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Research Paper

Estimation of the Experimental Drying Performance Parameters Using Polynomial SVM and ANN Models

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Abstract

The utilization of solar energy in Turkey is very popular because of yearly high solar radiation compared to other countries. One of the common usage area of solar energy is food drying processes. Foods are generally dried under direct sunlight. However, the quality of the dried product exposed to solar radiation reduces. Additionally, the food product dried in outdoors is also exposed to the negative effects of the external environment and thus adversely affects the product quality. In order to overcome these problems, many studies are carried out on solar assisted drying systems. It is very important to calculate or modeling the drying parameters for the design of solar assisted drying systems. In recent years, interest on calculative intelligence methods increases due to the fact that it has high predictive power in modeling of systems. In this study, performance parameters such as solar collector efficiency (η_c), drying rate (DR) and convective heat transfer coefficient (h_c) obtained from a solar energy assisted dryer for different products were estimated by Support Vector Machine (SVM) and Artificial Neural Network (ANN) models. Apple, red pepper and green pepper were chosen as the product to be dried. The accuracy criteria of the predicted results for each model were determined and compared. It was shown from the results that the best converging models of DR and η_c parameters were ANN and SVM_C, respectively. However, it was observed that SVM_L was the best convergent model for h_c values obtained from apple product, and ANN model was the best convergent model for h_c values obtained from other products.

Keywords: Drying, Solar Energy, Performance parameter, SVM, ANN.

1. INTRODUCTION

The drying, which is one of the oldest techniques used for food or agricultural products storage, is the basic process to reduce moisture from product [1]. Food drying is a complicated process where simultaneous heat and mass transfer take place. Removing the moisture from the product is the main principle of drying process [2]. The drying process begins with the solution of the bond forces between water and the product to be dried. This process requires a certain amount of energy. This energy (heat energy) should be given to the material without interruption during the drying period [3]. Solar energy is a clean energy source that is very popular especially in drying applications [4]. Turkey's average annual total sunshine duration is 2640 h (daily total is 7.2 h), and average total irradiation is 1311 kWh/m²-year (daily total is 3.6 kWh/m²). Turkey located between 36°N and 42°N latitude have an advantageous geographical location for solar energy [5]. Open sun drying is the most common method used to preserve agricultural products in most countries. However, this technique is affected from weather conditions and has the problems of contamination with dust, soil, sand particles, insects, the length of drying time, loss of time and product loss [6]. Solar energy assisted dryers are designed to eliminate these effects and reduce drying time [7].

There are many studies in the literature about solar energy assisted drying systems [8-17]. Çerçi and Akpınar [9] have developed a greenhouse type dryer. Drying process was performed in open sun drying and greenhouse type drying. Drying processes were carried out in the greenhouse dryer using natural and forced convection mode. They found that convective heat transfer coefficient values were 2.863 W/m²K for under open sun drying, 2.065 W/m²K for greenhouse drying with natural convection mode and 2.724 W/m²K for greenhouse drying with forced convection model. Sagia and Fragkou [16] made mathematical modelling with thin layer drying models by using experimental data obtained from various studies on drying behavior of fungi. They found that mathematical models are useful for modelling and analysis of heat and mass transfer during drying processes.

In recent years, many researchers have realized studies with

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different machine learning approaches [18-23]. In this study, drying performance parameters such as solar collector efficiency (η_c), drying rate (DR) and convective heat transfer coefficient (h_c) for different food products were estimated using polynomial Support Vector Machine models (SVM) and Artificial Neural Network model (ANN). The aim of this study is to determine the most appropriate computational intelligence method that can be used to determine different drying performance parameters and to present a sample study to the literature with these models. Parameters considered for the estimation were obtained from a study presented by the authors in the literature [24]. In the study, apple, red pepper and green pepper slices were dried using a solar energy assisted dryer while the system and experimental procedure was described in more detail elsewhere [24]. Matlab software was used for analysis and modelling.

