Biosystems Engineering and Renewable Energies

Journal homepage: https://bere.gau.ac.ir

GUASNR ISAMEM

Original Research Paper

Energy and exergy analysis of apple drying using fluidized bed method: A comparison of GMDH neural networks and ANN-GA models

Mohammad Vahedi Torshizi[1*], Arash Rokhbin[2], Armin Ziaratban[2]

[1] *Department of Biosystems Engineering, Tarbiat Modares University, Tehran, Iran*
[2] *Department of Biosystem Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran*

Biosystems Engineering and Renewable Energies 2025, 1 (1): 1-10

KEYWORDS

Apple
artificial neural networks
genetic algorithm
drying

*** Corresponding author**
mohammadvahedi4130@gmail.com

Article history
Received: 2024-10-20
Revised: 2024-12-3
Accepted: 2024-12-10

ABSTRACT

This study, which includes practical implications in the food processing industry, estimated the energy and exergy of apple drying using group method of data handling (GMDH) neural networks and a hybrid artificial neural network-genetic algorithm (ANN-GA) model. Osmotic and natural samples were tested in the form of apple cubes with a height of 5 mm and lateral dimensions of 6 × 6 mm, 8 × 8 mm, and 10 × 10 mm, dried by fluidized bed method at three air velocities of 4, 6, and 8 m s^{-1}, and temperatures of 40, 45, and 50 °C. The results showed that energy consumption, energy use ratio, exergy efficiency, and exergy loss were elevated by increasing the temperature and air velocity and reducing the sample sizes in natural and osmotic samples. It was also observed that the GMDH neural network exerted the linear correlation coefficients (R) of 0.95, 0.92, 0.91, and 0.91, for the prediction of energy consumption, energy use ratio, exergy loss, and exergy efficiency, respectively, outperforming the ANN-GA model. The weakest performance of the GMDH network was associated with the exergy efficiency. The ANN-GA exhibited the best prediction performance for energy consumption and the lowest exergy loss.

Abbreviations	
E_u	consumed energy
$\dot{m}_{da}$	dry air mass flow rate
h_{dai}	inlet air enthalpy
h_{dao}	outlet air enthalpy
ρ_a	air density
v_a	air speed inside the dryer
A_{dc}	the cross section that air crosses
C_{pda}	the specific heat capacity of air
T	outlet temperature
$T\infty$	ambient temperature
h_{fg}	indicative of latent heat of vaporization of water
w	air moisture content ratio
$Cpda$	the air's specific heat capacity
φ	relative moisture content
P_{vs}	saturated vapor pressure
P	air pressure
w_{dao}	outlet air moisture content ratio
w_{dai}	inlet air moisture content ratio
$\dot{m}_v$	the drying rate
$w_{(t)}$	initial weight
$w_{(t+\Delta t)}$	secondary weight
Δt	drying time interval
Ex_l	Inlet exergy
E_{xo}	outlet exergy
η_{en}	Exergy efficiency

1. Introduction

Food preservation through drying involves the removal of moisture to extend the shelf life and safeguard against decay. A lower moisture content helps preserve key qualities such as taste and nutritional value (Azadbakht and Vahedi Torshizi, 2020). Moreover, drying enhances the longevity of food items by curbing microbial and enzyme activities and slowing down chemical reactions. It also lightens the load and compacts the size, which eases packaging, transportation, and storage, thereby cutting down on associated expenses (Azadbakht et al., 2018). Osmotic dehydration (OD) is a process where water is partially extracted from food items of plant or animal origin by submerging them in a hypertonic solution. OD is commonly employed as a preliminary step before various drying techniques, including hot air, vacuum, freeze, and microwave drying. The global demand for fruits and vegetables has spurred the innovation of diverse food processing techniques. Among these, drying stands out for its ability to reduce food volume for easier transport, enhance storage potential due to diminished water activity, and minimize chemical reactions owing to decreased moisture (Vahedi Torshizi et al., 2020).

Nevertheless, considering the adverse effects of traditional drying methods on quality attributes like color, texture, flavor, density, and nutrients, there is a growing preference for produce that resembles its fresh state but has been subjected to low or moderate heat (Azadbakht et al., 2018). As a result, there has been a surge in efforts to discover alternatives devoid of these disadvantages. In this context, the osmosis process has gained increasing prominence recently. In the food industry, the drying process is a significant energy consumer, accounting for approximately 10% of the total energy usage. The extensive energy demands of food drying operations underscore their widespread application and industrial significance. According to the thermal efficiency of the drying process, the fluidized bed dryer is particularly favored for drying specific food products due to its superior heat and mass transfer rates, resulting in rapid drying. This type of dryer is versatile and can be used across various sectors, including the chemical, metallurgical, and pharmaceutical industries (Vahedi Torshizi and Kashaninejad, 2022).

Integrating artificial neural networks (ANNs) and genetic algorithms (GA) has been the subject of numerous research studies. Maleki et al. (2019) explored moisture estimation during pistachio drying in a cabinet dryer using thin-layer models and ANN. They evaluated ten mathematical-experimental models and ANN structures based on kinetic drying data. The experimental setup involved placing pistachio seeds in a thin layer on an aluminum sheet and monitoring moisture loss under various air temperatures and velocities. ANN data was divided into training (60%), validation (20%), and testing (20%) sets. The optimal model and ANN structure were identified through genetic algorithm optimization, achieving high accuracy based on the least squared error and highest correlation coefficients (Maleki et al., 2019). Akkoyunlu et al. (2020) investigated effective parameters in coal drying processes using a hybrid ANN-GA model. They applied the model to predict coal moisture under various conditions. The study highlighted the challenges of high costs and time constraints in experimental drying methods. Significant parameters were determined through a design of experiment (DoE) approach, excluding less impactful variables like air relative humidity. Pusat and Akkaya (2022) focused on predicting coal moisture content under varying drying conditions using a GMDH-type neural network. The model was developed to generate explicit equations for predicting moisture content during drying. Experiments involved 223 instances under different bed heights, coal sample sizes, air velocities, temperatures, and drying times. Results indicated that the model provided satisfactory accuracy (R^2 values in a range between 0.96 and 0.99) and was practical for diverse drying conditions due to its explicit nature.

Amini et al. (2021) examined the drying kinetics of basil seed mucilage (BSM) in an infrared dryer using an ANN-GA model and adaptive neuro-fuzzy inference system (ANFIS). The models predicted drying time (DT) and moisture ratio (MR) based on inputs like infrared radiation power, lamp distance, mucilage thickness, and treatment time. The ANN-GA model, featuring optimized hidden neurons, demonstrated high predictive accuracy (R = 0.97–0.99). Sensitivity analysis identified mucilage thickness and treatment time as crucial factors influencing drying outcomes. Kalathingal et al. (2020) integrated ANN with GA to optimize fluidized bed drying conditions for green tea leaves. Input parameters included temperature and air velocity, while outputs were drying time, total color difference (TCD), and total phenolic content (TPC). The model optimized conditions to 80 °C and 9 m s^{-1} using feedforward backpropagation. Validation results indicated strong alignment between actual and predicted values, achieving relative standard deviations of 5.7%, 0.46%, and 0.22% for drying time, TCD, and TPC, respectively. The study emphasized the model's efficacy in predicting quality retention under optimal drying conditions.

