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Modeling of rehydration behavior of freeze- and vacuum-dried damson plums by an enhanced Chebyshev network

Dondurarak ve vakumla kurutulmuş mürdüm eriklerinin rehidrasyon davranışının geliştirilmiş bir Chebyshev ağı ile modellenmesi

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Abstract

The aim of this paper is to investigate the rehydration properties of freeze- and vacuum-dried damson plums (Prunus insititia) at three different temperatures (25, 45 and 60°C). First, kinetic models (Weibull, Peleg, Exponential and First-order) were designed to construct mathematical models and analyze the rehydration kinetics. Second, an artificial Chebsyhev network was designed for modeling of the rehydration kinetics such that a novel extreme learning machine-based feature extraction layer is proposed to improve its modeling capability. The experimental data and artificial models were analyzed considering the randomly selected data sets, and the root mean squared errors (RMSE) were computed to compare accuracy of the models. Due to orthogonality and feature extraction, the proposed enhanced Chebyshev network was obtained as the best approximator model among tested models with the the lowest RMSE values to explain the rehydration behavior of damson plums. While the percentage RMSE values for kinetic models vary in the range of ~3.1 and 4.8%, the maximum and minimum percentage values for Chebyshev networks are 2.32% and 0.51%, respectively. It is concluded that the proposed Chebyshev network can be used as a parsimonious model in the embedded design of the rehydration and drying machines so that predefined rehydration and drying characteristics can be accurately defined.

Keywords: Rehydration, Feature extraction, Artificial chebyshev network, Freeze drying, Damson plum.

Öz

Bu çalışmanın amacı, dondurarak ve vakumla kurutulmuş mürdüm eriklerinin (Prunus insititia) üç farklı sıcaklıkta (25, 45 ve 60°C) rehidrasyon özelliklerini incelemektir. İlk olarak, kinetik modeller (Weibull, Peleg, Üstel ve Birinci derece) matematiksel modeller oluşturmak ve rehidrasyon kinetiğini analiz etmek için tasarlanmıştır. İkinci olarak, yapay bir Chebsyhev ağı, modelleme kabiliyetini geliştirmek için yeni bir aşırı öğrenme makinesi tabanlı özellik çıkarma katmanı önerilecek şekilde rehidrasyon kinetiğinin modellenmesi için tasarlanmıştır. Deneysel veriler ve yapay modeller, rastgele seçilen veri setleri dikkate alınarak analiz edilmiş ve modellerin doğruluğunu karşılaştırmak için hataların kök ortalama kareleri (RMSE) hesaplanmıştır. Diklik ve öznitelik çıkarımı nedeniyle önerilen geliştirilmiş Chebyshev ağı, mürdüm eriklerinin rehidrasyon davranışını açıklamak için en düşük RMSE değerleri ile test edilen modeller arasında en iyi yaklaşım modeli olarak elde edilmiştir. Kinetik modelleri için yüzde RMSE değerleri ~%3.1 ve 4.8 aralığında değişirken, Chebyshev ağları için maksimum ve minimum yüzde değerleri sırasıyla %2.32 ve %0.51'dir. Önerilen Chebyshev ağının, rehidrasyon ve kurutma makinelerinin gömülü tasarımında cimri bir model olarak kullanılabileceği ve böylece rehidrasyon ve kurutma özelliklerinin önceden doğru bir şekilde tanımlanabileceği sonucuna varılmıştır.

Anahtar kelimeler: Rehidrasyon, Öznitelik çıkarımı, Yapay Chebyshev ağı, Dondurarak kurutma, Mürdüm eriği.

1 Introduction

Vegetables and fruits have an important role in healthy nutrition with their high nutritional content and health-beneficial components. However, their high-water content and perishability cause postharvest spoilage which leads fast degradation of the quality [1]. Dried products can be used instead of fresh foods in many processed products due to their advantages such as transport and storage. Most of the dried fruits are rehydrated before consumption or subsequent operations [2]. Rehydration is the process of restoring the properties of the fresh product when the dry product is immersed in water. The rehydrated products should be as similar as possible with fresh raw materials. Rehydration process can be affected by the drying method, drying conditions and the temperature of the rehydration medium. Rehydration indicates the degree of the damage to the structure of cell of the product during the drying process [3]-[5]. In vacuum drying, while the heat transfer to the solid phase is significantly slowed down due to the absence of convection and the low water vapor pressure at the reduced evaporation temperature, but the removal of moisture is accelerated. Thus, vacuum drying process protects heat sensitive and easily oxidizable foods thanks to the process carried out in the absence of oxygen at low temperatures, so the color change and the loss of flavor can be prevented [6],[7]. However, loss of the quality of dried products cannot be completely avoided by using vacuum drying. Freeze drying is a sublimation process of ice fraction where water passes from solid to gaseous state to remove water from the foods. It is known as the most efficient drying method to preserve nutrients, taste, flavor and to obtain products having porous structures, and good rehydration capability [1],[8]. The rehydration rate of the freeze-dried foods is usually 4-6 times faster than that of conventional thermal

