Performance evaluation of GSA, SOS, ABC and ANN algorithms on linear and quadratic modelling of eggplant drying kinetic

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Abstract

In this study, kinetics of eggplant drying was modeled in the laboratory-scaled Food Drying Oven (FDO) with resistance heater was designed and manufactured. The temperature, energy consumption and drying time of FDO were recorded by keeping the temperature of at different temperatures as 40, 50 and 60 °C. These saved values were chosen as the input parameters of the model. The weight value of the eggplant was taken as the output parameter. Linear and quadratic equations were developed for modeling and constant coefficients of these equations were estimated with Artificial Bee Colony (ABC), Gravitational Search Algorithm (GSA), symbiotic organisms search (SOS) algorithms. In addition, the performances of these models were compared with the model developed with ANN in terms of performance and time. The results show that the lowest error of the developed linear and quadratic equations was obtained with SOS algorithm. The MSE metric results of ANN were fifty times higher than the performance of SOS algorithm, and the SOS algorithm reached best value three times faster than the ANN.

Keywords: food drying; eggplant drying; optimization; modeling.

Practical Application: Drying Machines, Control of Oven, Control of food drying process.

1 Introduction

Climate change is one of the most important problems of the 21st century. This problem has a negative effect on agricultural areas and productions. The population is growing and nutrition problems of this population are emerging day by day. According to the United Nations World Population Expectations 2015 Revision Report, it is estimated that the human population will increase from 7.6 billion to 9 ~ 10 billion in the current century. The Food and Agriculture Organization of the United Nations (due to the increasing population demand) estimates that food production should increase by 60% in 2050 compared to 2005 (Alexandratos & Bruinsma, 2012). Drying, which is one of the techniques to facilitate food supply despite increasing population and food consumption, has been used as a primary method relative to canning or cryopreservation relatively recently (Bradford et al., 2018).

Eggplant (Solanum melongena) is an important vegetable crop grown in various tropical and temperate regions of the world (Kashyap et al., 2003). Eggplant is an herbal product that is grown worldwide and can provide important nutritional benefits thanks to the abundance of vitamins, phenolics and antioxidants (Gürbüz et al., 2018). Eggplant is a highly productive product and is well adapted to hot and humid environments. Therefore, the price of eggplant is typically favorable while the price of other herbal crops is increasing. Eggplants are a particularly important source of food for low income consumers (Hanson et al., 2006). The interest in this plant is increasing rapidly because it is a good source of antioxidants (anthocyanin and phenolic acids) which are beneficial to human health (Gajewski et al., 2009). The high fiber and low soluble carbohydrate levels of eggplant

are a good choice to help treat type 2 diabetes (Nwanna et al., 2013). Many people, who have leukemia and lung cancer cells, show anti-carcinogenic effects by inducing apoptosis in cancer cells (Tajik et al., 2017).

According to 2016 whole World eggplant production data, it is observed that the production of 51288169 tons was cultivated in 1793978 hectares. Eggplant yield was calculated as 285891 hg/ha (Food and Agriculture Organization of the United Nations, 2018).

Kutlu have examined eggplant drying process by using a tray and microwave dryer and under different temperature and microwave powers combinations. The effect of the different methods on the drying characteristics of the eggplant and mathematical modeling develop of the drying process studied. As a result of this study, the highest rehydration rate was found to be 60 °C for tray drying (TD) and 180 W for microwave drying (MD) (Kutlu & İşci, 2016).

Some researchers have applied some pretreatments to increase the drying process. Thus, the drying time and therefore the energy consumption and the costs were reduced. In the study performed by Doymaz and Aktas on eggplant slices, the pre-treatment was applied as citric acid solution and blanching in the hot water. The characteristic of pre-treated and non-treated were compared and it is stated that drying time is decreased and rehydration capacity is increased (Doymaz & Aktas, 2018). Ertekin and Yaldiz preferred laboratory-scale fluid bed dryer for drying, unlike the current studies (Ertekin & Yaldiz, 2004).