The present study aims to analyze the energy and exergy of apple drying using the fluidized bed method, focusing on the effects of varying temperatures, air velocities, and sample sizes. It seeks to compare the predictive performance of the GMDH neural network and the hybrid ANN-GA models in estimating critical parameters such as energy consumption, energy use ratio, exergy efficiency, and exergy loss. The findings are expected to provide valuable insights into optimizing drying processes for enhanced energy efficiency and minimized exergy losses, offering practical implications for industrial food processing and preservation applications.

2. Material and methods

2.1. Sample preparation

Golden Delicious apples were selected for drying. The apples were cut manually into cubes in three areas with a height of 5 mm and lateral dimensions of 6 × 6, 8 × 8, and 10 × 10 mm. The drying was performed in a fluidized bed dryer at 40, 45, and 50 °C and inlet hot air velocities of 4, 6, and 8 m s^{-1}. The drying was carried out once with the osmotic pre-treatment process and once without pretreatment to use the results in analyzing the energy and exergy.

2.2. Preparation of osmotic solution

The osmotic solution was prepared for the dehydration of samples using commercial sugar at a concentration of 40%. In addition, the solution temperature was set at 50 °C in the osmosis process. The samples with the exact dimensions without osmotic pre-treatment placed in the dryer were kept in the solution for two hours for the initial dehydration process. After 2 h, the samples were extracted from the solution and dried. Finally, the samples were dehydrated in the dryer using the osmosis process, and the natural samples were placed separately in the drying chamber (Figure 1).

2.3. Experimental procedure

A centrifugal blower (3hp CDF90L_2) supplied airflow, while an ST_941 sensor (± 0.1 °C) measured outlet temperature. A LUTRON AM-2416 anemometer (± 0.1 m s^{-1}) tracked wind speed and an automated controller (± 1 °C) regulated the dryer temperature. Samples, weighed every 5 min using a Dj 2000A scale (± 0.01 g), were dried at 40, 45, and 50 °C with air velocities of 4, 6, and 8 m s^{-1}. Experiments were conducted at 20 °C and 50% humidity and were repeated thrice.

2.4. Analysis of energy utilization

Energy utilization was expressed using the first law of thermodynamics, as follows (Syahrul et al., 2003)

$$\mathrm{Eu} = \dot{m}_{da} \times (h_{dai} - h_{dao}) \tag{1}$$

where the air mass flow rate was obtained using Eq. (2) (Aghbashlo et al., 2008)

$$\dot{m}_{da} = \rho_a \times v_a \times A_{dc} \tag{2}$$

and dryer air enthalpy was obtained using Eq. (3) (Corzo et al., 2008).

$$h_{da} = C_{pda} \times (T - T_\infty) + h_{fg} \tag{3}$$

Inlet and outlet air-specific heat capacities were calculated using Eq. (4) (Corzo et al., 2008).

$$C_{pda} = 1.004 + 1.88 \times w \tag{4}$$

During energy and exergy analysis of the apple fruits drying process, Eq. (5) was used for the transformation of relative moisture content to the air moisture content ratio (kg water/kg dry air) (Topic, 1995).

$$w = 0.622 \times \frac{\varphi \times P_{vs}}{P - P_{vs}} \tag{5}$$

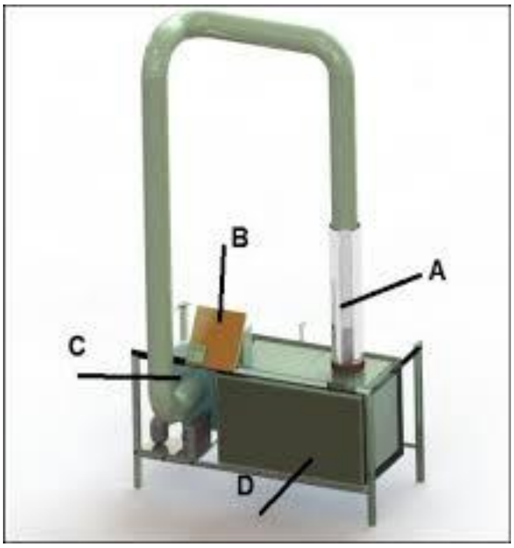

Figure 1. Schematic illustration of testing apparatus. (A) Fluidizing chamber, (B) heater control, (C) fan, and (D) heater chamber

The inlet and outlet air moisture content ratio was obtained using Eq. (6) (Akpinar, 2004) (Nazghelichi et al., 2010).

$$w_{dao} = w_{dai} + \frac{\dot{m}_v}{\dot{m}_{da}} \quad (6)$$

$$\dot{m}_v = \frac{w_t - w_{t+\Delta t}}{\Delta t} \quad (7)$$

The energy utilization ratio was obtained from Eq. (8) (Akpinar, 2004)

$$\text{EUR} = \frac{\dot{m}_{da} \times (h_{dai} - h_{dao})}{(h_{dai} - h_{dae})} \quad (8)$$

where EUR is consumed energy, $\dot{m}_{da}$ is dry air mass flow rate $h_{dai,}$ is inlet air enthalpy, and h_{dao} is outlet air enthalpy, and h_{dae} is environment air enthalpy.

2.6. Analysis of exergy

Eq. (9) was employed to calculate exergy, representing a functional exergy equation with a steady flow (Midilli and Kucuk, 2003)

$$Ex = \dot{m}_{da} \times C_{pda} \times \left[(T - T_\infty) - T_\infty \times Ln\frac{T}{T_\infty}\right] \quad (9)$$

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. (10) (Akpinar, 2004).

$$Ex_l = Ex_i - Ex_o \quad (10)$$

Exergy efficiency can be defined as consumed exergy for drying products compared with exergy drying air in the drying system, obtained using Eq. (11) (Corzo et al., 2008).

$$\eta_{en} = \frac{Ex_i - Ex_l}{Ex_i} = 1 - \frac{Ex_l}{Ex_i} \quad (11)$$

2.7. Combination of ANN and GA

Biological neural networks inspire the ANNs. ANNs are learning algorithms that predict system outputs based on specific inputs by adjusting weights and biases. During the learning process, ANNs are modified to minimize the error between predicted outputs and target values. Among their significant applications is function approximation (Ziaratban et al., 2017).

This study employed a feed-forward network with three layers and five neurons in the hidden layer. The transfer function used was tan-sig (as described in Eq. 12). The network took inputs such as drying time, inlet hot air velocity, air temperature, sample sizes, and drying type (encoded as 1 for regular drying and 2 for osmotic drying). Initially, the data were normalized within the range of -1 to 1 using Eq. (13) before being fed into the network. Additionally, the GA was utilized to optimize the weights and biases of the ANN. The tournament method was employed for chromosome selection, with crossover and mutation rates set at 60% and 1%, respectively. Finally, statistical parameters, including mean absolute error (MAE) (Eq. 14) and mean square error (MSE) (Eq. 15), were used to assess the network's efficiency in both the test and train sections. The linear correlation coefficients were calculated using Eq. (16).

$$\tan - \text{sig} = \frac{2}{(1+e^{-2x})} - 1 \quad (12)$$

$$X_n = 2 \times \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \quad (13)$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} |P_i - O_i|}{n} \quad (14)$$

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

$$R = \frac{n\sum_{i=1}^{n} Y_{predicted} \times Y_{actual} - \sum_{i=1}^{n} Y_{predicted} \times \sum_{i=1}^{n} Y_{actual}}{\sqrt{\sum_{i=1}^{n} Y_{predicted}^2 - \left(\sum_{i=1}^{n} Y_{predicted}\right)^2} \times \sqrt{n\sum_{i=1}^{n} Y_{actual}^2 - \left(\sum_{i=1}^{n} Y_{actual}\right)^2}} \quad (16)$$

Figure 2 shows a block diagram of the processes related to running the combination of ANN and GA. As can be seen, the GA starts to work by running the program and randomly selecting the weights and biases. It will continue to establish the optimal weights and biases for creating a new population of crossover, mutation, and training of ANN.