2. MATERIAL METHOD

Figure 1 shows the schematic view of the solar assisted drying system used in the study [2,3,7,24]. As can be seen from the figure, system consists of two main sections: a solar air collector and a drying chamber. The ambient air entering the solar air collector (state 1) is heated in the collector and sends to the drying cabinet (state 2) via a blower. Drying air takes the moisture from the food product and leaves from the system (state 3). In the system, the case of the air solar collector with a size of 195x95x12 cm (1.70 m^2) was made of plexiglass and its lower and side surfaces were covered with glass wool insulation material to reduce heat losses. For the circulation of air, a speed controlled radial blower with 70W power and 650 m^3/ h of flow rate (max.) was used. In order to prevent air leaks, all the connection points and spots, where air passes, are closed using silicon. Possible heat losses were prevented by covering the drying chamber with aluminum coated glass wool mattress with 5 cm thick. The drying chamber in which the products are placed was made of wood. The crops to be dried were placed inside the drying chamber with the help of a tray. The chamber also contains a sight glass made of transparent plastic material for the monitoring of the products. A tray of approximately 0.5 m^2, on which the products are dried inside the dryer, was manufactured from aluminum perforated wire to allow the air passage. The products with a thickness of 4 mm were placed homogeneously on the tray. After the products were placed in the drying chamber by means of the tray through the product inlet, the tray was connected to the electronic precision scale with the hanger system inside the chamber.

Measurements were made at different points on the system to determine the performance of the system and the drying characteristics of the products to be dried (Figure 1). A computer aided data acquisition system was used to measure different parameters (temperature, moisture, air velocity, weight and radiation) and to record the data at 15 min intervals. In addition to the temperature measurements carried out in the collector, blower and at the entrance and exit of

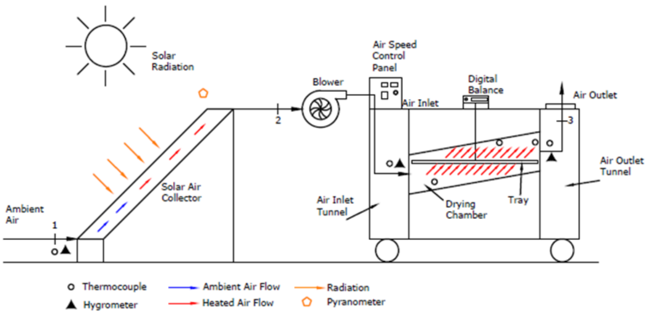

Figure 1. Schematic views of air collector drying system [2,3,7,24]

the drying chamber, relative humidity was also measured at the collector inlet (ambient air) and at the entrance and exit of the drying chamber. The solar radiation was measured with an irradiation sensor placed in such a way that it has the same slope as that of the collector. In order to determine the air flow rate circulating in the system, the air velocity was measured using an anemometer in the air tunnel located at the outlet of the drying chamber [24]. Error analysis was performed using the method proposed by Holman [25]. Table 1 contains information about the devices used to make measurements in the system and about the error analysis.

Table 1. Devices used in measurements and the uncertainty of the calculated parameters.

Measurement	Device	Accuracy
Temperature	COLE PARMER K type thermocouple	0.1 °C
Relative humidity	EPLUSE humidity transmitter	2-3 %
Weight	DİKOMSAN electronic balance	0.1 g
Air velocity	TESTO 435 with air speed probe	0.1 m/s
Solar Radiation	TRITEC Irradiation sensor	±5 %
Data recording	IOTECH PD3001data logger	16 bit
Calculated Parameter		**Uncertainty (%)**
h_c		3.88
DR		2.70
η_c		2.88

3. CALCULATIONS

In the study, η_c is calculated by using Equation 1 [24, 26]. The DR is calculated by using Equation 2 [24, 27]. The h_c value is calculated using expression of Nusselt number (Nu) by Equation (3) and Equation (4) [18,24,28]. The utilized heat rate for evaporating moisture is calculated by using Equation (5) [18,24,28]. Table 2 gives the equations used for calculations.

Where, , is moisture evaporated (g), A_c is collector are (m^2), I is solar radiation (W/m^2), C_p is specific heat of air (J/kg °C), is mass flow (kg/sec), T_e is outlet temperature (°C), T_i is inlet temperature (°C), K_v is thermal conductivity of humid air (W/m°C), X is characteristic dimension (m), C and n are constants, Re is Reynolds number, Pr is Prandtl number, is evaporating moisture, T_p is product temperature (°C), T_c is chamber temperature (°C), A_t is tray area (m^2), t is time (second), λ is latent heat of vaporization, ρ_v is density of humid

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air (kg/m³), μ_v is viscosity (kg/ms).