Modeling of drying kinetics for eggplant slices drying process is studied by many researchers. It has been found in many studies that well - known modeling methods such as Newton, Page, Logarithmic, and Mytilene have been used. RMSE (root mean square error) and chi-square were preferred for the evaluation of modeling. The accuracy of the modeling results generally varies according to the drying temperature ranges and the type of dryer used (Akpinar & Bicer, 2005; Azimi et al., 2012; ElKhodiry et al., 2015). Chayjan and Kaveh, used different modeling from previous studies, have performed eggplant drying using microwave-convection dryer under different microwave powers, ambient temperature and air flow rate. The results of drying process modeled with six different models and ANN (Chayjan & Kaveh, 2016).

The aim of this study is to develop kinetics of eggplant by using simpler modeling (linear and quadratic) techniques. The another goal is to determine weight (kg), dry-based moisture content (g water / g dry matter), wet-based moisture content (g water / g dry matter), humidity rate, drying rate (g water / g dry matter. s) and amount of consumed energy versus time. These model parameters were obtained by experimental results were used as input parameters of the developed model. The estimating of coefficients of the models were aimed by using Artificial Bee Colony (ABC), Gravitational Search Algorithm (GSA), symbiotic organisms search (SOS) algorithms. Furthermore, the results obtained by the algorithms are compared with the ANN model in terms of different statistical metrics and calculation time.

2 Materials and methods

In this section, information about the experimental setup used in eggplant drying is given. Also, mathematical expressions and optimization algorithms that is used for modeling are explained. Detailed mathematical model of algorithms are not presented, just main structure of the algorithms is briefly explained. Equations of algorithms can be obtained in detail from the reference articles of the developers.

2.1 Drying process of eggplant

The resistance heater oven designed and manufactured by authors and its volume is 0.084 m3. In accordance with the Regulation of the European Parliament and the Council on Food Ingredients and Ingredients dated 27/10/2004 (EC) No 1935/2004, stainless steel 304 steel in compliance with the European Union legislation has been selected.

The drying time of the food can be set in minutes and hours by using time relay and the system stops automatically when its duration is over. The thermostat closes the circuit when the set ambient temperature is exceeded and works simultaneously with the fan-motor pair.

In order to determine the drying parameters, the ambient temperature, humidity and weight of the food were recorded during drying. DHT11 (humidity sensor) measures the relative humidity in the oven and the thermocouple measures the ambient temperature. Thanks to the load cell, the weight of the food is sensed by load cell at the determined time intervals. The weight
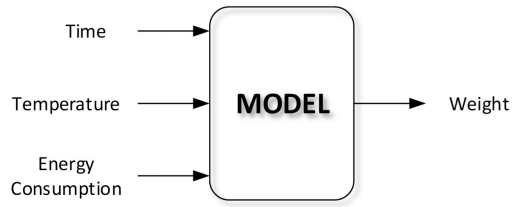

Figure 1. Modeling scheme of drying kinetic.

Table 1. Characteristics of the devices used in the experimental setup.

Device Name	Properties of device	Range of properties
Thermocouple	measuring range	-20 °C ~ 85 °C
	measurement accuracy	0.25 °C
Load Cell	weight capacity (maximum)	3 kg
	operating temperature range	-20 ~ +85 °C
Timer	ambient temperature	0 ……. 50 °C
	storage temperature	-25 …….70 °C

sensor is located under the tray of drying bed. An Arduino based control system was developed to sense and save data. Characteristics of the devices are presented in Table 1.

2.2 Algorithms and modelling

In this study, two different models as linear and quadratic were developed for modeling of drying kinetic by using Artificial Bee Colony (ABC), Gravitational Search Algorithm (GSA), symbiotic organisms search (SOS) algorithms. The output parameter of the models is the moisture loss which occurs after the drying process, in other words the weight value. The input variables of the models are the drying time, the temperature and the energy consumption of the drying oven. The model scheme is given in Figure 1. The equations used in modeling are given in Equation 1 and 2.

$$Weight = c_1 + c_2 M + c_3 T + c_4 E \tag{1}$$

$$\begin{aligned} Weight = c_1 + c_2 M^2 + c_3 T^2 + c_4 E^2 + c_5 M \times T + \\ c_6 M \times E + c_7 T \times E + c_8 M + c_9 T + c_{10} E \end{aligned} \tag{2}$$

where, M, T, E represents the time elapsed during the drying process, temperature and energy consumption, respectively. The "c" parameters are the constants of the modeling equations. It is aimed to estimate these variables with the highest accuracy by using different algorithms.