2.8. GMDH-type artificial network

In self-organizing ANNs, input variables, the number of active neurons, layer count, and hidden layer neurons are automatically organized through an iterative process. This modification of the model structure aims to achieve the best data prediction. The central challenge lies in approximating the actual function f with an approximate function $\hat{f}$. Given an input vector X (x_1, x_2, x_3, ..., x_m), the output $\hat{y}$ is predicted as closely as possible to the actual output y. The relationship between input and output variables can be expressed using a complex discrete form of the Volterra functional series, known as the Kolmogorov-Gabor polynomial (Amanifard et al., 2008; Fathi et al., 2011)

$$y = \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} a_{ij} x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} a_{ijk}\, x_i x_j x_k + \dots \quad (17)$$

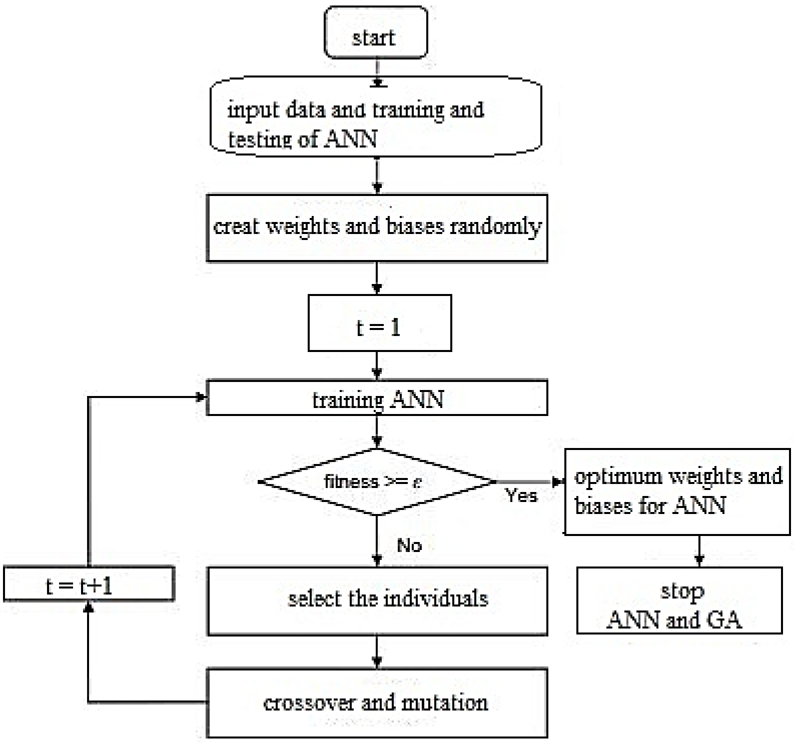

Figure 2. Block diagram of the combination of artificial neural networks and genetic algorithms

where M is the number of input variables ($x_1, x_2, ..., x_M$) of coefficients ($a_1, a_2, ..., a_M$). Eq. (18) expresses partial quadratic polynomials consisting of two variables:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1x_i + a_2x_j + a_3x_ix_j + a_4x_i^2 + a_5 \quad (18)$$

In this approach, a network of interconnected neurons incorporates partial quadratic descriptions to establish the mathematical relationship between input and output variables, as expressed in Eq. (17). The coefficients (ai) in Eq. (18) are determined through regression techniques. Specifically, the difference between the actual output (y) and the calculated output ($\hat{y}$) is minimized for each pair of input variables (x_i and x_j). The model is constructed as a polynomial tree using the quadratic form from Eq. (18), with coefficients obtained via least squares optimization. Essentially, the coefficients for each quadratic function (G_i) are derived using Eq. (19) to best fit the output within the input-output data pair (Ziaratban et al., 2017).

$$E = \frac{\sum_{i=1}^{M}(y_i - G_i())^2}{M} \rightarrow \min \quad (19)$$

The statistical parameters standard deviation (SD) (Eq. 20) and RMSE (Eq. 21), were used to evaluate the performance of GMDH, in addition to MSE and linear correlation coefficient (R).

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \quad (20)$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}} \quad (21)$$

3. Results and Discussion

3.1. Modeling of energy consumption

The study's findings indicate that increased air temperatures, increased inlet air velocity, and reduced sample size increase energy consumption. Figures 3 and 4 illustrate the trend of energy consumption across different conditions. Notably, elevated temperatures lead to more significant moisture content reduction. In other words, as temperatures rise, mass and moisture content decrease, increasing energy usage. These results align with the study of Aviara et al. (2014) on exergy and energy changes in native cassava using a tray dryer. Additionally, we observed that larger sample sizes retain more moisture content for a fixed energy input. This occurs because the evaporation rate of moisture content slows down over time, limiting the effectiveness of energy penetration for moisture removal. This result aligns with Nazghelichi et al. (2010), who reported an energy and exergy analysis of drying carrot pieces.

Figure 5 shows the data related to the train and test samples. The measured and predicted data are displayed in blue and red, respectively. The hybrid ANN-GA could predict the energy consumption procedure in most cases except those with very sudden changes. The values of MSE of the test, MSE of the train, MAE of the test, MAE of the train, and R were 0.02, 0.03, 0.11, 0.11, and 0.93, respectively.

Figure 6 shows the results of the prediction of energy consumption by comparing the predicted and actual data. It is evident that the GMDH offers superior prediction performance for the overall trend. The targets (actual data) and the GMDH network's output exhibit more significant overlap. However, the R-value is lower for ANN-GA when comparing the R-values obtained for energy consumption prediction using the GMDH network and the hybrid ANN-GA approach. Consequently, we can assert that the GMDH network demonstrates higher efficiency across various conditions in predicting energy consumption within the dryer. Figure 6 also depicts error values and the error distribution based on a normal distribution (highlighted in red). The MSE, RMSE, SD, and R values were 0.12, 0.35, 0.35, and 0.95, respectively.