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dried ones, making the freeze-dried products a good option for ready-to-eat instant meals [9]. As the rehydration rate is affected by the drying method, rehydration at higher temperatures increases the rehydration rate due to the effect of higher temperature on the wall of cell and tissue [10]. From a processing point of view, it is important to know how fast rehydration can be performed, as well as how the process variables will affect rehydration rate and how to estimate rehydration time under given conditions [11].

Models used to describe the rehydration process can be theoretical and empirical. The theoretical models based on Fick's First and Second Laws of Diffusion are complex as they contain many parameter and so functions, and therefore may not be suitable for practical calculations in the most cases. Empirical models confirmed by empirical data such as the Weibull distribution and Peleg equation can be utilized as accurate analytical mathematical tools for estimating and optimizing the rehydration kinetics [12],[13]. The effect of ultrasound and ethanol pre-treatments on pumpkin for rehydration and drying behaviors are investigated in Rojas et al. [14] and the rehydration behavior was explained by the Peleg model. Air-dried mushrooms of Morchella esculenta was investigated at various temperatures using Peleg and Weibull models for the effect of temperature on the rehydration behavior [15]. The Weibull and Peleg distribution models were also utilized to model rehydration kinetics of air-dried Shiitake mushroom where it was analyzed that lower immersion time and desirable texture were obtained using conventional rehydration [16]. The effect of temperature on the mass transfer kinetics during rehydration process was also investigated for aloe vera using Weibull model [17]. In Lopez-Quiroga et al. [18], fresh tomatoes were first freeze-dried and subsequently rehydrated at different temperatures where four rehydration models were used to fit the experimental data and resultingly, the Exponential and Weibull models provided the most accurate descriptions of the rehydration. The pumpkin was dried with different techniques and rehydration kinetics were modeled with different models where the Weibull model provided the best rehydration fitting curve [19].

For the modeling of time series and measured input-output data, nonlinear mathematical models are usually used to understand the process behavior. Orthogonal polynomials-based models are effective for the systems with less complexity and number of data [20],[21]. In Lee et al. [22], the rehydration process based on capillary movement rather than diffusion of water in the fruit samples were modeled using the Lucas Washburn equation. Mass transfer kinetics during osmotic dehydration of fruits and kaffir lime peel were modelled using artificial neural networks [23], [24]. Predictive models were developed to describe dehydration and rehydration kinetics for instant rice [25]. A simple polynomial model, artificial neural-network and least-squares support vector machine were used to model dehydration of mahaleb pure where support vector machine regressor model was obtained as the optimal model [26].

In this paper, damson plums which can be consumed as a snack in dried form, and as a cold stewed fruit or as an ingredient yoghurt, etc. were dried by freeze and vacuum drying processes. Rehydration properties of the dried products in water were investigated at different temperatures where the rehydration behavior was modelled using artificial models. In the literature, studies in which rehydration behavior was determined mostly used well-known kinetic models. In this way, it is aimed to reveal the rehydration properties of damson plums, which show the physical and chemical changes that occur during the drying process, as a quality index. In the present work, an enhanced Chebyshev network is proposed by using extreme learning-based feature extraction of input data where its modeling performance is compared to the conventional Chebyshev network and known distribution models. The main purpose of the feature extraction layer is to improve the modeling performance of the Chebyshev network with a smaller number of parameters since the memory of the microcontrollers in industry is very small to embed a largely parameterized network particularly artificial neural network etc. It is planned that the modeling results will contribute the determining reconstitution properties of the damson plums also fruits having similar rehydration behavior.

2 Materials and experiments

2.1 Material

Damson plum (*Prunus domestica* L.) fruits that were mature enough, dark-blue in color and almost the same size were purchased from a local market of Turkey. Each fruit was first divided into two equal parts, the seed was removed, and then sliced with the help of a knife. Immediately after slicing, the equal sized slices were placed in trays for freezing and vacuum drying. The primary moisture content of the fresh fruit was 3.813±0.004 kg moisture/kg dry matter that was determined using standard oven method at 70°C for 2 days [27]. Before the freeze-drying process, freezing was carried out at -80°C for 24 hours and the frozen fruits were transferred to a freeze dryer (CHRIST, Alpha 1-4 LSC, Germany). Vacuum drying method was performed in a vacuum oven (Nuve EV 018, Turkey) with a 15 L internal chamber at 50°C under 50 mbar of inside pressure. Both drying processes were terminated when the moisture content of the final product was below 10%.