The objective function of the developed models is given in Equation 3. This optimization problem is minimizing difference between predicted and measured, in other words main aim is to obtain the error as the smallest.

$$Min(f) = \frac{1}{n} \sum_{i=1}^{n} \left(W_i^{predicted} - W_i^{measured} \right)^2 \tag{3}$$

Input and output variables are normalized to the range of 0.9 - 0.1. The formula used when normalizing is presented in Equation 4.

$$w_N = 0.8 \times \left[\frac{w_i - w_{\min}}{w_{\max} - w_{\min}} \right] + 0.1 \qquad (4)$$

The weight value of the eggplants has been recorded during drying process for three different temperature values as 40, 50 and 60°C. The energy consumption of the FDO is read through the energy meter and thus input variables are created. Totally, 57 data were recorded and 48 of them were used for training and others were used for the test performance of the algorithms. In addition, another metric used for comparison algorithms with each other that elapsed times (reaching stop criteria) are presented in the table.

2.2.1 Artificial Bee Colony (ABC) algorithm

Artificial Bee Colony (ABC) Algorithm was developed by Karaboga in 2005. This optimization algorithm was inspired by the intelligent behavior of honey bee swarm (Karaboga & Basturk, 2007). It is categorized into the swarm-based class of the population-based optimization algorithms (Nozohour-leilabady & Fazelabdolabadi, 2016).

The algorithm runs the process of searching food and improving the quality of food by different bees that have different tasks and structure. In order to realize this process, three different bees are employed as namely worker, onlooker and scout. ABC mainly consists of four phases: initialization, employed bee phase, onlooker bee phase, and scout bee phase. After the initial phase, the worker, scout and scout bee phases are in the continuous loop and run until stop criteria is reached for the specified value. In the initial phase, food points in the searching space are determined by random selection (Yurtkuran & Emel, 2016).

The main objective is to maximize the amount of nectar in the hive. The position of a food source represents a possible solution to the optimization problem; whereas the amount of a food source corresponds to the quality of the associated solution (Nozohour-leilabady & Fazelabdolabadi, 2016).

The amount of nectar, the quality of the source are the fitness values of the food source. The amount of the employed bee is produced as the amount of food source determined. Employed bees are responsible for investigating food sources. Information about the food sources (location, quality, etc.) found by the employed bees is transmitted by onlooker bees. When the result of optimization problem is not developed over loop, means the amount of the food sources are under defined limit, the new sources are replaced by exhausted resources. Scout bee is responsible for finding new food sources. Thus, exploitation process is performed by employed and onlooker bees whereas scouts perform exploration of solutions (Kumar, Kumar, & Jarial, 2017).

The ABC algorithm was applied different kinds of optimization problems and recent studies have been conducted on development of hybrid algorithms by combining other algorithms with ABC. Some researchers developed "improved ABC algorithms" to decrease weakness of it. In the literature, it is seen that ABC algorithm lags behind in many applications. The main reason is that the search pattern of both employed and onlooker bees is good at exploration but poor at exploitation. (Pang et al., 2018; Xu et al., 2013)

2.2.2 Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm (GSA) was developed by Rashedi et.al based on Newtonian laws of gravitation and motion (Rashedi et al., 2009). Superposition of the gravitational forces, dependency to the distance, and the relation between mass values and fitnesses make this algorithm unique (Rashedi et al., 2018). Depending on laws, each piece attracts the other part with a certain force, which is the gravitational force. The objects refer to agents and force produces from their mass. All these objects attract each other by the force of gravity, and this force causes the movement of all objects towards objects with a heavier mass. (Illias et al., 2017; Özkaraca, 2018). The performance of agents in the optimization problem is scaled by their mass and positon of them are related to a solution of the problem.