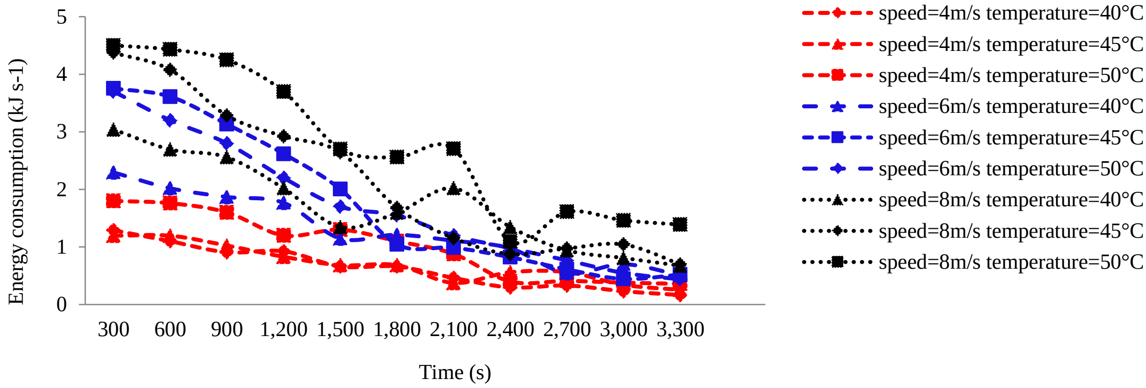

Figure 3. Energy consumption at a constant lateral size of 6 mm

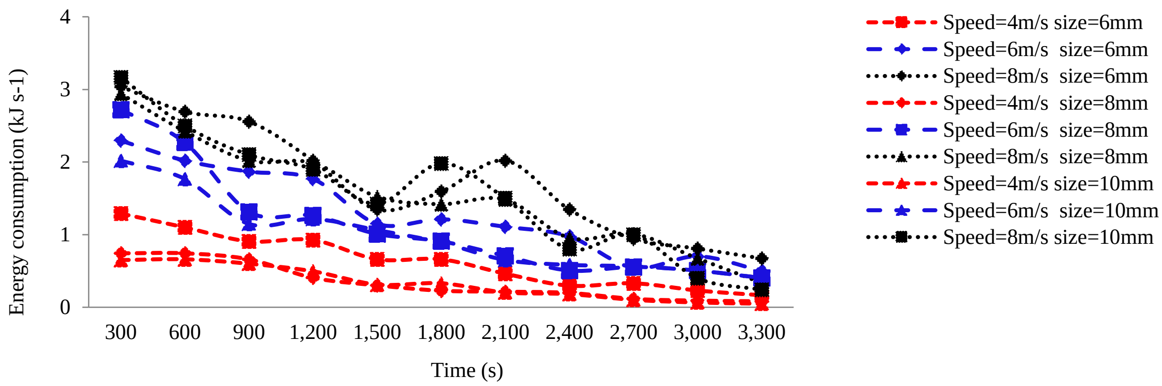

Figure 4. Energy consumption at a constant temperature of 40 °C

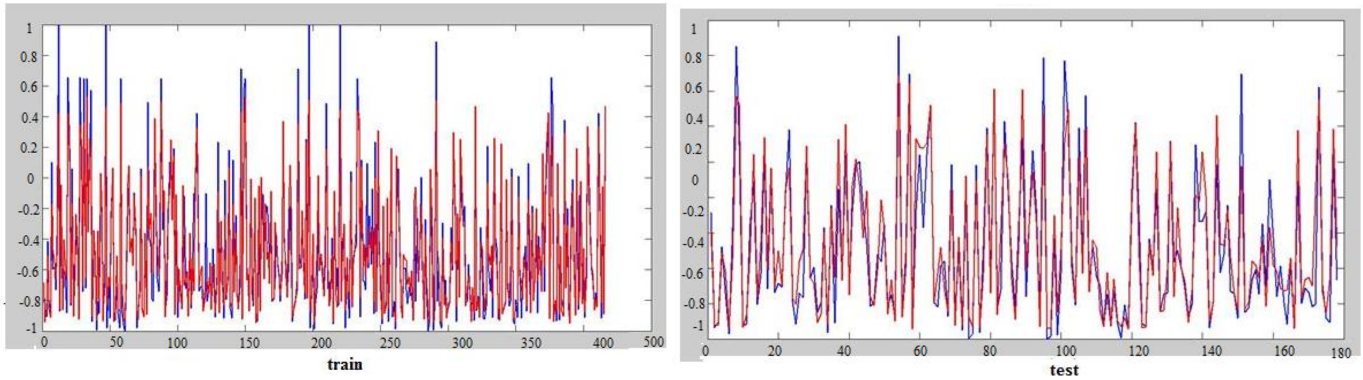

Figure 5. Prediction of energy consumption in both the test and train samples.

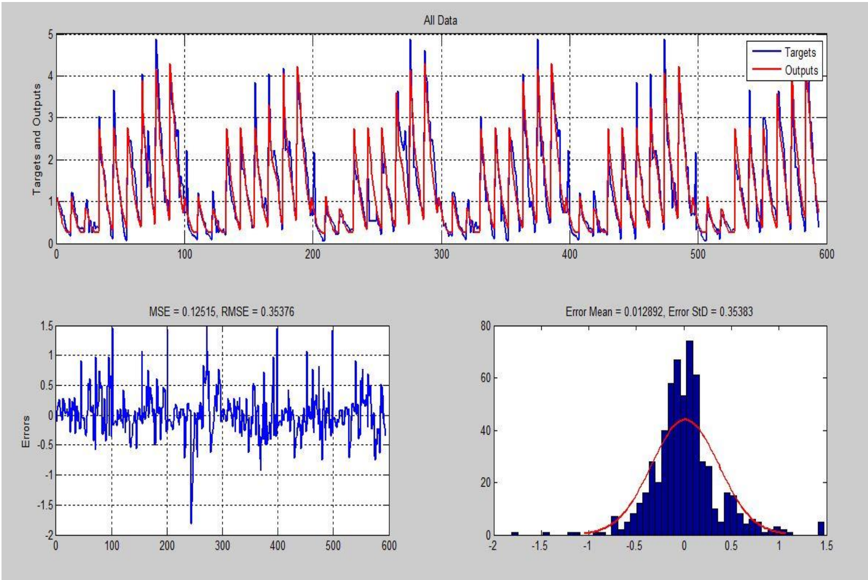

Figure 6. The predicted and actual amounts of energy consumption and error distribution

3.2. Modeling of energy use ratio

The results from the performed tests revealed that the energy use ratio was reduced by increasing the temperature and velocity and decreasing the size. Figures 7 and 8 show the energy use ratio in different conditions. According to Eq. (10), energy efficiency depends on air mass flow; when the speed goes up, the mass flow will be high, and a high energy efficiency will be gained. This result is in accord with Azadbakht et al. (2017), who reported an energy and exergy analysis of drying potato cubes. Figure 9 presents the training and test data. The measured data are shown in blue, and the predicted ones are in red. The hybrid ANN-GA, as shown in Figure 9, could predict the energy use ratio in most cases except those with very sudden changes. The values of MSE of the test, MSE of the train, MAE of the test, MAE of the train, and R using this model are 0.05, 0.03, 0.16, 0.14, and 0.90, respectively.

Figure 10 shows the error distribution for different values. The values of all observational data and output of the GMDH network are shown in the top box. As can be seen, the lower values overlapped more, and the GMDH network performed relatively weakly during the sudden increases. The difference distribution between outputs and targets can be seen in the bottom left box. Moreover, in red, the comparison of the error distribution with a normal distribution in the bottom correct box. The values of MSE, RMSE, STD, and R were respectively 0.003, 0.06, 0.057, and 0.92, respectively. A comparison of the MSE obtained from the two methods revealed that the GMDH network successfully predicts the changes in the energy use ratio.