Table 2. The equations used for calculations

$$\eta_c = \frac{\dot{m}.C_p.(T_e - T_i)}{I.A_c} \tag{1}$$

$$DR = \left(\frac{M_{t+dt} - M_t}{dt}\right)_{d.b.} \tag{2}$$

$$h_c = \frac{Nu \cdot K_v}{X} \tag{3}$$

$$h_c = \frac{K_v}{X} \cdot C \cdot (Re \cdot Pr)^n \tag{4}$$

$$\dot{Q}_e = 0.016 \cdot h_c \cdot [P(T_p) - \gamma \cdot P(T_c)] \tag{5}$$

$$\dot{m}_{ev} = \frac{\dot{Q}_e}{\lambda} \cdot A_t \cdot t \tag{6}$$

$$Z = 0.016 \cdot \frac{K_v}{X \cdot \lambda} \cdot [P(T_p) - \gamma \cdot P(T_c)] \cdot A_t \cdot t \tag{7}$$

$$\frac{\dot{m}_{ev}}{Z} = C \cdot (Re \cdot Pr)^n \tag{8}$$

$$\ln\left|\frac{m_{ev}}{Z}\right| = \ln C + n \cdot \ln(Re \cdot Pr) \tag{9}$$

$$Y = b_1 \cdot X + b_0 \tag{10}$$

$$Y = \ln\left|\frac{m_{ev}}{Z}\right|, b_1 = n, X = \ln(Re \cdot Pr), b_0 = \ln C \tag{11}$$

$$\rho_v = \frac{353.44}{(T_a + 273.15)} \tag{12}$$

$$K_v = 0.0244 + 0.6773 \cdot 10^{-4} \cdot T_a \tag{13}$$

$$C_v = 999.2 + 0.1434 \cdot T_a + 1.101 \cdot 10^{-4} T_a^2 - 6.7581.10^{-8} \cdot T_a^3 \tag{14}$$

$$\mu_v = 7.718 \cdot 10^{-5} + 4.620 \cdot 10^{-8} \cdot T_a \tag{15}$$

$$P[T] = \exp\left[25.317 - \frac{5144}{(T_a + 273.15)}\right] \tag{16}$$

3.1. Support Vector Machine (SVM)

It is stated that the SVM method, which is one of the important types of machine learning, provides successful results for many different fields in the recent years [29-33]. Support vector machines are learning systems using the hypothesis field of linear functions in a multi-dimensional feature area and this learning strategy was first developed by Vapnik [34]. In addition to the classification of SVM with linear separator hyper plane, there may also be situations where linear separation cannot be made in the original input field. In these cases, functions called kernel are used. The kernel converts the linear problem to non-linear problems by mapping to property fields. Radial-based, polynomial and two-layer sigma neural networks are some of these core functions [35]. In this study, the polynomial kernel function was used to estimate the performance parameters of the solar-assisted drying system for the drying of different food products. Three different polynomial kernels used in this study are linear-degree 1 (SVM_L), quadratic-degree 2 (SVM_Q) and cubic-degree 3 (SVM_C). The basic kernel functions and parameters used in support vector machines is given Equation 17 [34,36].

$$K(x,y) = ((x \cdot y) + 1)^d \tag{17}$$

4. 3.2. ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network works in a similar principle to the human nervous system. The ANN model has a very serious usage in the learning process and estimation of data. The nerve structure called neuron works in connection with many different processing elements. First, these neurons take information from other sources. Next, non-linear operations are applied to this information. Finally, the final output is obtained [37]. In this study, the drying parameters obtained for the drying of different products in a solar assisted dryer were estimated with ANN. Different ANN models (total of 3 layers) were performed for each drying performance parameters. A total of 3 layers were performed to estimate drying rate, convective heat transfer coefficient and collector efficiency values. The input layer, which is the first of these layers for drying rate and convective heat transfer coefficient, consists of 8 neurons. The input layer for collector efficiency consists of 6 neurons. For all performance parameters, the first of the hidden layers consists of 10 neurons and the second consists of 1 neuron. Finally, there is 1 neuron in the output layer. In the information sets of drying rate, convective heat transfer coefficient and collector efficiency parameters, there are 312 input and 39 output, 320 input and 40 output, 240 input and 40 output information respectively. 60% of this information was used in the training process and 20% in the validation process and the test process. Feed Forward Back Propagation Algorithm, which has the most common usage as learning algorithm, has been selected. Levenberg Marquardt Algorithm was used for tra-

Table 3. The input and output values used for polynomial SVM models and ANN model to predict DR

