Optimization and estimation processes of the exergetic parameters for onion drying in a multi-stage semi-industrial continuous dryer: A Comparative assessment of RSM and ANFIS modeling

Iman Golpour[a], Mohammad Kave[b], Ana M. Blanco-Marigorta[c], J. Daniel Marcos[d]

[a] Urmia University, Urmia, Iran, Imangolpour@gmail.com
[b] Department of Petroleum Engineering, College of Engineering, Knowledge University, Erbil, Iraq, sirwankaweh@gmail.com
[c] Universidad de Las Palmas de Gran Canaria, Las Palmas G.C., Spain, anamaria.blanco@ulpgc.es, CA
[d] Universidad Nacional de Educación a Distancia, UNED, Madrid, Spain, jdmarcos@ind.uned.es

Abstract:

The aim of this research work is to evaluate the capability of RSM and ANFIS modeling to optimize and predict the exergy performance for onion drying process. The experiments were accomplished in a multi-stage semi-industrial continuous dryer at the ranges of the air temperatures (40-70°C), air velocities (0.50-1.50 m/s) and belt linear speeds (2.5-10.5 mm/s). A central composite design (CCD) in RSM with a second-order polynomial model was adopted to investigate the effects of independent variables on three response parameters: exergy loss (0.0182−0.0555 kJ/s) for minimizing, and exergy efficiency (62.33–89.25%) and exergetic improvement potential rate (0.025-0.061 kJ/s) for maximizing. The Takagi–Sugeno ANFIS model and the hybrid learning algorithm were applied to predict the exergy parameters. After variance statistical analysis, all the models obtained in RSM were significant, as well as all operating variables had a notable effect on all the responses. The results depicted that the highest coefficient of determination by applying ANFIS model for predicting the exergy loss, exergy efficiency and improvement potential rate achieved 0.9962, 0.9985 and 0.9924, respectively while the values of R^2 for the prediction of these responses in RSM were 0.9479, 0.9688 and 0.9993, respectively. The corresponding optimal conditions for the combined responses were at the air temperature of 40 ◦C, air velocity of 1 m/s and belt linear speed of 10.50 mm/s with the maximum desirability of 1.00, whereas the optimized values for exergy loss, exergy efficiency and improvement potential rate acquired 0.045 kJ/s, 76.756% and 0.025 kJ/s, respectively.

Keywords:

Onion, Multi-stage semi-industrial continuous dryer, Exergy analysis, RSM, ANFIS

1. Introduction

Onion (*Allium cepa L.*) as one of the most used agro-industrial products is generally applied with several varieties in food recipes in the world to add a luscious taste to the foods [1], [2]. The growth of onion production around the world has made it as the second most significant vegetable crop after tomato with a global production of 6.6×10^7 t [3]. In addition, it can be used as one of the efficacious medicinal compounds with many benefits such as hypocholesterolemia and antioxidants for various diseases including cardiovascular, blood cholesterol, cancer and cataracts [2], [4]. In recent decades, dried onion with suitable quality properties consisting of flavor and color have been demanding in the industry of the food production [5]. Drying process of fresh fruits and vegetables with decreasing moisture content can provide storage stability and increase shelf life of such products [6]. Anyway, there are several kinds of drying methods for instance open-sun, microwave, infrared, convective, vacuum and the rest of hybrid techniques that can be commonly employed to dry the vegetables under different drying operations [4]. Accordingly, it is required to utilize the thermal potential of the drying agent in each contact with the dispersed materials to reduce cost and energy and increase system performance, which can be provided with the help of multi-stage dryers for declining energy consumption and enhancing the quality of final healthy product [4].

In general, thermodynamics analysis plays a significant role in the energy efficiency assessment of the thermal and industrial systems like drying technology to save energy consumption and optimize operation conditions of drying process [7]. Moreover, energy analysis on the basis of the first law of the thermodynamics restricted to energy conservation and the energy quantity in the whole system does not provide any information about the energy quality and optimal energy transformation [8]. The exergy analysis by respect to the first and second laws of thermodynamics as an important technique in thermal assessment could provide possibilities of thermodynamic improvement of the process with determining the location and amount of irreversible production during any industrial processes like drying systems [9], [10]. In the recent years, several research works have been accomplished on energy and exergy evaluation in the drying processes of different products such as turmeric slices [11], , potato slices [12], rosemary leaves [13], cantaloupe slice [14], and pumpkin seeds [15]. Energy and exergy assessment was done for okra drying process. According to the obtained results, exergy efficiency varied from 49.15 to 63.47% while the sustainability index varies from 2.14 to 2.77 [16].