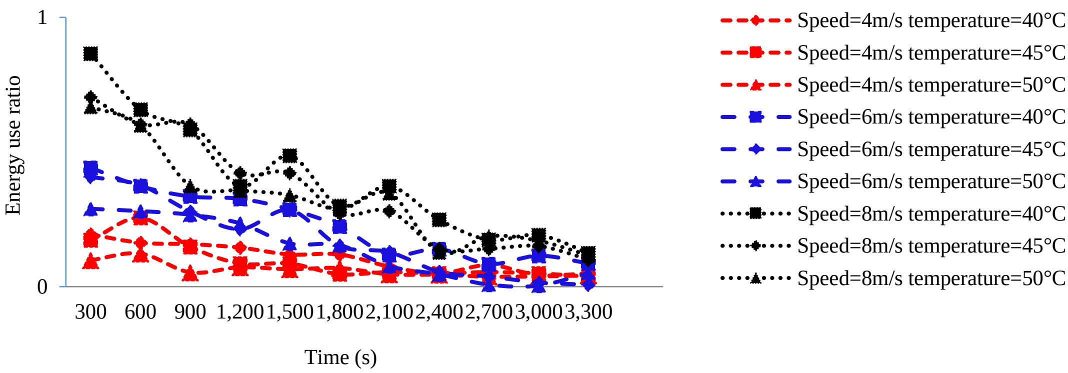

Figure 7. Energy use ratio at a constant lateral size of 6 mm

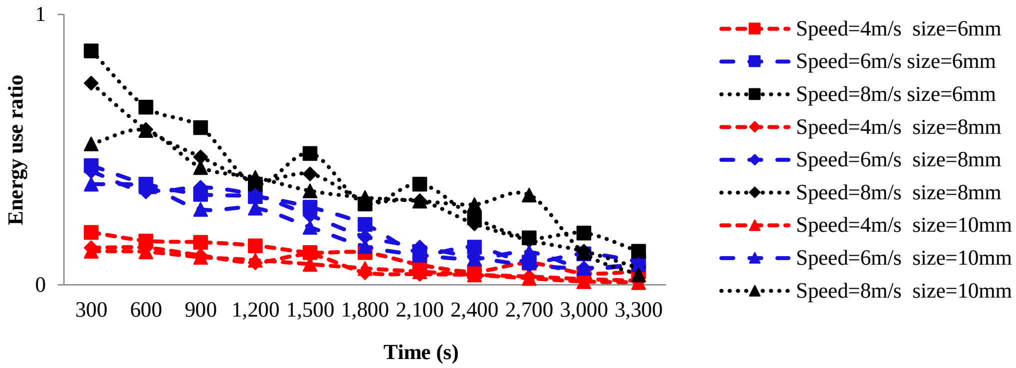

Figure 8. Energy use ratio at a constant temperature of 40 °C

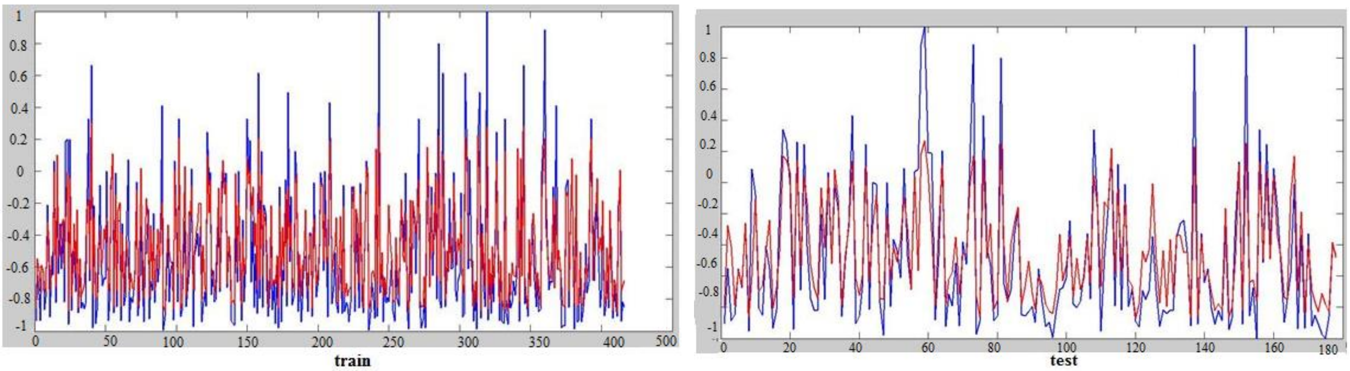

Figure 9. Predict changes in the energy utilization ratio in both the test and train samples

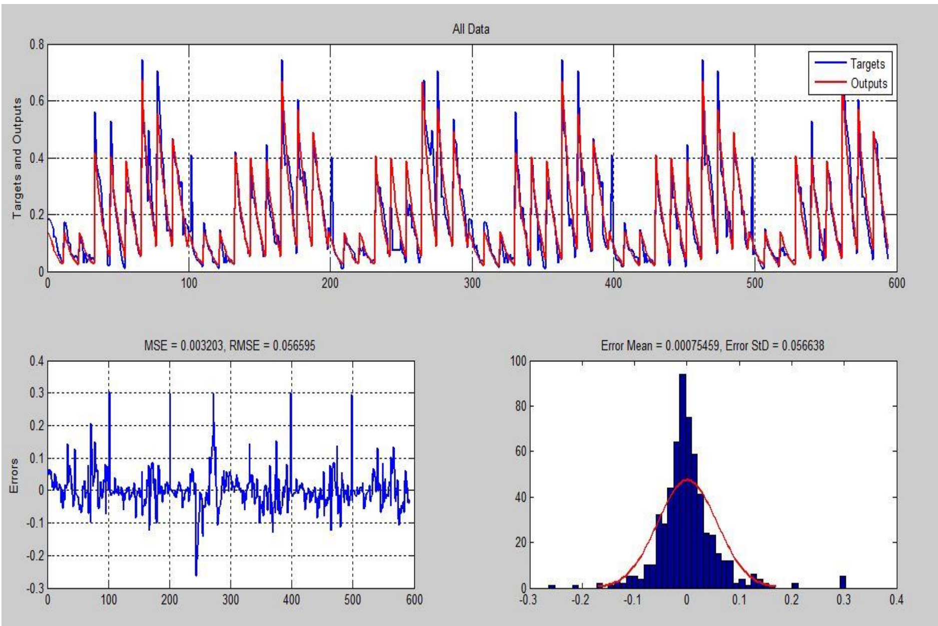

Figure 10. The predicted and actual amounts of energy use ratio and error distribution

3.3. Modeling of exergy efficiency

The results indicate that exergy efficiency increases with higher temperatures and velocities and a reduced sample size. The evolution of exergy efficiency is depicted in Figures 11 and 12. Notably, exergy efficiency is closely tied to temperature and energy consumption. Since energy consumption also rises with increasing temperature, it can be inferred that exergy efficiency improves as temperature increases. This finding aligns with the research of Akpinar (2004) on drying red peppers using a convection dryer.

Enhancing the velocity can increase the exergy efficiency since elevated inlet air velocity can promote entropy (which depends on the velocity of the particles) and dry air enthalpy due to the increasing volume of inlet air, resulting in a high exergy efficiency. This finding is in accord with previous research on pomegranate drying by microwave (Nikbakht et al., 2014). Figure 13 shows the observational data in blue and the predicted data in red. As can be seen, there is only one sudden decline in the test and three ones in the train. In other cases, the hybrid ANN-GA could predict changes in efficiency with acceptable accuracy. The values of MSE of the test, MSE of the train, MAE of the test, MAE of the train, and R were 0.01, 0.03, 0.08, 0.10, and 0.91, respectively.