Input							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
Drying time	Min.	15	15	15	585	585	585
Radiation (I)	W/m²	33.77	27.91	12.37	1033.27	944.33	872.06
Ambient Temperature (T_i)	°C	26.54	26.33	26.18	37.62	33.43	32.74
Ambient Rel. Hum. (Rh_i)	%	16.66	48.71	50.65	42.92	69.12	75.29
Chamber Temperature (T_c)	°C	30.77	29.42	30.52	49.33	44.65	44.28
Chamber Rel. Hum. (Rh_c)	%	7.37	28.17	27.23	37.23	61.58	67.83
Product Temperature (T_p)	°C	21.53	23.37	26.82	40.21	35.41	38.46
Product Weight (W_p)	g	267.65	901.38	879.85	1141.26	1753.54	1524.39
Output							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
DR	(g_w/g_{dm})/min	0.0002	0.0029	0.0007×10^{-2}	0.0221	0.0216	0.0219

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Table 4. The input and output values used for polynomial SVM models and ANN model to predict h_c

Input							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
Drying time	Min.	0	0	0	585	585	585
Radiation (I)	W/m²	33.77	27.91	12.37	1033.27	944.33	872.06
Ambient Temperature (T_i)	°C	25.88	26.33	25.52	37.62	33.43	32.74
Ambient Rel. Hum. (Rh_i)	%	16.66	45.18	50.65	44.10	69.12	76.83
Chamber Temperature (T_c)	°C	29.05	29.42	30.38	49.33	44.65	44.28
Chamber Rel. Hum. (Rh_c)	%	7.37	28.17	27.23	39.16	61.58	67.83
Product Temperature (T_p)	°C	20.62	23.33	25.77	40.21	35.41	38.46
Product Weight (W_p)	g	267.65	901.38	879.85	1172.35	1777.50	1545.03
Output							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
h_c	W/m²K	1.3923	3.9663	2.2716	1.4229	3.9907	2.2960

Table 5. The input and output values used for polynomial SVM models and ANN model to predict η_c

Input							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
Drying time	Min.	0	0	0	585	585	585
Radiation (I)	W/m²	33.77	27.91	12.37	1033.27	944.33	872.06
Ambient Temperature (T_i)	°C	25.88	26.33	25.52	37.62	33.43	32.74
Ambient Rel. Hum. (Rh_i)	%	16.66	45.18	50.65	44.10	69.12	76.83
Chamber Temperature (T_c)	°C	29.05	29.42	30.38	49.33	44.65	44.28
Chamber Rel. Hum. (Rh_c)	%	7.37	28.17	27.23	39.16	61.58	67.83
Output							
	Unit	Min			Max		
		Apple	R. Pepper	G. Pepper	Apple	R. Pepper	G. Pepper
η_c	%	12.85	37.03	34.69	56.93	53.36	57.53

