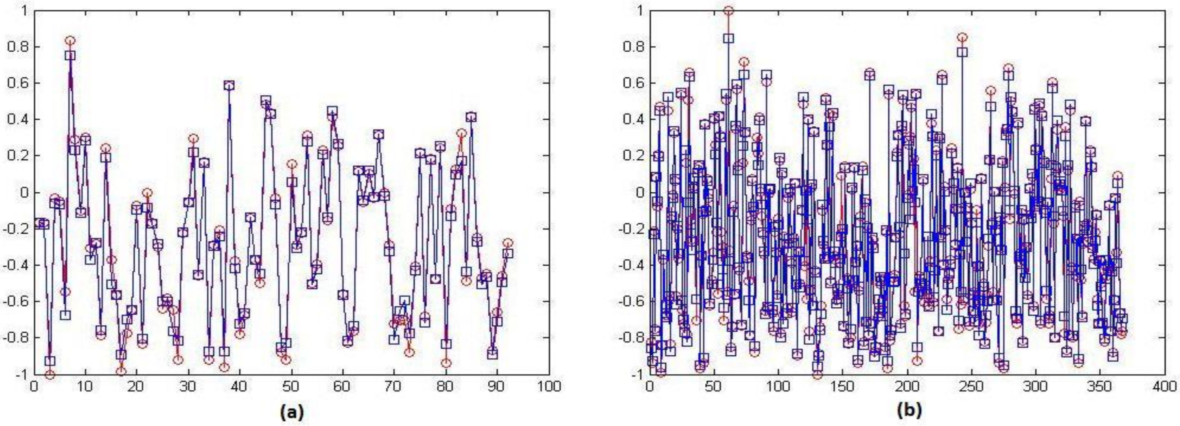

Figure 7. Overlap of predicted and measured data for the energy utilization ratio in test (a) and train (b)

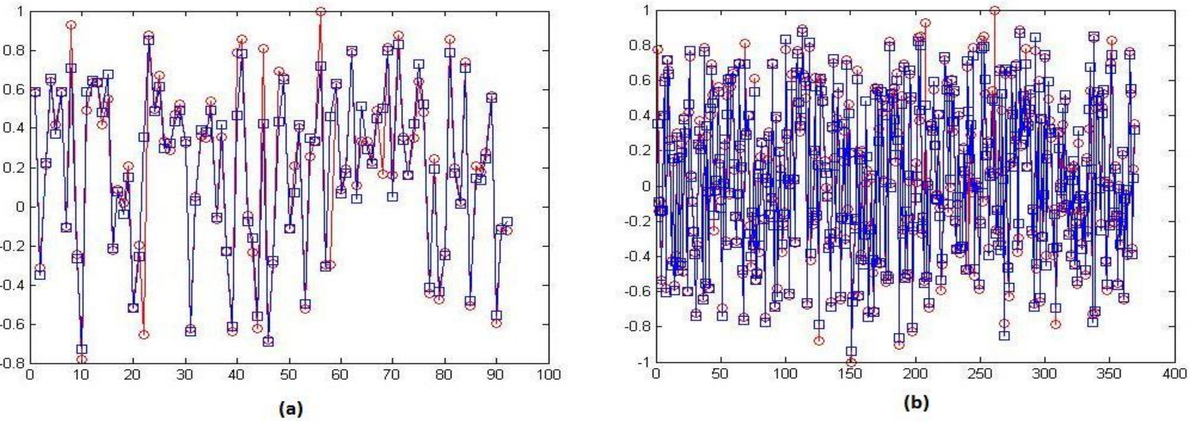

Figure 8. Overlap of predicted and measured data for exergy efficiency in test (a) and train (b)

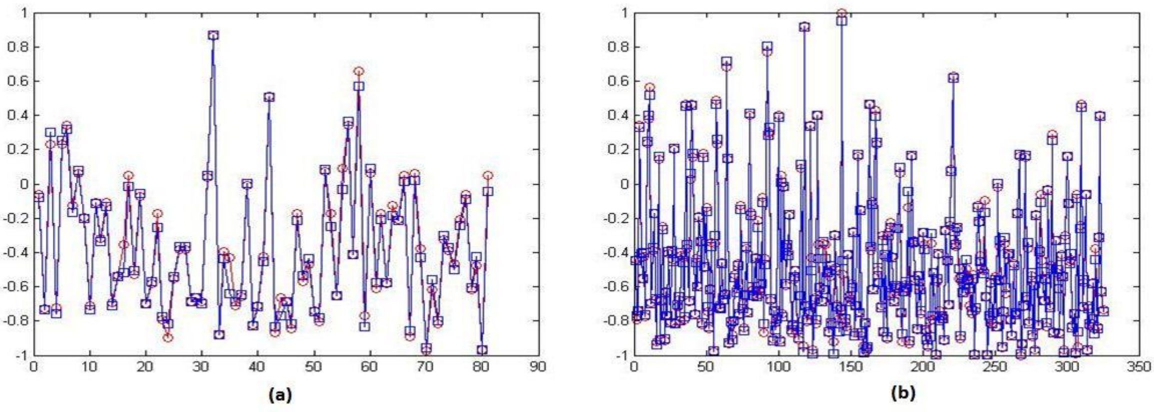

Figure 9. Overlap of predicted and measured data for exergy loss in test (a) and train (b)

Table 1. Statistical parameters related to energy and exergy analysis using artificial neural networks

Variable	MAE_{train}	MAE_{test}	$RMSE_{train}$	$RMSE_{test}$	R^2
Energy utilization	0.0214	0.0401	0.1536	0.0269	0.99727
Energy utilization ratio	0.138	0.0348	0.03	0.0312	0.99803
Exergy loss	0.0221	0.0444	0.0165	0.0304	0.99704
exergy efficiency	0.0135	0.0211	0.0103	0.0187	0.99636

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Competing interests

No competing financial interests or personal relationships are known to the authors that could have influenced this study.

Data availability statement

The data supporting the results of this study are available from the corresponding author upon reasonable request.

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