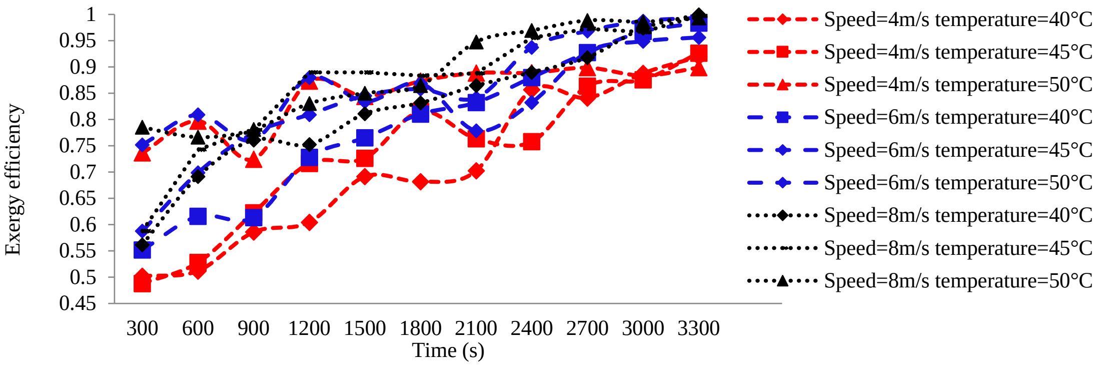

Figure 11. Exergy efficiency at a constant lateral size of 6 mm

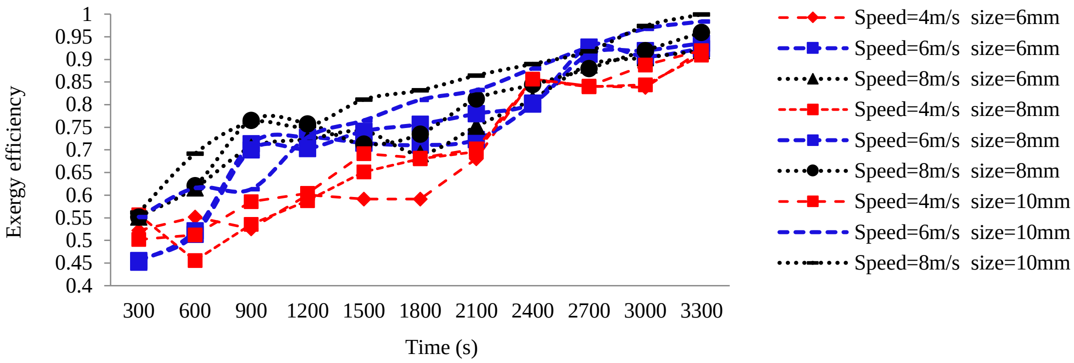

Figure 12. Exergy efficiency at a constant temperature of 40 °C

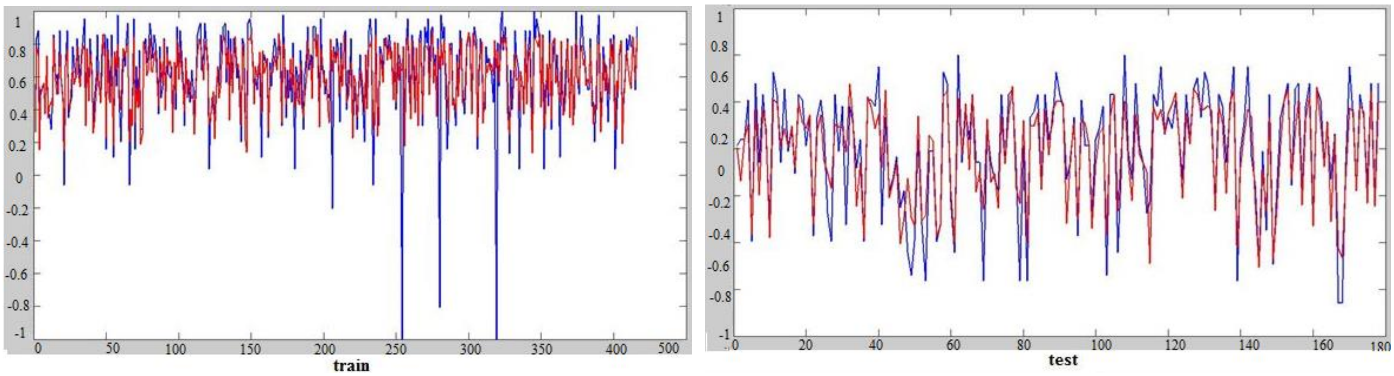

Figure 13. Predicted and actual values of exergy efficiency in both the test and train samples.

In Figure 14, the top box depicts the overlap between the measured data and the GMDH network's outputs. The network performs successfully in most cases, except for three instances where a sudden drop in efficiency occurs. The bottom-left box illustrates the error distribution resulting from the disparity between observed and predicted data in the GMDH network. Additionally, the bottom-right box compares this error distribution to the normal distribution (highlighted in red). Notably, the error distribution exhibits a higher density than the normal distribution. The calculated values for MSE, RMSE, SD, and R are 0.004, 0.046, 0.063, and 0.912, respectively. Furthermore, a comparison between the MSE obtained from the GMDH network and that from ANN-GA reveals the superior performance of the GMDH network.

3.4. Modeling of exergy loss

The test revealed that the exergy loss was improved by increasing the temperature and velocity and reducing the size. The changing procedure in exergy loss is shown in Figures 15 and 16. The exergy loss was elevated by increasing the temperature. It can be stated that with increasing temperature, parameters such as mass, heat, and friction are increased while exergy loss is also increased. Karagüzel et al. (2012) studied peas and beans in a fluid bed dryer and reported the same results. In addition, they reported that the dryer's increasing air velocity increases the inlet flow rate. Another finding of the current study is that because the flow rate is directly related to exergy, its increase is accompanied by the elevated wasted exergy. This result is consistent with the results of Akpinar (2005) on drying eggplant slices in the cyclone-type dryer.

Figure 17 illustrates the observational data in blue and the predicted data in red. The values of MSE of the test, MSE of the train, MAE of the test, MAE of the train, and R were 0.04, 0.06, 0.15, 0.16, and 0.88, respectively. Figure 18 shows the overlaps of the measured data and outputs of GMDH in the top box, indicating good overlap between them. The MSE, RMSE, SD, and R values were 0.049, 0.22, 0.23, and 0.91, respectively. The comparison of the R-values demonstrated that the R obtained from the GMDH network was higher than that of ANN-GA, proving the accuracy of results obtained from the images and a better performance of the GMDH network than the combined ANN-GA model.

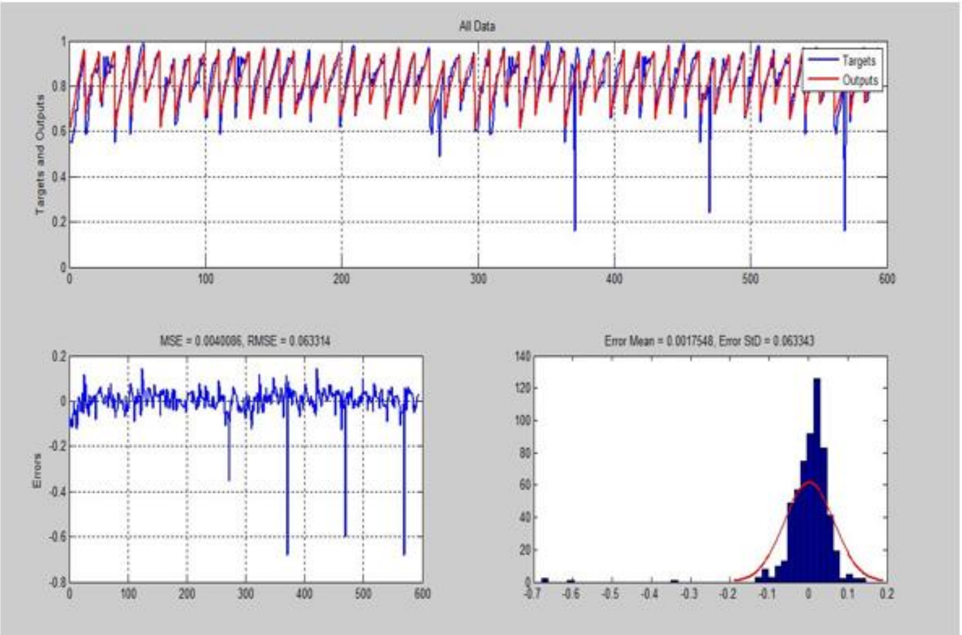

Figure 14. The predicted and actual amounts of exergy efficiency and error distribution