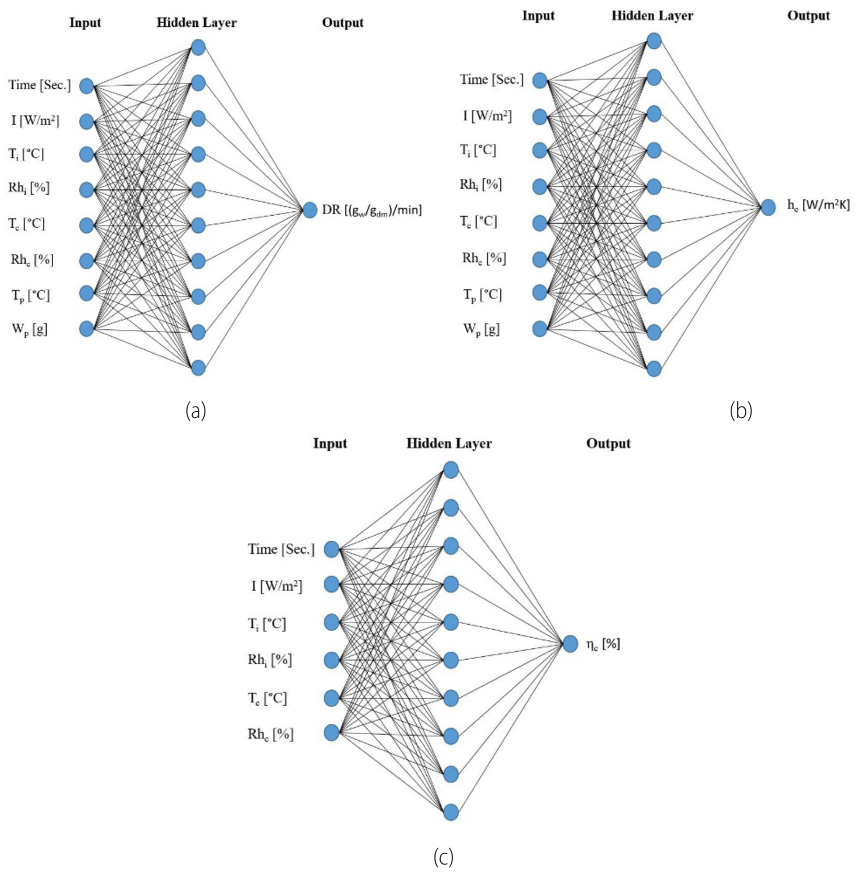

Figure 2. ANN structures for drying rate-DR (a), convective heat transfer coefficient-h_c (b) and solar collector efficiency-η_c (c)

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ining. The TANSIG function was selected as the Activation Function. The input and output values of DR, h_c and η_c used for polynomial SVM models and ANN model were given in Table 3-5 respectively. Since there are different input parameters that affect each performance parameter, different input values were applied to predict all performance parameters. Figure 2 shows the network structures performed to estimate drying rate, convective heat transfer coefficient and collector efficiency parameters by ANN.

4.1. 3.3. Accuracy Criteria

In this study, different food products were dried with a solar energy assisted dryer and DR, h_c and η_c values were obtained from the experiments [24]. In addition, these performance parameters were estimated by polynomial SVM models and ANN model. In order to determine the performance of the predictions, the accuracy criteria, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values were taken into consideration. These accuracy criteria are determined by using equation 18 and 19 [38].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i{}^2} \quad (18)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \quad (19)$$

Here, e is the difference between the actual value and the estimated value, n is the number of data.

5. RESULTS AND DISCUSSION

In this study, firstly the drying characteristics (DR, h_c and η_c) of different products (apple, red pepper and green pepper) dried with a solar energy assisted drying system were analyzed by using the experiments [24] carried out in the climate conditions of Osmaniye province. Then DR, h_c and η_c values were estimated using polynomial SVM models and ANN model. Variation of η_c during drying process for different products is given in Figure 3. The efficiency value of the solar collector varies between 13-58% for apple drying process, between 37-53% for red pepper drying process and between 34-57% for green pepper drying process [24].

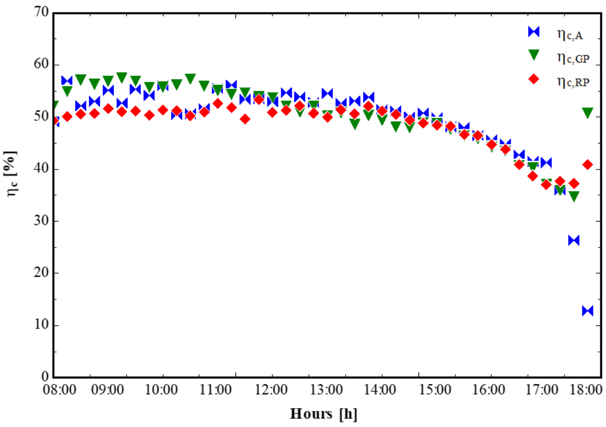

Figure 3. Variation of η_c during drying process for different product [24]

Figure 4 and 5 exhibit variation of the DR and h_c values for drying process of different products, respectively. It has been observed that the rate of drying has decreased over time and DR values varied between 0.0194x10^{-2} and 2.2091 (g_w/g_{dm})/min for apple, between 0.2872x10^{-2} and 2.1594 (g_w/g_{dm})/min for red pepper, 0.0007 x 10^{-2} and 2.1850 (g_w/g_{dm})/min for green pepper. The average DR values were found as 0.8034x10^{-2} (g_w/g_{dm})/min for apple slices, 0.9960x10^{-2} (g_w/g_{dm})/min for red pepper slices, 1.0299x10^{-2} (g_w/g_{dm})/min for green pepper slices. During the drying process, h_c values were varied between 1.3923 and 1.4230 W/m^{2}K for apple slices, between 3.9663 and 3.9907 W/m^{2}K for red pepper slices, between 2.2715 and 2.2960 W/m^{2}K for green pepper slices. The average h_c values were found as 1.4134 W/m^{2}K for apple, 3.9801 W/m^{2}K for red pepper slices, 2.2877 W/m^{2}K for green pepper slices. In addition, C and n constant values were found as 1.0053 and 0.2509 for apple slices, 1.0003 and 0.3692 for red pepper slices and 1.0008 and 0.3062 for green pepper slices, respectively [24].