The algorithm places random agents in the search space according to the defined problem. Then, the fitness values of these agents are calculated. All values are updated by calculating the masses and gravity values. The masses in different directions are calculated. In the next stage, the velocities and acceleration of these masses are calculated. The positions of the agents are recalculated according to the updated values. The fitness values of the updated agents are recalculated and this continues until the stop criteria are met. Thus, at the end of the algorithm, the optimum result for the defined problem is provided by the most severe agent that have slow moving and high attraction force.

The studies in the literature related GSA are applied to solve several optimization problems. Additionally, as other algorithms, some researchers developed hybrid algorithms. The parameters of the GSA considerably effect algorithm performance and loop time (Guvenc & Katircioglu, 2015).

2.2.3 Symbiotic Organisms Search (SOS) Algorithm

The SOS algorithm is effective metaheuristic algorithm that is developed and proposed by Cheng and Prayogo in 2014 based on symbiotic interaction between organisms to improve their overall competitiveness in the ecosystem (Xiong et al., 2018). Some organisms do not live alone because they are interdependent on other species for survival and food value (Tejani et al., 2016; Umam & Santosa, 2018). The relationship between organisms in the nature is defined three different realtion as mutualism, commensalism, and parasitism. In mutualism, both organisms have benefits. In commensalism, only one organism benefits and the other is not affected. In paratism, an organism has benefits, while the other is damaged.

Initially, the organisms are produced randomly up to number of populations. These organisms increase their production within the framework of these relations. At the end of each phase, organisms that give better results are replaced by worse ones that do not improve the solution. (Cheng & Prayogo, 2014; Verma et al., 2017). In terms of mathematically, each organism represents as a vector in the search space.

The Algorithm repeatedly uses a population of the possible solutions to converge to an optimal position where the global optimal solution lies. The algorithm used mutualism, commensalism, and parasitism mechanisms to update the positions of the solution vector in the search space (Abdullahi et al., 2016). The simplicity of the SOS algorithm, in contrast to other optimization algorithms, requires only two parameters to run the algorithm. These are the number of population and the number of generations (Nama et al., 2017).

2.2.4 Artificial Neural Network (ANN)

Artificial neural network is a complex modeling structure that resembles information communication among human brain nerves. A model is created between the input and output by neurons that also have memory and learning characteristics. The model has three layers as input, output and hidden and the neurons of the layers are connected to each other by weights. Additionally, each neuron has its own bias value. These weight values and bias values are tried to be estimated by the developed model. (Dursun & Ozden, 2017). Inputs and output layers' data are obtained from experimental data. Thus, the model estimates experimental output value depending on input value. In Figure 2, developed ANN model is shown. Input variables are time (drying duration), temperature (inside of FDO) and energy consumption of the FDO. The output variable is weight of the product. 3-4-4-1 represents that number of input is three, number of output is one and number of hidden layers' neurons are four.
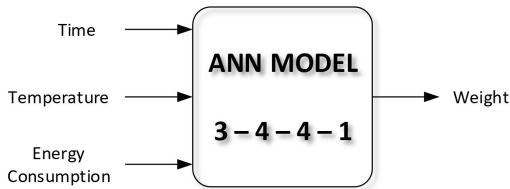

Figure 2. ANN model and input, output variables.

3 Results and discussion

3.1 Performance comparison

The performances comparisons of three different algorithms for linear, quadratic and ANN modeling are presented in Table 2. Four different metrics were taken into account in the performance evaluation of the algorithms. In all assessments of the metrics, ANN provided the highest performance that means minimum error. ANN is powerful algorithms that have good learning process. In contrary, it is obvious that implementation, structure of algorithm and then forward propagation processes are much more complex.

The results obtained in linear modeling showed that almost all algorithms had nearly the same results. In the quadratic modeling, the SOS algorithm provides better performance.

When the results were evaluated in terms of drying process and energy consumption, the experiment at 60 °C was completed in less time but caused more energy consumption. Drying process at 40 °C was terminated longer but consumed less energy. Time and energy cost should be made according to the need for comparison.

3.2 Time comparison

Considering the calculation time of the algorithms, it was observed that the SOS algorithm reached a very fast result. Although ANN was able to reach best performance approximately 3 times slower than the SOS algorithm, it was determined that the MSE values were 50 times more accurate. The elapsed time to reach best result of the algorithms are summarized in Table 3.