Soft-computing methods for instance Adaptive neuro-fuzzy inference system (ANFIS) as an intelligence technique combines two powerful techniques including an adaptive neural network (NN) and a fuzzy inference system (FIS) [17]. It has recently attracted special attention in research works regarding exergy analysis of drying process for agricultural products like fruits and vegetables because the ability to learn this system is appropriate for identifying their behaviors and such complex processes to which mathematical models do not simply apply to solve multifaceted nonlinear problems [2], [7], [18].Taghinezhad et al. [19] investigated the prediction of the drying parameters and quality of turnip slices by ANFIS modeling. They concluded that energy efficiency was between 0.89% and 15.23%) and dryer efficiency varied from 2.11% to 21.2% whereas the ANFIS model predicated the response parameters with R^2>0.96.

The optimum use and the considered techniques of management for energy consumption in an industrial production process because of great costs of energy, environmental concerns and fossil-fuel recourses, are very vital for investment sustainability. Determination of optimal drying process variables is commonly done in the food industries so as for solving the quality of dried healthy product or optimize the cost-effectiveness of production process [20], [21]. Overall, optimization of operating process parameters can be applied for the aim of increasing the efficiency of an industry process. Response surface method (RSM) is an advanced mathematical and statistical approach on the basis of the fit of the polynomial model to empirical data which states the influence of the experimental data on the considered results so that identifies the relationships between independent variables and their interactive effects on the obtained responses to attain the best performance of system with obtaining the optimum conditions and responses. This powerful tool is used experimental design, modeling and optimization of a process [20]. Vahedi Torshizi et al. [22] modeled and analyzed the exergy parameters of an ohmic heating (OH) process in drying sour orange juice by the application of ANN and RSM. The results showed that the accuracy of ANN was greater than RSM to predict the exergy loss, exergy efficiency, and exergetic improvement potential rate. Zalazar-Garcia et al. [15] used RSM approach to optimize the exergy, energy, and sustainability assessments of pumpkin seeds in hybrid convective air-dryer. in this study, the energetic and exergetic efficiency of the relevant dryer obtained 13.4 % and 41.77 %, respectively. The exergetic improvement potential rate and sustainability index amounts are related to the parameter of exergy loss. In a research study, modeling and optimization for Konjac Vacuum drying was done by the use of RSM and ANN methods. The results demonstrated that the RSM model was superior in predicting capacity (R^2>0.92; MSE<1.46) than the ANN model [23].

To the best of our knowledge, no researchers have reported the modeling and optimization of the exergetic parameters of a novel hot air-convective drying for onion samples in a Multi-Stage Semi-industrial continuous belt (MSSICB) dryer using ANFIS modeling and RSM procedure. Therefore, the objectives of this study were to investigate the comparison of ANFIS and RSM techniques to model and predict the exergy loss, exergy efficiency, and exergetic improvement potential rate as well as assessment of the effect of drying operating conditions and interactive effects on these responses.

2. Material and methods

2.1. Preparing sample and experimentation procedure

Fresh onion samples employed for these experiments were purchased from a local market located in Hamedan, Iran. Before beginning the drying experiments, the prepared onion samples were cleaned and were put in plastic bags and then stored in a refrigerator at 4±1°C to keep primary moisture content. Onions randomly taken from the samples has been hand peeled, weighed and cut into manually the desired slices with 40 mm thickness using a domestic cutting machine in the direction parallel to the vertical axis. Approximately 50g of samples with distinct thickness were randomly taken out of the laboratory refrigerator, weighed and measured with the standard oven method at 105 ± 1 ◦C for 24h for obtaining the initial moisture content [6]. Finally, the initial moisture content of onion samples with three repetitions was determined as 89.12 % (w.b.) [24]. Drying experiments were conducted in a Multi-Stage Semi-industrial continuous belt (MSSICB) dryer available in Kaveh et al. [18] for drying onion samples at three levels of drying air temperatures (40, 55, 70 ◦C), three levels of inlet air velocity (0.5, 1, 1.5 m/s) and also three levels of belt linear speed (2.5, 6.5, 10.5mm/s). Main drying chamber, belt movement system, heat generation system blower and control panel are the main parts of this kind of dryer that. Table 1 shows the characteristics of the experimental measurement tools used during experimental test. Before doing experiments, the considered dryer was run for 30 min without a sample to reach steady state and intended temperature. All drying experiments were done in triplicate.