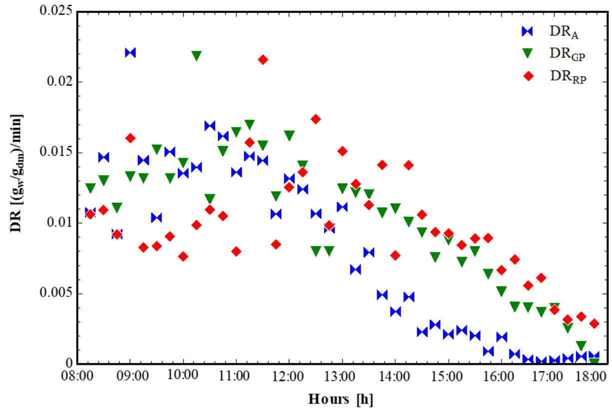

Figure 4. Variation of the DR values during drying process for different product [24]

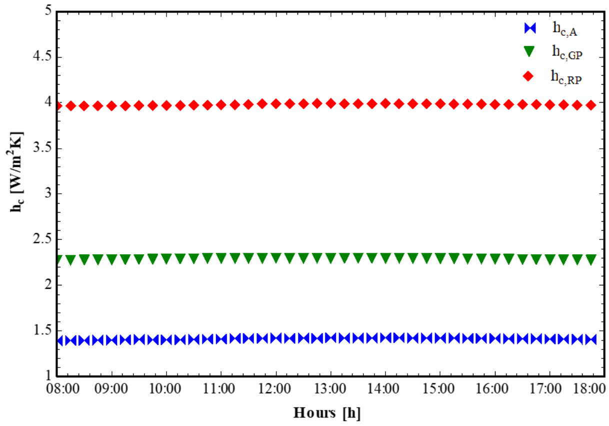

Figure 5. Variation of h_c values during drying process for different product [24]

In this study, DR, h_c and η_c values obtained by drying apple, red pepper and green pepper in a solar assisted dryer were estimated by polynomial SVM and ANN models. RMSE and MAE values given in Table 6 are used to determine the performance of the estimations. DR values are best predicted by the ANN model for all products. The h_c values of apple slices were best estimated by SVM_L model, but the h_c values of red pepper and green pepper slices were best estimated by ANN model. Estimation of experimentally obtained η_c

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values during drying of all products was performed by the best SVM_C method. Table 7 shows the accuracy criteria obtained for performance parameters in the literature. It was observed that the accuracy criteria obtained in this study give acceptable results when compared with the literature.

Table 6. Accuracy results of the models

Parameter	Product	Model	RMSE	MAE	R^2	Epoch
DR	Apple	ANN	0.001066408	0.000584221	0.9698	20
		SVM_L	0.002833013	0.002346657	0.7837	-
		SVM_Q	0.002590737	0.001992391	0.8431	-
		SVM_C	0.003173243	0.002532474	0.7376	-
	Red Pepper	ANN	0.002125115	0.001632173	0.7176	6
		SVM_L	0.002542184	0.002032765	0.6159	-
		SVM_Q	0.004775523	0.003932029	0.1713	-
		SVM_C	0.007077473	0.005503955	0.3938	-
	Green Pepper	ANN	0.001950538	0.001467057	0.8560	12
		SVM_L	0.003412684	0.002752114	0.7796	-
		SVM_Q	0.008181755	0.006227085	0.0437	-
		SVM_C	0.009192591	0.006368667	0.1501	-
h_c	Apple	ANN	0.000700034	0.000583431	0.9961	11
		SVM_L	0.000647039	0.000551914	0.9965	-
		SVM_Q	0.000852939	0.000712349	0.9942	-
		SVM_C	0.001756525	0.001559501	0.9722	-
	Red Pepper	ANN	0.000315103	0.000247558	0.9991	13
		SVM_L	0.000939006	0.000887537	0.9968	-
		SVM_Q	0.001043954	0.000933099	0.9866	-
		SVM_C	0.002441669	0.001954482	0.9300	-
	Green Pepper	ANN	0.000289112	0.000208491	0.9987	20
		SVM_L	0.000632797	0.00088158	0.9962	-
		SVM_Q	0.00102846	0.000532599	0.9947	-
		SVM_C	0.002634382	0.001932113	0.9296	-
η_c	Apple	ANN	1.317713639	0.986534597	0.9766	9
		SVM_L	3.969052479	1.749772308	0.8240	-
		SVM_Q	1.638731971	1.065426984	0.9701	-
		SVM_C	0.800964654	0.661964769	0.9912	-
	Red Pepper	ANN	0.611879421	0.448985972	0.9824	6
		SVM_L	1.693990697	1.218770976	0.8646	-
		SVM_Q	0.858459749	0.594509268	0.9653	-
		SVM_C	0.424738967	0.314045676	0.9914	-
	Green Pepper	ANN	3.005891005	1.245582428	0.7960	6
		SVM_L	2.735130978	1.17323392	0.8175	-
		SVM_Q	2.631461549	1.001995357	0.8365	-
		SVM_C	0.486331346	0.457946875	0.9938	-