3.3 Regression results

The results of Linear and Quadratic modeling for GSA, SOS and ABC algorithms are presented in the following figures. For ANN, a single model was created. Different number of hidden layers were performed and the best one (two hidden layers with four neurons) that provided minimum error is given.

Table 2. Different metric results of the algorithms performance.

Algorithms	Model	Type	RMSE	MAE	MAPE	MSE
ABC	Linear	Training	0.071099	0.045353	15.550735	0.005055
		Test	0.089196	0.054179	13.877693	0.007956
	Quad	Training	0.053372	0.037745	14.384840	0.002849
		Test	0.071498	0.044552	17.716821	0.005112
GSA	Linear	Training	0.071578	0.045389	15.665504	0.005123
		Test	0.090466	0.053103	13.617131	0.008184
	Quad	Training	0.035943	0.025431	11.121689	0.001292
		Test	0.048728	0.029310	14.238150	0.002374
SOS	Linear	Training	0.071147	0.045316	15.541302	0.005062
		Test	0.089336	0.054230	13.892955	0.007981
	Quad	Training	0.034420	0.024252	10.427963	0.001185
		Test	0.041285	0.027459	13.516038	0.001704
ANN	4x4 LM	Training	**0.003100**	**0.001771**	**0.509552**	**0.000010**
		Test	**0.022575**	**0.017426**	**6.200131**	**0.000510**

Table 3. Time Comparison of the proposed algorithms.

Algorithm	Model	Time (seconds)	MSE
ABC	Linear	13.2102	0.045353
	Quadratic	22.2987	0.037745
GSA	Linear	3.7821	0.045389
	Quadratic	4.9198	0.025431
SOS	Linear	0.7704	0.045316
	Quadratic	0.8824	0.024252
ANN	4x4 LM	2.1504	0.000510

The regression results of linear and quadratic models developed using ABC algorithm are presented in Figure 3 and 4, respectively. When the test data were taken into consideration, the linear model was obtained as 94.781% and the quadratic model was obtained as 96.112%.

The regression results of the linear and quadratic models developed using the GSA algorithm are presented in Figure 5 and 6, respectively. When the test data were taken into consideration, the linear model was obtained as 94.74% and the quadratic model was 98.401%.
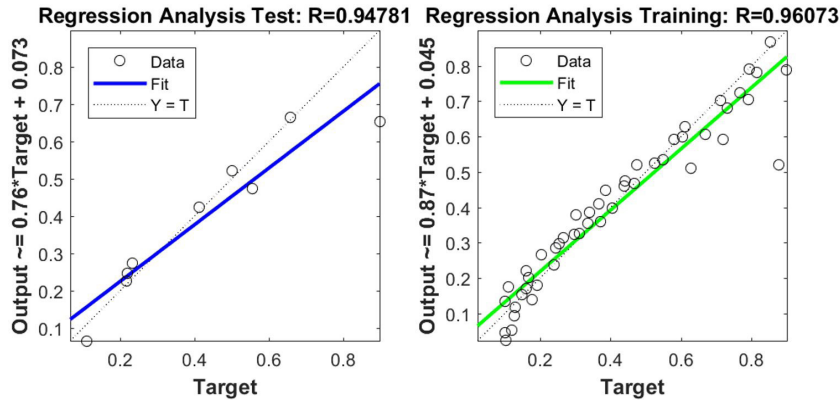

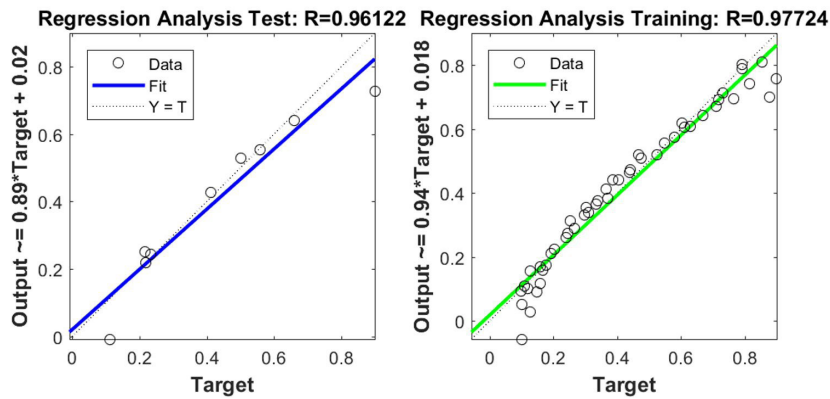**Figure 3**. The regression results of linear models for ABC algorithm.