2.2 Rehydration

Dried damson plum slices were rehydrated by immersing in 25, 45 and 60°C of water bath (Memmert, WNB 22, Germany). Each dried sample was weighed before the experiments, then immersed in distilled water at a constant temperature with sample to pure water ratio of 1:20 (weight:volume) and removed after a predetermined time. The superficial water remaining on the surface of the samples was gently removed with a tissue paper and the samples were reweighed. A new sample was used for each rehydration time and the experiments were continued until the weight change was stabilized. All rehydration experiments were duplicated.

2.3 Distribution models

To determine the rehydration kinetics of dried samples four common distribution models namely Peleg, Weibull, first-order and exponential association were applied [18].

$$M = M_0 + \frac{t}{k_1 + k_2 t} \tag{1}$$

Where, M is defined as the moisture content (kg water/kg dry matter), M_0 is given as the initial moisture content of the sample (kg water/kg dry matter), t is time (min), k_1 is a kinetic rate constant and k_2 is a characteristic constant of the model. The moisture content of the equilibrium point (M_e, k_g water/ kg dry matter) is computed by

$$M_e = M_0 + \frac{1}{k_2} \tag{2}$$

for long rehydration times. The Me is added as an additional bias parameter in the Weibull model as

$$M = M_e + (M_0 - M_e)exp\left[-\left(\frac{t}{\beta}\right)^{\alpha}\right] \tag{3}$$

where, where β and α are the scale and the shape parameters, respectively.

$$M = M_e + (M_0 - M_e)\exp(-Kt) \tag{4}$$

$$M = M_e[1 - \exp(-Ht)] \tag{5}$$

Where, K and H are the kinetic constants of the first order kinetic model and exponential association equation, respectively.

2.4 Chebyshev network model

The nonlinear generator polynomials with recurrence relations can produce enough polynomial functions to represent any nonlinear function. Some of the polynomials are orthogonal with a weighting function in a defined interval. The orthogonal basis function sets are accepted and proved as an universal function approximator basis [28] with promising function approximation abilities [29] and thus, any analytical function might be approximated by orthogonal basis functions with very small approximation or modeling errors [20]. Some of the well-known orthogonal function sets are compared by the recurrence equation, completeness properties and the intervals of definitions in Table 1.

Table 1. Fundamental properties of some orthogonal basis function sets.

Basis Function Set	Completeness	Interval of Definition	Recurrence Equation
Fourier Series	No	[0,T]	No
Bessel Series	No	[0,1]	Yes
Legendre Pol.	Yes	[-1,1]	Yes
Chebyshev Pol.	Yes	[-1,1]	Yes

The orthogonality property of a polynomial function set $P(x) = [P_1(x)\ P_2(x) \dots\ P_M(x)]$ is defined by the inner product of functions as

$$\int_a^b P_i(x)P_j(x)dx = \begin{cases} 0 & \text{if } i \neq j \\ K_i & \text{if } i = j \end{cases} \tag{6}$$

where, $x \in [a,b] \in \mathcal{R}^n$ and M is the order of the polynomial. If K_i is a positively fixed constant and then the given polynomial basis function set is defined as orthogonal in $[a,b]$. In addition, if $K_i = 1$, then the given function set is defined as orthonormal. The universal approximation property of an orthogonal basis function sets are defined in the next theorem.

Theorem 1[29]: Any $f(x)$ function $f(.)\colon [a,b] \to \mathcal{R}$ can be approximated by utilizing $P(x)$ orthogonal basis function sets given as

$$f(x) = \sum_{i=1}^{M} \hat{\theta}_i P_i(x) + \varepsilon \tag{7}$$

where, ε is function approximation or modeling error, M is known as the number of polynomial basis functions, and $P_i(x)$ is the ith orthogonal basis function. The function approximation error,

$$\lim_{M\to\infty} \int_a^b \left(f(x) - \sum_{i=1}^{M} \hat{\theta}_i P_i(x)\right)^2 dx = 0 \tag{8}$$

converges to the zero with the enough number of the basis functions. The $\hat{\theta}_i$ are the weights or unknown parameters to be optimized. First-order Chebyshev polynomial functions are generated by the following recurrence equation $T_n(x) = 2xT_{n-1}(x) + T_{n-2}(x) \quad 0 < n \leq M$. Chebyshev polynomials have first four functions as $T_0(x) = 1$, $T_1(x) = x$, $T_2(x) = 2x^2 - 1$ and $T_3(x) = 4x^3 - 3x$. The given Chebyshev polynomials are constructed as odd and even function pairs [30,31]. These construct an orthogonal set in $[-1,1]$ with $1/\sqrt{1-x^2}$ weighting functions.