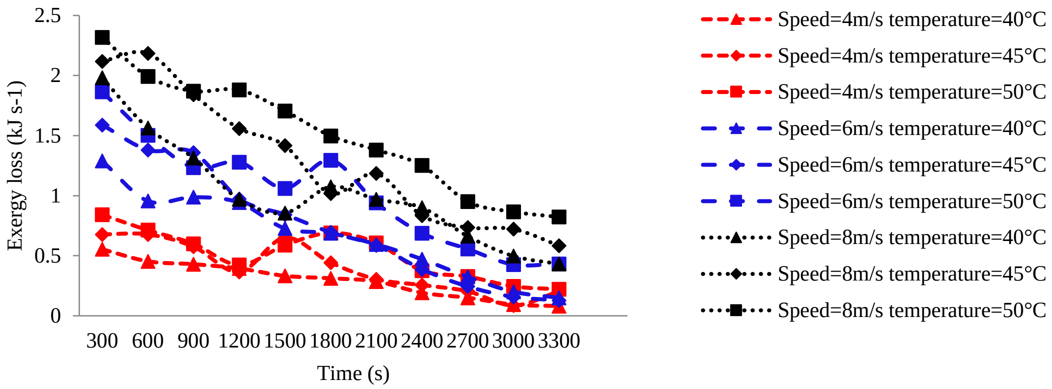

Figure 15. Exergy loss at a constant lateral size of 6 mm

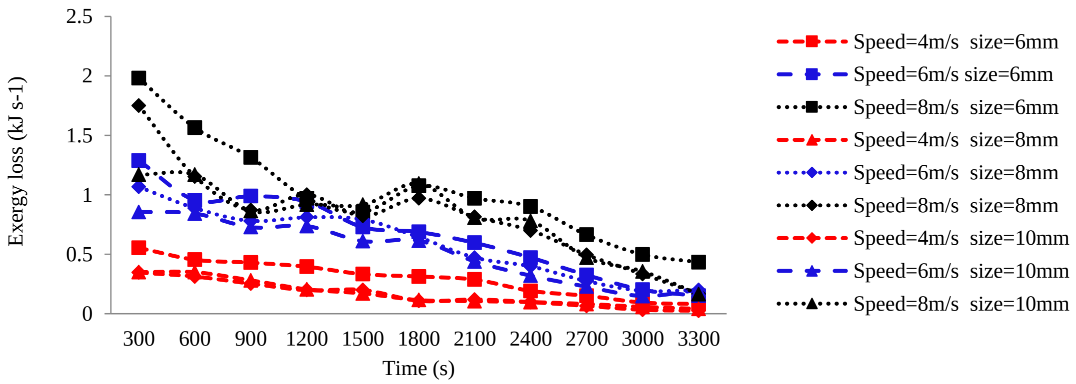

Figure 16. Exergy loss at a constant temperature of 40 °C

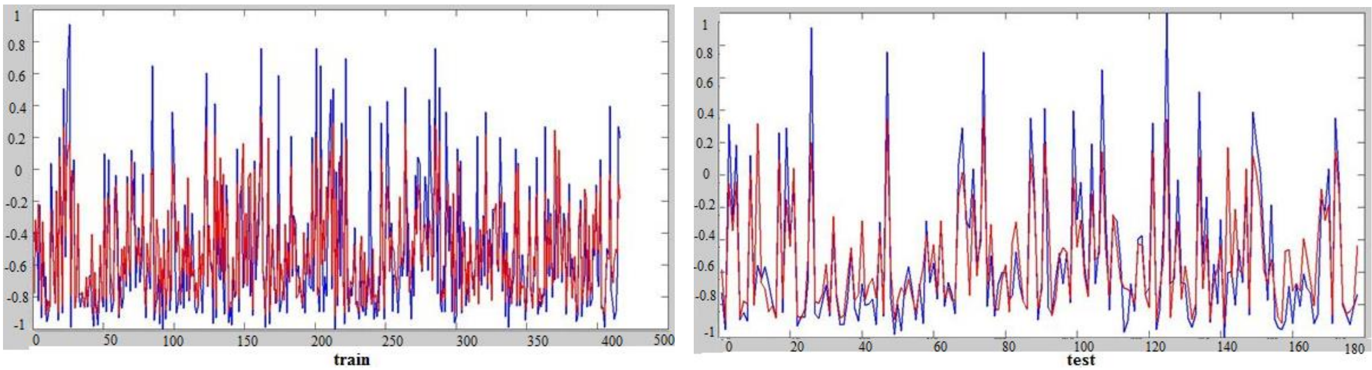

Figure 17. Predicted exergy loss in both the test and train samples.

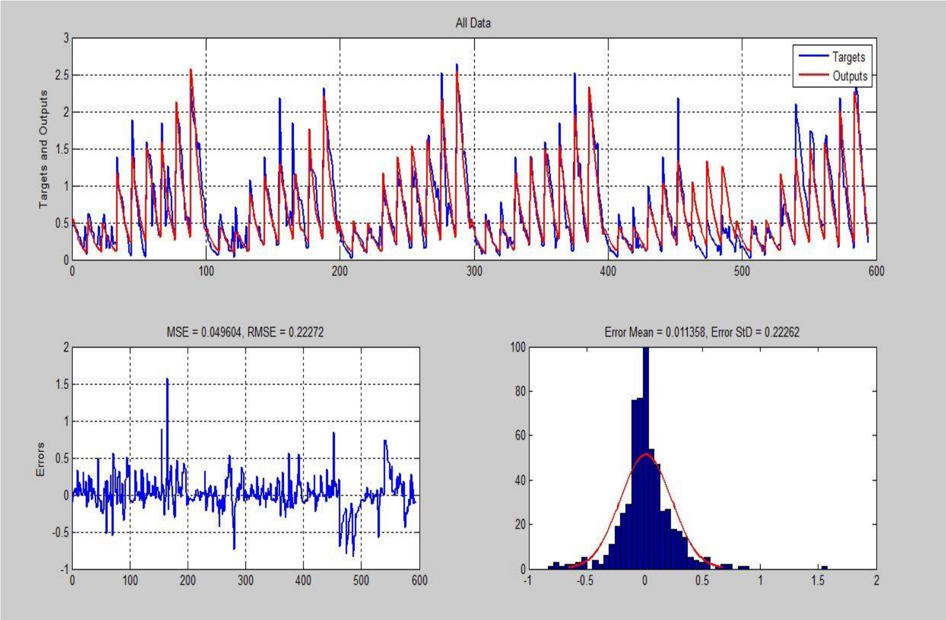

Figure 18. The predicted and actual amounts of exergy loss and error distribution

4. Conclusions

This study demonstrates that the ANN-GA and GMDH networks performed satisfactorily predicted energy and exergy values under various drying conditions. Notably, the GMDH network outperformed the ANN-GA in predicting four key parameters: energy use ratio, exergy efficiency, exergy loss, and energy consumption. Specifically, the GMDH networks excelled in predicting energy consumption, while their weakest performance was related to exergy efficiency. Conversely, the ANN-GA achieved the best performance in predicting energy consumption but had the lowest performance in exergy loss. Both algorithms, being evolutionary, exhibit versatility. Interestingly, minimal variations occurred in their performance when altering the sample type within the dryer. Overall, accurately approximating energy and exergy changes under varying operating conditions is valuable for machinery design and optimization, particularly for energy-intensive processes like food drying. Additionally, we recommend exploring a hybrid GMDH-GA approach for predicting energy and exergy changes in future studies.