Table 1. The used measurement tools during the drying experiments

Tools	Measurement	Model	Accuracy
Digital balance	Weight	AND-GF 6000	0.001 g
Thermometer	Temperature	Lutron	±1 ◦C
Humidity meter	Relative humidity of the environment	YK 2005 RH	1%
Anemometer	Inlet air speed	YK80-AM, Taiwan	±0.1m/s

2.2. Theoretical principle

In this study, the major features of drying chamber, inlet and outlet terms of product and air, the heat loss to environment were evaluated. Prior carrying out the exergy analysis based on the first and second law of the thermodynamics, mass and energy balance were done based on the first law of the thermodynamics.

$$\sum \dot{m}_{in} = \sum \dot{m}_{out} \tag{1}$$

General equation of mass conversation can be considered as Equation (1) [25]:

Moreover, the general energy balance also is expressed by application of equation (2). [22]:

$$\sum \dot{En}_{in} = \sum \dot{En}_{out} \tag{2}$$

In general, the exergy balance equation utilized for the drying system is adopted by the equation (3) [26]:

$$\sum \dot{Ex}_{in} = \sum \dot{Ex}_{out} + \sum \dot{Ex}_{L} \tag{3}$$

The physical exergy rate of fresh or dried onion obtained by equation [27]:

$$Ex^{ph} = \dot{m}_p c_p \left[(T - T_0) - T_0 \ln\left(\frac{T}{T_0}\right) \right] \tag{4}$$

where the specific heat of onion product as a function of MC is considered as follows [28]:

$$c_p = 1.84 + 2.34\omega \tag{5}$$

In addition, the exergy rate of air drying was obtained by following relation [28]:

$$\dot{Ex} = m_{da} c_{pda} (T_a - T_0) - T_0 \left[c_{pda} \ln\left(\frac{T_a}{T_0}\right) \right] + T_0 \left[R \ln \frac{1 + 1.6078\omega_0}{1 + 1.6078\omega_a} + 1.6078\omega_a R \ln \frac{\omega_a}{\omega_0} \right] \tag{6}$$

The mass flow rate of drying air can be obtained by respect to the following equation [29]:

$$\dot{m}_a = \rho_a V_a A_{dc} \tag{7}$$

where the relationship of specific humidity and the relative humidity content of the air (φ) is identified as below [28]:

$$\omega_a = 0.622 \frac{\varphi P_{vs,a}}{P_a - P_{vs,a}} \tag{8}$$

Also, the specific heat of the drying air is computed as [30]:

$$c_{pda} = \frac{1.004 + 1.88\omega}{1000} \tag{9}$$

Equation (10) was employed to obtain the exergy loss of drying chamber:

$$\dot{E}x_L = \dot{E}x_{in} - \dot{E}x_{out} \quad \text{or} \quad \dot{E}x_L = \left(1 - \frac{T_0}{T_{dc}}\right)\dot{Q}_L \tag{10}$$

Also, exergetic efficiency can be described by using the following equation [27]:

$$\psi_{ex} = \frac{\dot{E}x_{in} - \dot{E}x_L}{\dot{E}x_{in}} \tag{11}$$

Van Gol (1997) concluded that maximum improvement potential according to the exergetic efficiency of a heating process occurs as exergy loss is the lowest so that is used in several parts of the important economic analysis. Hammond & Stapleton [31] suggested this parameter as an assessment form by equation (12):

$$\dot{I}P = (1 - \psi_{ex})(\dot{E}x_{in} - \dot{E}x_{out}) \tag{12}$$

2.3. Adaptive neuro-fuzzy inference system (ANFIS) modeling

ANFIS is an intelligence approach to estimate the continuous functions in a distinct set by combing the fuzzy logic and the artificial neural network (ANN). The fuzzy inference system can be considered an adaptive fuzzy inference inventory as the comparative training logarithms is used that refers to as ANFIS. Overall, a FIS in ANFIS modeling can be created with the help of a series of specific input and output datasets so that the BP algorithm, either alone or in combination with the least squares method, can adjust the parameters of the membership functions [32], [33]. Commonly, ANFIS system is employed as a progressive network structure by application of a Takagi–Sugeno fuzzy system to formulate the behavior of a process by applying descriptive if-then rules as well to search for fuzzy decision rules for performing well on the considered tasks. By considering the first order of this model along with a two input, one output system having two membership functions for each input, ANFIS is a five-layer feedforward neural structure included in fuzzification layer, rule layer, normalization layer, defuzzification layer, and summation layer as shown schematically in Fig. 2 [19]. MATLAB 2017 is used to develop and assess the ANFIS model. A Sugeno-type fuzzy inference system with investigation of the trap mf, dsigmf, gauss mf, gaussus 2mf, gbell mf, pimf, trimf and psigmf, membership functions and also 1000 epochs, MFs of 3-3-3-3 to each input was used to find the optimal model while their membership degree was also achieved by using trial and error parameters. 70% of the data (644) were applied for training whereas the rest of 30% of data (275) were randomly considered for testing. A hybrid training algorithm consists of error back propagation algorithm and minimum square error method was used to train and fit with the fuzzy system. In this study, air temperature, air velocity, drying time and belt linear speed were utilized as the inputs of ANFIS while the exergy loss, exergy efficiency, and exergy improvement potential were as the outputs (Figure 1).