Comparison of experimental data and ANN model, which is the best converge to DR, for three different food products, is given in Figure 6, R^2 values were 0.9698 (apple), 0.7176 (red pepper) and 0.8560 (green pepper) for the DR values estimated by ANN. Figure 7 shows the comparison of the models with the best convergence of the h_c parameter obtained in the drying of different food products with experimental data. While SVM_L model had the highest R^2 value (0.9965) for the h_c of apple product, the highest R^2 values of red pepper and green pepper products were obtained from ANN models (0.9991 and 0.9987). Figure 8 presents the comparison of the models (SVM_C) that best converge the η_c parameters obtained during the drying of three different products with experimental data. R^2 values obtained from SVM_C model for apple, red pepper and green pepper were found as 0.9912, 0.9914 and 0.9938, respectively. In the study, it was observed that the machine learning models used to estimate the parameters affecting the food drying converged each parameter differently. Therefore, it has been concluded that the most suitable model for utilization among the models formed to estimate each performance parameter is important.

Table 7. Accuracy results of the models in literature

Product	Drying method	Output parameters	Input variables	Result	Ref.
Grape	Greenhouse	h_c	Drying Time, Ambient Temperature, Product Temperature, Relative Humidity, Reynolds Number. Prandtl Number, Radiation	MAE_{MLP}=0.0815 $RMSE_{MLP}$= 0.1088	[18]
Potato	Indirect Solar Dryer	DR	Air temperature, Drying Time, Air velocity, Product type, Drying time	R^2_{ANN}=0.9752-R^2_{ANFIS}=0.9900	[19]
Kiwifruit	Hybrid Hot Air-Infrared Dryer	DR	Time, IR Lamps, Air Temperature and Air Velocity	R_{ANN}^2=0.9998 MSE_{ANN}= 3.5E-5	[20]
-	Solar still	Thermal Efficiency (η_c)	Julian day, Ambient Temperature, Wind Speed, Relative Humidity, Solar Radiation, Total Dissolved Solids of Feed, Total Dissolved Solids of Brine	$RMSE_{ANN}$ = 1.147	[21]

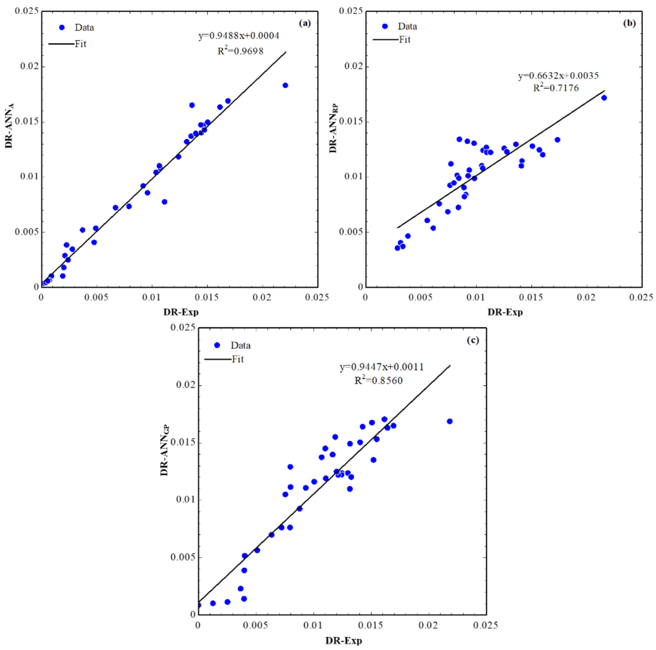

Figure 6. The comparison of experimental data and models which best converges to the DR parameters for apple (a), red pepper (b) and green pepper (c)