Figure 4. The regression results of quadratic models for ABC algorithm.
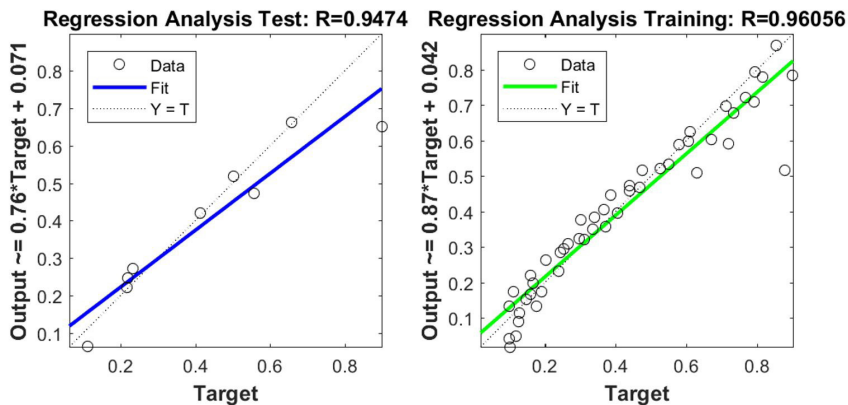

Figure 5. The regression results of linear models for GSA algorithm.

The regression results of the linear and quadratic models developed using the SOS algorithm are presented in Figure 7 and 8, respectively. When the test data were taken into consideration, the linear model was obtained as 94.756% and the quadratic model was 98.887%.

The regression result of two hidden layers and four perception models developed using ANN is given in Figure 9. Based on the test data, 99.793% of the results were obtained.

As a result, performance assessment of regression analysis considering best quadratic mode results for test data is 96.112%, 98.401%, 98.887% which were obtained for of ABC, GSA and SOS algorithms, respectively. The best performance in regression analysis is observed for the SOS algorithm, which provides the fastest results. However, it was behind the value of ANN with 99.793%.
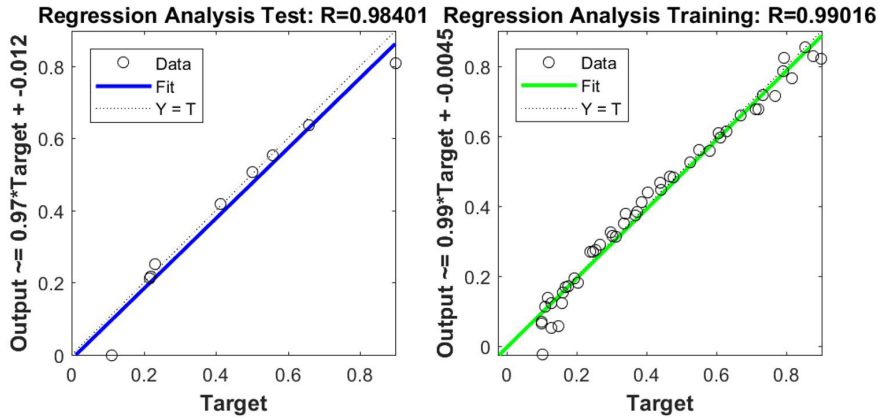