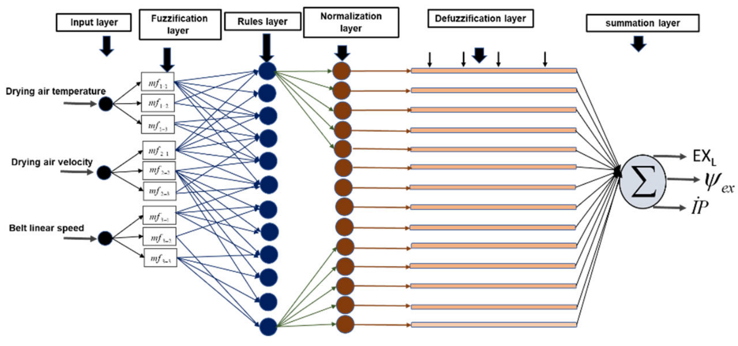

Fig. 1. Structure of ANFIS model

Two statistical indices namely the determination coefficient (R^2) and the root mean squared error (RMSE) are employed to evaluate the fitting performance of the model by the comparison of the actual and predicted values. The goodness of fit of the best models, is determined by higher R^2 values and the lowest RMSE. the values of R^2 and RMSE are calculated by the equations (13) and (14) [32]:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}\right) \tag{13}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{14}$$

2.4. Response surface method (RSM)

The drying data were statistically evaluated by a polynomial model type in Design Expert software versions 13.0 (Stat-Ease Co, USA) to the considered equations to optimize the drying process factors. Significant influences of independent factors and their interaction influences on the responses was identified by the variance analysis (ANOVA) on a confidence level above 95% ($p< 0.05$). RSM modeling was applied to survey the influences of drying process factors (air temperature, air velocity, drying time and belt linear speed) on the three responses (exergy loss, exergetic efficiency and improvement potential). A face centered central composite design (CCD) consists of 20 experimental runs designed by independent factors and their levels was utilized. The multiple linear regression (MLR) analysis of the drying experimental data of onions concluded the second order polynomial (quadratic) model to predict the given responses. The experimental data for drying process of onion samples were adopted to a second order polynomial model as follows [24]:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_{11} X_1^2 + \alpha_{22} X_2^2 + \alpha_{33} X_3^2 + \alpha_{12} X_1 X_2 + \alpha_{13} X_1 X_3 + \alpha_{23} X_2 X_3 + \varepsilon \tag{15}$$

The relationships between the considered responses were appraised by the use of the coefficient of determination (R^2), adjusted R^2, predicted error sum of squares (PRESS) and predicted R^2 [34]. The desired goals for each factor and the responses were selected. During the optimization process, in addition to the independent factors were in the distinct range while the exergy loss was minimized and exergetic efficiency and improvement potential rate were maximized.

Finally, a multi-objective optimization has been done by application of the desirability function (D_x). The desirability function (D_x) is described by using Eq. (16).

$$D_X = \left(Y_1 \times Y_3 \times Y_3\right)^{\frac{1}{3}} \tag{16}$$

Also, the parameter of D_x varies between $0<D_x<1$ and describes how well the dependent factors are fitted with the given level of independent factors. The values of the three levels of the three input factors were reported in Table 2.

Table 2. The experimental data based on central composite design for drying process

Independent factors		Coded levels		
		Low (-1)	Mid (0)	High (+1)
	Symbols	Real levels		
Drying air temperature, °C	X_1	40	55	70
Drying air velocity, m/s	X_2	0.50	1	1.50
Linear belt speed, mm/s	X_3	2.50	6.50	10.50

3. Results and discussion

3.1. ANFIS modeling

Three independent factors including drying air temperature, drying air velocity and belt linear speed were applied to predict three output parameters namely exergy loss, exergetic efficiency, and exergetic improvement potential rate. After designing various ANFIS models by application of test and error approach and to determine the number of fuzzy rules in predicting output parameters, the results were evaluated. In this analysis the number of membership function laws was changed from 3 to 5 whereas 81 fuzzy laws by using a function namely Gaussian membership (gaussmf) demonstrates the best structure of ANFIS modeling. The obtained results including training algorithm, type of MFs for each output, RSME and R^2, are shown in Table 3. A low RSME=0.0091 and a high correlation coefficient of 0.9962 were acquired for the relationship of predicted and experimental data to predict exergy loss (Table 3). Furthermore, For the prediction of exergetic efficiency by ANFIS technique, the highest value of R^2 obtained 0.9985 with RMSE=0.0040 (Table 3). The results in demonstrates that Guassian (gaussmf) types of MFs performed and suggested R^2 and RSME values. According to the results assessment by ANFIS, the results showed that there was not any overfitting and ANFIS model R^2=0.9924 and RSME=0.0120 can predict the exegetic improvement potential rate with the best performance and accuracy. In this evaluation, the best training algorithm and type of MFs for each output were hybrid and linear, respectively. By exergy analysis of drying quince [7] and cantaloupe slice [14], the researchers showed that the ANFIS model can forecast the drying properties of the products with an acceptable accuracy.