References

Aghbashlo, M., Kianmerh, M. H., & Arabhosseini, A. (2008). Energy and exergy analysis of thin-layer drying of potato slices in a semi-industrial continous band dryer. *Drying Technology*, *26*, 1501–1508. https://doi.org/10.1080/07373930802412231

Akkoyunlu, M. C., Pekel, E., Akkoyunlu, M. T., & Pusat, S. (2020). Using hybridized ANN-GA prediction method for DOE performed drying experiments. *Drying Technology*, *38*(11), 1393–1399. https://doi.org/10.1080 /07373937.2020.1750027

Akpinar, E. (2004). Energy and exergy analyses of drying of red pepper slices in convective type dryer. *International Communications in Heat and Mass Transfer*, *31*(8), 1165–1176. http://doi.org/10.1016/j.icheatmasstransfer.2004.08.014

Akpinar, E. K. (2005). Energy and exergy aanalyses of drying of eggplant slices in a cyclone type dryer. *Journal of Mechanical Science and Technology, 19*(2), 692–703. https://doi.org/10.1007/BF02916191

Amanifard, N., Nariman-Zadeh, N., Borji, M., Khalkhali, A., & Habibdoust, A. (2008). Modelling and Pareto optimization of heat transfer and flow coefficients in microchannels using GMDH type neural networks and genetic algorithms. *Energy Conversion and Management*, *49*(2), 311–325. https://doi.org/10.1016/ j.enconman. 2007.06.002

Amini, G., Salehi, F., & Rasouli, M. (2021). Drying kinetics of basil seed mucilage in an infrared dryer: Application of GA-ANN and ANFIS for the prediction of drying time and moisture ratio. *Journal of Food Processing and Preservation*, *45*(3). https://doi.org /10.1111/jfpp.15258

Azadbakht, M., Aghili, H., Ziaratban, A., & Torshizi, M. V. (2017). Application of artificial neural network method to exergy and energy analyses of fluidized bed dryer for potato cubes. *Energy*, *120*, 947–958. https://doi.org/10.1016/j.energy.2016.12.006

Azadbakht, M., & Vahedi Torshizi, M. (2020). The antioxidant activity components change of pears subject to static and dynamic loads the antioxidant activity components change of pears subject to static and dynamic loads. *International Journal of Fruit Science*, *20*, 1255–1275. https://doi.org/10.1080 /15538362. 2020. 1718053

Azadbakht, M., Vahedi Torshizi, M., Noshad, F., & Rokhbin, A. (2018). Application of artificial neural network method for prediction of osmotic pretreatment based on the energy and exergy analyses in microwave drying of orange slices. *Energy*, *165*, 836–845. https://doi.org/10.1016/j.energy.2018.10.017

Corzo, O., Bracho, N., Vásquez, A., & Pereira, A. (2008). Energy and exergy analyses of thin layer drying of coroba slices. *Journal of Food Engineering*, *86*(2), 151–161. https://doi.org/10.1016/j.jfoodeng.2007.05.008

Fathi, M., Mohebbi, M., & Razavi, S. M. A. (2011). Application of fractal theory for prediction of shrinkage of dried kiwifruit using artificial neural network and genetic algorithm. *Drying Technology*, *29*(8), 918–925. https://doi.org/10.1080/ 07373937. 2011.553755

Kalathingal, M. S. H., Basak, S., & Mitra, J. (2020). Artificial neural network modeling and genetic algorithm optimization of process parameters in fluidized bed drying of green tea leaves. *Journal of Food Process Engineering*, *43*(1). https://doi.org/10.1111/jfpe.13128

Karagüzel, İ., Tekİn, E., & Topuz, A. (2012). Energy and exergy analysis of fluidized bed drying of chickpea and bean. *Scientific Research and Essays*, *7*(46), 3961–3973. https://doi.org/10.5897/SRE11.2003

Maleki, B., Ghazvini, M., Ahmadi, M. H., Maddah, H., & Shamshirband, S. (2019). Moisture estimation in cabinet dryers with thin-layer relationships using a genetic algorithm and neural network. *Mathematics*, *7*(11), 1042. https://doi.org/ 10.3390/math7111042

Midilli, A., & Kucuk, H. (2003). Energy and exergy analyses of solar drying process of pistachio. *Energy*, *28*(6), 539–556. https://doi.org/10.1016/S0360-5442(02)00158-5

Nazghelichi, T., Kianmehr, M. H., & Aghbashlo, M. (2010). Thermodynamic analysis of fluidized bed drying of carrot cubes. *Energy*, *35*(12), 4679–4684. https://doi.org/ 10.1016/j.energy.2010.09.036

Nikbakht, A. M., Motevali, A., & Minaei, S. (2014). Energy and exergy investigation of microwave assisted thin-layer drying of pomegranate arils using artificial neural networks and response surface methodology. *Journal of the Saudi Society of Agricultural Sciences*, *13*(2), 81–91. https://doi.org/ 10.1016/j.jssas.2013.01.005

Pusat, S., & Akkaya, A. V. (2022). Explicit equation derivation for predicting coal moisture content in convective drying process by GMDH-type neural network. *International Journal of Coal Preparation and Utilization*, *42*(6), 1852–1865. https://doi.org/10.1080 /19392699.2020.1774563

Syahrul, S., Dincer, I., & Hamdullahpur, F. (2003). Thermodynamic modeling of fluidized bed drying of moist particles. *International Journal of Thermal Sciences*, *42*(7), 691–701. https://doi.org/ 10.1016/S1290-0729(03)00035-8

Topic, R. (1995). Mathematical model for exergy analysis of drying plants. *Drying Technology*, *13*(2), 437–445. https://doi.org/10.1080/07373939508916963

Vahedi Torshizi, M., Azadbakht, M., & Kashaninejad, M. (2020). A study on the energy and exergy of Ohmic heating (OH) process of sour orange juice using an artificial neural network (ANN) and response surface methodology (RSM). *Food Science & Nutrition*, *8*(8), 4432–4445. https://doi.org/ 10.1002/fsn3.1741

Vahedi Torshizi, M., & Kashaninejad, M. (2022). Investigation of Changes in the Qualitative Properties of Sour Orange Juice during the Ohmic Heating Process. *Food Engineering Research*, *21*(2), 1–14. https://doi.org/10.22092/fooder.2022.353850.1297

Ziaratban, A., Azadbakht, M., & Ghasemnezhad, A. (2017). Modeling of volume and surface area of apple from their geometric characteristics and artificial neural network. *International Journal of Food Properties*, *20*(4), 762–768. https://doi.org/10.1080/ 10942912.2016.1180533