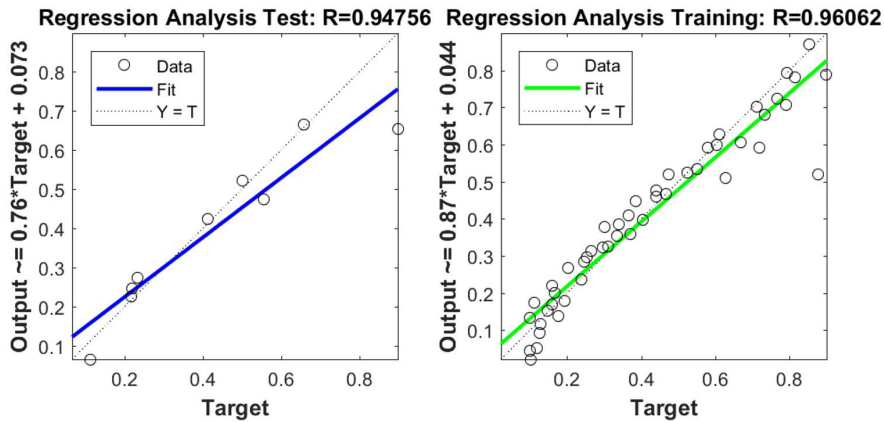**Figure 6**. The regression results of quadratic models for GSA algorithm.

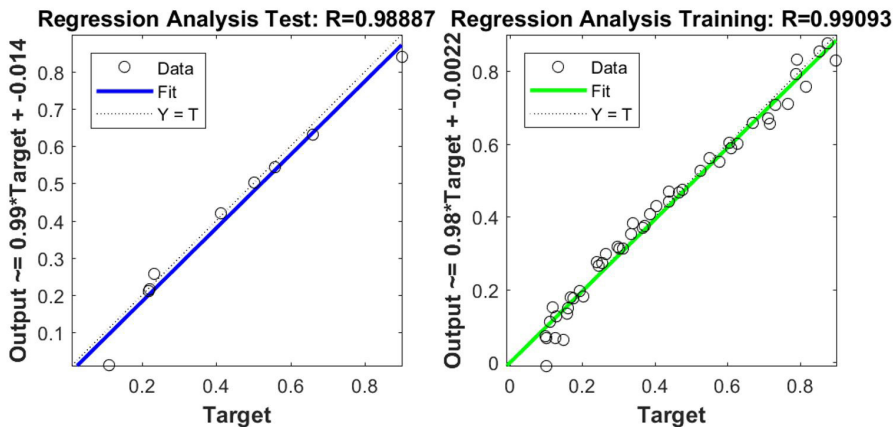**Figure 7**. The regression results of linear models for SOS algorithm.

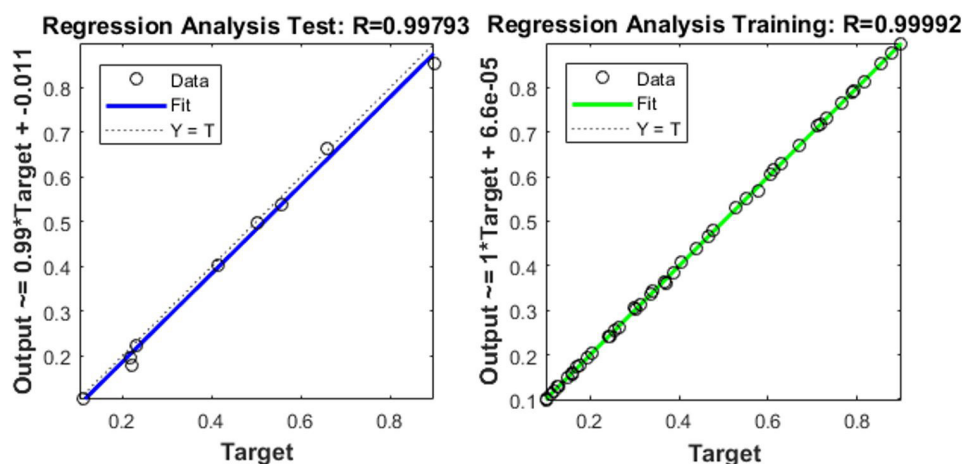**Figure 8**. The regression results of quadratic models for SOS algorithm.

Figure 9. The regression results of ANN algorithm.

Table 4. Constant parameters of the algorithms for linear modeling.