Table 3. The ANFIS results for prediction of exergetic parameters

Characteristics	Training algorithm	Type of MFs for each output	R^2	RSME
EX_L	Hybrid	Linear	0.9962	0.0091
ψ_{eff}	Hybrid	Linear	0.9985	0.0040
$\dot{I}P$	Hybrid	Linear	0.9924	0.0120

3.2. RSM Performance

3.2.1. Analysis of variance (ANOVA)

The design optimization process was by respecting the central composite design (CCD), where a quadratic mathematical model was investigated for all response factors. The variance analysis (ANOVA) of the responses (exergy loss, exergetic efficiency, and exergetic improvement potential rate) is given in Table 4. According to this Table, the best regression model to predict the related responses were reported on the basis of the statistical parameters like the values of determination coefficient (R^2), and predicted R^2, adjusted R^2, adequate precision, variation coefficient (CV), Lack of Fit and adequate precision. Overall, F-value higher than unity demonstrates more accuracy of factors and P-value lower than 0.05 advocates the compatibility of the given model. The results in Table 4 showed that the F-value of the models for EX_L, ψ_{ex} and $\dot{I}P$ were 14.14, 134.73 and 1182.09, respectively while the model p-value for EX_L is equal to 0.0010 and for ψ_{ex} and $\dot{I}P$ were less than 0.0001, which shows the accuracy and compatibility of the obtained model ($p<0.01$) (Table 4). Anyway, it means that the models obtained to predict the theses responses were significant. In this case, as shown in Table 5, the main model linear terms including air temperature (X_1), air velocity (X_2) and belt linear speed (X_3) were significant with probability level of 95% ($p<0.05$) while other quadratic and interaction terms including X^2_2, X^2_3, X_{32}, X_1X_2, X_1X_3, and X_2X_3 were not insignificant for the related models of exergy loss (EX_L) and exergetic efficiency (ψ_{ex}) ($p>0.05$). The quadratic term of X^2_1 with p-value=0.0002 possess meaningful effect only for predicting the exergetic improvement potential rate as represented in Table 4 ($p<0.01$). In the statistical viewpoint, it is concluded that air temperature (X_1) is most dominant variable influencing EX_L, ψ_{ex} and $\dot{I}P$ respectively, followed by other variables ($p<0.0001$). The values of R^2 to predict the relevant responses (EX_L, ψ_{ex} and $\dot{I}P$) were obtained 0.9479, 0.9688 and 0.9993 respectively that demonstrates the competency of the chosen models (Table 4). Hence, this high values of goodness of fit (R^2=) in the given design shows that only 5.21%, 3.22% and 0.07% of total variation could not be reflected using the RSM models, respectively. The statistical results depicted that there is a reasonable agreement (difference less than 0.20) between the values of "Predicted R^2" (0.7083) and "Adjusted R^2" (0.8808) for predicting the exergy loss (Table 4) [35], [36]. The value of "Adeq precision" for predicting this parameter (Exergy loss) was 12.21 that demonstrating the ratio of the signal to noise that can supply a comparison between the range of predicted amounts at desired design points and the mean error of the prediction for exergy analysis. The signal to noise ratio obtained in this research work (12.21) for predicting exergy loss is an acceptable value because the minimum value for "Adeq precision" is 4 in the viewpoint of statistical analysis [36], [37]. Also, according to the Table 4, a satisfactory agreement between the values of "Pred R^2" (0.9351) and "Adj R^2" (0.9616) was obtained to predict the exergetic efficiency while the "Pred R^2" and "Adj R^2" values to predict and exergetic improvement potential rate were and 0.9895 and 0.9985, respectively. In addition, the values of "Adeq precision" in the ANOVA results for the exergetic efficiency and exergetic improvement potential rate attained 36.22 and 109.66 respectively that were remarkably larger than the desired amount (4) indicating the suitable ration of signal compared to noise. So, the obtained models could be used to survey the optimum conditions within the design space in predicting the analyzed parameters (exergetic efficiency and exergetic improvement potential rate). Moreover, the variation coefficients (C.V.) of 10.31%, 1.55% and 1.29% attained illustrates the reproducibility and repeatability of the models (Table 4). The quadratic model has been selected for the responses of exergy loss (PRESS=0.0008) and exergetic improvement potential rate (PRESS= $8.3536e^{-06}$) while linear model had best performance to predict the exergetic efficiency (PRESS=40.77) compared to other given models. Finally, drying air temperature was known as the most significant factor in predicting response parameters.