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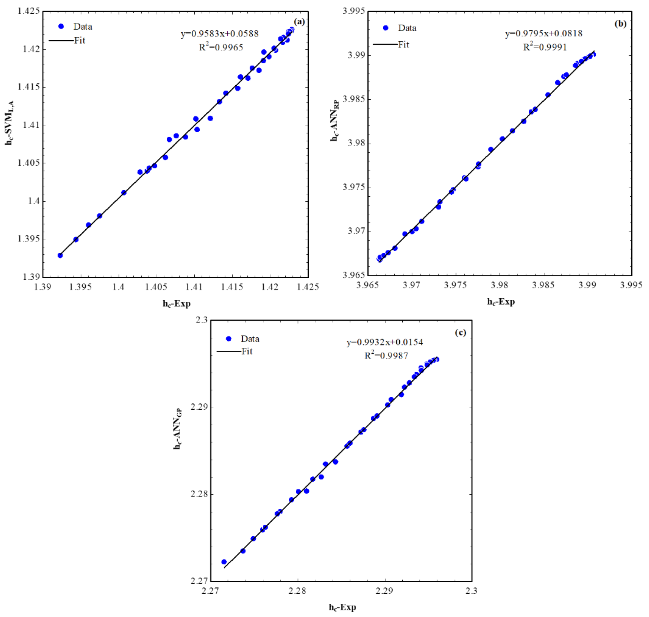

Figure 7. The comparison of experimental data and models which best converges to the h_c parameters for apple (a), red pepper (b) and green pepper (c)

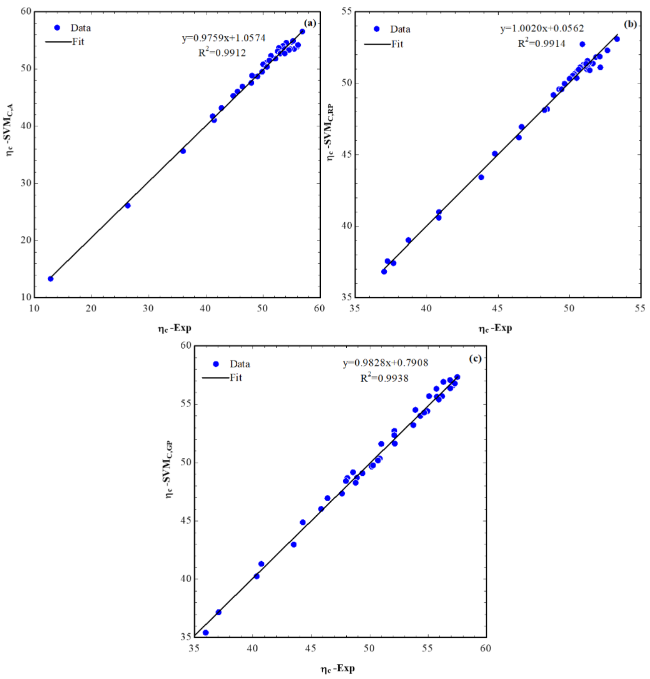

Figure 8. The comparison of experimental data and models which best converges to the η_c parameters for apple (a), red pepper (b) and green pepper (c)

6. CONCLUSION

In this study, the performance parameters obtained from an experimental study in the literature [24] were estimated by using computational intelligence models. Apple, red pepper and green pepper slices were dried in the solar energy assisted system. Different parameters such as temperature, humidity, radiation and weight were measured during the experiments. DR, h_c and η_c values were calculated using experimental data [24]. It was shown from the experimental results that DR and h_c values vary according to the structure, porosity, shape, thermophysical properties and experimental conditions of the product. It was determined that η_c parameter affected by climatic conditions. The DR, h_c and η_c values were estimated by using polynomial SVM models and ANN model. The best results were obtained from the ANN model and SVM_C model for estimating DR and η_c values for three different products, respectively. The best estimate of the h_c values of both products except apple product was performed with ANN model. However, the best convergence was obtained by SVM_L model for estimating the h_c value of apple product. It was observed from the study that the models formed for each parameter converged differently and parameters which are particularly important in drying systems designs should be modeled accurately. It was also observed that in general, the results obtained converged well compared to the results obtained in the literature and these results were acceptable. The results obtained from this study are useful for modeling drying performance parameters with different computational intelligence methods.

7. CONFLICTS OF INTEREST

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