Algorithm	c1	c2	c3	c4
ABC	0.89381	-0.99917	-0.33404	0.27550
GSA	0.88781	-0.99999	-0.33243	0.28395
SOS	0.89378	-1.00000	-0.33506	0.27758

Table 5. Constant parameters of the algorithms for quadratic modeling.

Algorithm	c1	c2	c3	c4	c5
ABC	0.82752	0.02380	0.01229	-0.06904	-0.78226
GSA	0.91634	0.30918	0.09544	0.28321	-0.49211
SOS	0.93487	0.33032	0.08536	0.55269	-0.45923
Algorithm	c6	c7	c8	c9	c10
ABC	0.03611	0.01347	-0.84141	-0.00891	0.23481
GSA	-0.76562	-0.32868	-0.99990	-0.00230	0.12936
SOS	-0.80670	-0.49484	-0.99846	0.06854	-0.04055

Table 6. The weights between inputs and first hidden layer.

Weights – Input to 1st Hidden Layer		
-6.0966	-1.4638	-6.4050
-0.5111	-0.0553	-0.0125
2.1135	-1.4554	0.2232
-10.4064	-10.2302	-1.9069

Table 7. The weights between first and second hidden layer.

Weights – 1st to 2nd Hidden Layer			
-6.0896	9.2884	1.3904	-0.6588
-2.6007	5.1993	1.3155	-0.4053
-1.4934	17.7064	3.1842	0.3315
1.5907	-7.5853	-1.5376	-10.1093

Table 8. The weights between second hidden layer and output.

Weights – 2nd Hidden Layer to Output			
0.9924	-0.9612	0.2629	-0.6338

Table 9. The bias values of neurons for hidden layers and output.

Biases		
1st Hidden Layer	2nd Hidden Layer	Output
1.9860	2.4942	-0.1942
0.2014	1.0190	
-0.7955	-4.4015	
-7.1535	-11.3592	

3.4 Parametric results

For the linear and quadratic models given in Equation 5 and 6, the constant parameters were estimated by algorithms and the results were evaluated by test data. The four constants in the equation for the linear model are presented in the Table 4. Ten values (c_x) used in quadratic modelling are presented in the Table 5. The weight value of the dried product can be easily calculated by typing constant values modeled in equations depending on time, temperature and energy consumption.

$$Weight = c_1 + c_2M + c_3T + c_4E \tag{5}$$

$$Weight = c_1 + c_2M^2 + c_3T^2 + c_4E^2 + c_5M \times T + \\ c_6M \times E + c_7T \times E + c_8M + c_9T + c_{10}E \tag{6}$$

The model created with ANN has high accuracy, but the result is not easily accessible, as in linear and quadratic modeling. In order to obtain the result, the network structure must be "feed-forward" further, which is carried out by complex processes. Weight and bias values of ANN network obtained at the end of the training period are given in the tables from 6 to 9. As given before in Figure 3, 3-4-4-1 network structure was created for this data set. There are three variables at the entrance and one variable at the output. Two hidden layers have four neurons.

In Table 6, the weight values of the connections between the three input variables and the first hidden layer (4 neurons) are presented as 4x3 matrix.

In Table 7, the weight values of the connections between the first hidden layer (4 neurons) and the second hidden layer (4 neurons) are presented in a 4x4 matrix.

In Table 8, the weight values of the connections between the second hidden layer (4 neurons) and the output are presented as 4x1 matrix.

In Table 9, the bias values of neurons (two hidden layers and output) are presented in matrix form.

4 Conclusion

In this study, the modeling of kinetics of eggplant samples dried in 3 different temperatures in a food drying oven was studied. In addition to the classical methods used in modeling, the

performance of ANN algorithm was also evaluated. SOS algorithm provides the best performance and fastest result in linear and quadratic modeling. According to the MSE performance metric, ANN gives 50 times better performance than the SOS algorithm, which gave the best result in the quadratic model. According to the results of regression analysis ANN is 99.793% and quadratic modeling is 98.887%. In terms of duration of algorithms, SOS has reached the best result 3 times faster than ANN. Although it can be seen that ANN modeling with high accuracy, the complex structure and the difficulty of realization are also taken into account. As a result, the drying kinetics of eggplant was performed with high accuracy by ANN.

Acknowledgements

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