Based on the ANOVA, the related terms of models which were insignificant ($p > 0.05$) to predict the responses have been removed from the final equations formulated with the coded coefficient as expressed in Table 5. The quadratic and linear equations representing the variation of the exergy loss, exergetic efficiency, and exergetic improvement potential rate in terms of coded variables (X_1, X_2 and X_3) are supplied in Table 5. The exergy loss and improvement potential rate raised with increase of drying air temperature and drying air velocity and declined with increasing belt linear speed. This result can also be affirmed by related coefficients to positive signs obtained for air temperature and drying air velocity in the regression equation of the exergy loss and improvement potential rate as well as the negative coefficients of belt linear speed (X_3) (Table 5). Only term of X_{22} was found to be significant in the squared model to predict the exergetic efficiency with a constant coefficient of 3.95. However, for exergy loss, the greatest influence on associated with the inlet drying air temperature followed by drying air velocity. According to the regression equation related to exergetic efficiency in Table 6, the negative coefficients obtained for drying air temperature and air velocity showed that exergetic efficiency was negatively affected by these factors while the positive coefficient calculated for belt linear speed showing the direct relation of this parameter with exergtic efficiency [24].The belt linear speed had the highest effect for improving the exergtic efficiency while drying air velocity, with the highest negative coefficient of -3.74 was the most effective variable to decrease exergtic efficiency, followed by drying air temperature (Table 5).

3.2.2. Influence of independent factors on responses

The interaction influence of the drying process factors on the responses of exergy loss and improvement potential rate were represented in Figs 3 a,b. According to the obtained results shown in Fig. 3 for exergy loss, this parameter raises with the increase in air drying temperature and air velocity and the decrease in belt linear speed so that the maximum amount of this parameter occurred at beginning the drying process. The results dedicated that the highest value of exergy loss (0.0555 kJ/s) occurred in the 70 ◦C air temperature, 1.5m/s air velocity and 2.5 mm/s belt linear speed whereas the lowest amount of this parameter was 0.0182 kJ/s with 40 ◦C air drying temperature, 0.5 m/s air drying velocity and also 10.5 mm/s belt linear speed (Figure 3 a). It could be argued that raising the drying air temperature amplifies the heat and mass transfer rates and then increase the exergy loss [29]. High drying air temperatures is included more exergy, so more proportion of the inlet drying air exergy is utilized for water evaporation process that caused the exergy loss due to entropy generation [38]. Also, the changes of improvement potential rate affected by drying air temperature, air drying velocity and belt linear speed attained by using RSM technique are illustrated in Figs 3b. 4. Furthermore, the amount of exergetic improvement potential rate changed between 0.009 kJ/s and 0.034 kJ/s under different experimental operating conditions. Figure 3b indicates that two operating factors (air drying temperature and velocity) have an increasing influence on the parameter of the improvement potential rate while it had an inverse proportion compared to the exergy efficiency of drying process. Form this figure, it can be resulted that EX_L minimized at the highest values of belt linear speed (2.50 mm/s) (Figure 3). The exergetic improvement potential rate of drying chamber declined when the inlet air temperature and air velocity raised due to an increase in the exergy efficiency of drying chamber at higher drying temperatures [29]. Moreover, the linear influence of drying air temperature air velocity and belt linear speed on exergy efficiency of drying process of onion samples in semi industrial continuous dryers are shown in Fig. 3c. The results showed that the range values of exergy efficiency obtained between 64.02% and 91.62% so that the maximum values (91.62%) were found to be for 40 drying air temperature, 0.50 air velocity and 10.50 mm/s belt linear speed while minimum value of this parameter obtained 64.02% in drying air temperature of 70 ◦C, air velocity of 1.50 m/s and belt linear speed of 10.50 mm/s (Figure 3c). By respecting the obtained results, increasing the drying air temperature decreased the exergy efficiency significantly owing the inverse relationship of exergetic efficiency with the exergy of inlet drying air. These findings were in the agreement with the results attained by [29], [39]. It should be noted that the improvement of the exergetic efficiency also occurred with enhancing drying air velocity by promoting the efficient utilization of provided exergy to the drying chamber. Similar results for the influence of drying air velocity on the parameter of exergy efficiency in an industrial pasta drying process was also represented by Colak et al. [26]. The major reason for the low value of exergy efficiency during drying process is the significantly high exergy loss and the small amount of exergy used for moisture evaporation in comparison with the provided exergy [29]. Accordingly, declining the heat transfer of the dryer wall by using installation and airproofing could decrease the exergy loss.

Table 5. The quadratic equations related to the responses compared independent factors

Dependent factors	Equations
Exergy loss	$Y_1 = 0.0372 + 0.0145X_1 + 0.0054X_2 - 0.0057X_3$
Exergetic efficiency	$Y_2 = 79.32 - 6.81X_1 - 3.74X_2 + 3.98X_3$
Exergetic improvement potential rate	$Y_3 = 0.0209 + 0.0097X_1 + 0.0014X_2 - 0.0018X_3 + 0.0009X_1^2$

Table 4. The ANOVA results for predicting models

	Exergy loss			Exergetic efficiency			Improvement potential rate		
Source	Sum of Squares	F-value	p-value	Sum of Squares	F-value	p-value	Sum of Squares	F-value	p-value
Model	0.0025	14.14	0.0010	608.93	134.73	< 0.0001	0.0008	1182.09	< 0.0001
X_1-Air temperature	0.0018	89.08	< 0.0001	370.55	245.97	< 0.0001	0.0007	10034.87	< 0.0001
X_2-Air velocity	0.0002	11.88	0.0107	111.74	74.17	< 0.0001	0.0000	198.39	< 0.0001
X_3-Belt linear speeds	0.0003	13.15	0.0084	126.64	84.06	< 0.0001	0.0000	352.36	< 0.0001
X_1X_2	6.727E-06	0.3404	0.5779	-	-	-	5.760E-08	0.7723	0.4087
X_1X_3	1.217E-06	0.0616	0.8112	-	-	-	1.225E-07	1.64	0.2408
X_2X_3	1.197E-06	0.0606	0.8126	-	-	-	1.600E-07	2.15	0.1864
X_1^2	0.0001	5.52	0.0511	-	-	-	3.583E-06	48.04	0.0002
X_2^2	0.0001	2.85	0.1351	-	-	-	9.792E-08	1.31	0.2895
X_3^2	0.0001	3.03	0.1253	-	-	-	9.500E-09	0.1274	0.7317
Residual	0.0001			19.58	-	-	5.221E-07		
Lack of Fit	0.0000	0.5169	0.6927	19.58	-	-	5.221E-07		
Pure Error	0.0001			0.0000	-	-	0.0000		
Cor Total	0.0027			628.52	-	-	0.0008		
C.V. %	10.31			1.55	-	-	1.29		
Adeq Precision	12.21			36.22	-	-	109.66		
R^2=0.9479	Predicted R^2=0.7083	Adjusted R^2=0.8808		R^2=0.9688	Predicted R^2=0.9351	Adjusted R^2=0.9616	R^2=0.9993	Adjusted R^2=0.9616	Adjusted R^2=0.9985

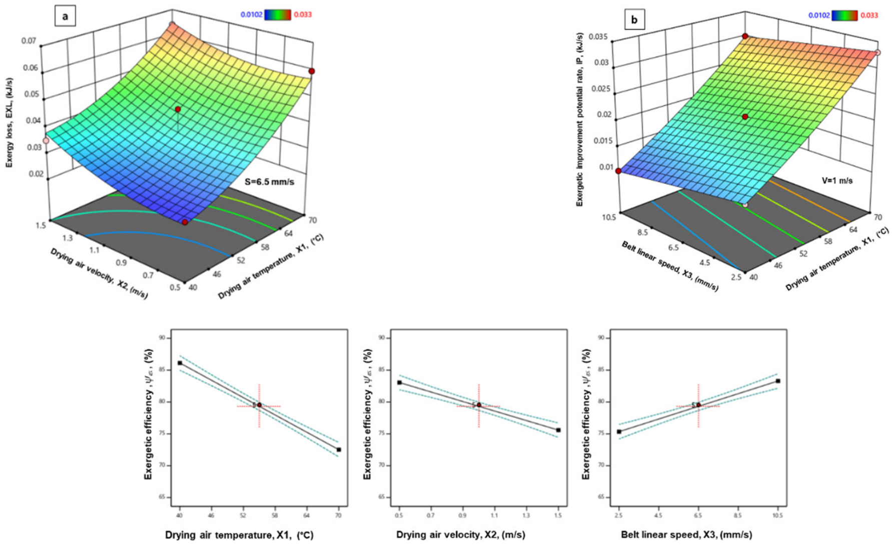

Fig. 3. 3D and 2D surface plots of RSM modeling demonstrating interaction influences of independent factors on responses: a) Influence of drying air temperature and drying air velocity on exergy loss b) Influence of drying air temperature and belt linear speed on the improvement potential rate c) Influence of drying air temperature, air velocity and belt linear speed on exergetic efficiency

3.2.3. Optimization of drying process parameters

The optimal process conditions given by the model were chosen the first solution calculated by RSM with a maximum desirability 1.00. Similar findings (D=1) were found in the research work of Corzo et al. [33] for optimization of drying properties of coroba slices. It was determined that the amounts were forecasted to be close enough to the experimental amounts. The obtained results of optimization process for exergy loss, exergetic efficiency and improvement potential rate of each independent and response were given in Table 6. In this study, the identified optimal conditions obtained equal 40°C for air temperature, equal 1 m/s for air velocity, equal 10.50 mm/s for belt linear speed. Under these optimum conditions, the optimal parameters for the responses of exergy loss, exergetic efficiency and improvement potential rate attained 76.756%, 0.045 kJ/s and 0.025 mm/s (Table 6). It should be mentioned that there is a great agreement between the RSM results and the related experiments for dependent parameters (exergy loss, exergetic efficiency, and exergetic improvement potential rate).

Table 6. Optimization process results by desirability function of RSM.

Parameters	T (◦C)	V (m/s)	S (mm/s)	ψ_{eff} (%)	EX_L (kJ/s)	$\dot{IP}$ (kJ/s)	Desirability
Optimum values	40	1.00	10.50	76.756	0.045	0.025	1.00

4. Conclusions

Several experiments were conducted at drying air temperatures of 40, 55 and 70 °C, drying air velocity of 0.50, 1.00 and 1.50 m/s, belt linear speed of 2.50, 6.50 and 10.50 mm/s in a MSSICB dryer and analyzed on the basis of central composite design by RSM to optimize the drying process and to predict the dependent variables by ANFIS modeling. In order to optimizing the MSSICB dryer, independent variables were in the range and exergy efficiency and improvement potential rate must be as maximum and exergy loss must be as minimum. Coefficient of determination (R^2) by ANFIS method for predicting these parameters were 0.9962, 0.9985 and 0.9924, respectively. Moreover, it is clear that the drying air temperature plays a more important role in optimization compared to other factors. In addition to the significance of models, the operating factors had significant effects on all responses. In the experiments of this drying process, the optimal conditions were found to be 40 °C for drying air temperature, 1.00 m/s for air velocity and 10.50 mm/s for belt linear velocity while the optimum values of the responses with by maximum desirability function (D = 1.00). were 76.756%, 0.045 kJ/s and 0.025 kJ/s for exergetic efficiency, exergy loss and improvement potential rate, respectively.

Anyway, the high values of the coefficients of determination (0.9479, 0.9688 and 0.9993) for predicting exergy loss, exergy efficiency and improvement potential rate depicts the acceptable accuracy of the quadratic model. The ANFIS results compared with RSM showed that ANFIS model had better performance in correlating non-linear relationships for predicting the responses of exergy loss, exergy efficiency while RSM model offered higher accuracy to predict the improvement potential rate relative to ANFIS. It is worth mentioning that optimization of operating conditions of drying process, predicting the exergetic parameters and regression model equations could be very benefit for designing and manufacturing the industrial dryers.

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Nomenclature		MSSICB	multi-Stage Semi-industrial continuous belt
Notations		s	Belt linear speed (mm/s)
MC	moisture content (% wet weight)	**Greek letters**	
m	weight of product (g)	ρ	density (kg/m^3)
ANFIS	adaptive neuro-fuzzy inference system	ψ	exergy efficiency (%)
t	time (s)	φ	relative humidity of air (%)
$\dot{En}$	energy rate (kJ/s)	ω	humidity ratio (kg water/ kg dry air)
$\dot{m}$	mass flow rate (kg/s)		
T	temperature (°C)	α	coefficient term of RSM's model
P	atmospheric pressure (kPa)	**Subscripts**	
A	area (m^2)	vs	saturated vapor
V	drying air velocity (m/s)	0	initial
c_p	specific heat (kJ/kg°C)	L	heat loss
R	gas constant (8.3143 kJ/ mol)		
U	overall heat transfer coefficient (kW/m^2 °C)	in	inlet
h	enthalpy (kJ/kg)	L	loss
h_{fg}	latent heat of vaporization (kJ/kg)		
RMSE	root mean square error	w.b.	wet basis
R^2	correlation coefficient	out	output
$\dot{Ex}$	exergy rate (kJ/s)	ph	physical
ex	specific exergy (kJ/ kg)	in	inlet
$\dot{Q}$	heat transfer rate (kJ/s)	out	outlet
$\dot{IP}$	improvement potential rate (kJ/s)	ex	exergy
y	actual value	p	product
$\hat{y}$	predicted value	fp	fresh product
$\bar{y}$	average value	dp	dried product

RSM	response surface method	da	drying air
D	total desirability function	tp	triple point
Y	desirability function of each response in RSM	evp	evaporation
X	independent factor	dc	drying chamber

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