$$\int_{-1}^{1} \frac{T_i(x)T_j(x)}{\sqrt{1-x^2}} dx = \begin{cases} 0 & if\ i \neq j \\ \pi/2 & if\ i = j \neq 0 \\ \pi & if\ i = j = 0 \end{cases} \tag{9}$$

When the function parameters are not given in the orthogonality interval, normalization process is conducted on the inputs. Resultantly, the output of the Chebyshev network model (CNM) is formulized as

$$\hat{y} = \hat{\theta}^T \varphi(\mathrm{x}) \tag{10}$$

where, $\hat{\theta}$ are the weighting parameters of the orthogonal function set, $\varphi(\mathrm{x})$ is regressor vector of the Chebyshev polynomials defined as

$$\varphi(\mathrm{x}) = [1\ \mathrm{T_1(x_1)} \dots \mathrm{T_M(x_1)} \dots \mathrm{T_1(x_n)} \dots \mathrm{T_M(x_n)}]^{\mathrm{T}} \tag{11}$$

Where $x \in [\mathrm{a,b}] \in \mathcal{R}^n$, M is the number of Chebyshev polynomials and n is given as the number of the inputs.

2.4.1 Enhanced Chebyshev network

The conventional Chebyshev network is enhanced by using a feature-extraction layer as shown in Figure 1. The input data is passed through a weighting matrix which is a random parameter matrix and determined by well-known random-learning strategy. The random-learning strategy of parameters was already proposed and used for extreme learning machines [32] which is here adapted for feature extraction. The feature extraction matrix adds noise effect and provides regularization for tuning of robust parameters. Mathematically, the weighting matrix transforms the input data to an extended feature space where the features can easily be discriminated by a decision layer. Therefore, feature extraction matrix can also be considered as a distance matrix in metric learning [33]. In the design stage of feature extraction matrix, there is used a random assignment loop then for each assigned feature extraction matrix, the output parameters are optimized, and training performance is recorded. After many training steps, optimal output weighting parameters are recorded. These parameters are corresponding to the best training performance and used to obtain testing performance. By doing that the optimal parameters are to be tested via completely unknown data which is important for the generalization capability of the designed artificial model.

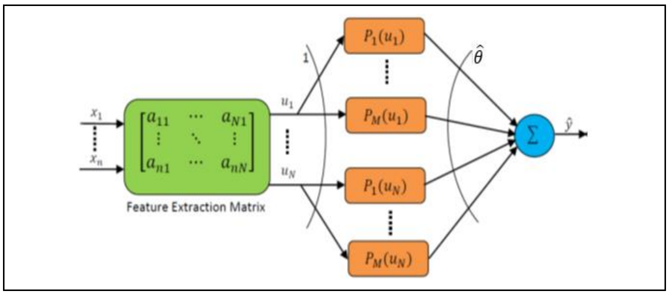


Figure 1. Enhanced Chebyshev network model.

3 Optimization and performance of the models

This section presents the optimization method and performance criteria of the polynomial models.

3.1 Parameter optimization

The designed regression models are here basically nonlinear models that perform a nonlinear static mapping. For a general regression function $\hat{y} = \hat{\theta}_w{}^T \varphi(\mathrm{x}, \hat{\theta}_i)$, the $\hat{\theta}_w$ and $\hat{\theta}_i$ are unknown parameters to be optimized. The $\hat{\theta}_0$ are the output weighting parameters and $\hat{\theta}_i$ are the internal parameters of the nonlinear functions. In this work, Levenberg-Marquardt optimization,

$$\hat{\theta} = (J^T J + \mu I)^{-1} J^T e \tag{12}$$

is used to optimize the unknown parameters using input-output training data. The J is the Jacobian matrix, I is the identity matrix, e is the batch regression error vector and $\mu > 0$ an adjustable parameter during optimization. The parameter optimization of the nonlinear polynomial models is achieved via Levenberg-Marquardt optimization using MATLAB software. However, the parameters of the distribution models are constructed by curve fitting function of MATLAB where there is used maximum likelihood estimation to estimate parameters.

3.2 Statistical analysis of modeling performance

To determine the quality of fit of the kinetic models, adjusted root mean squared errors (RMSE) values were computed as

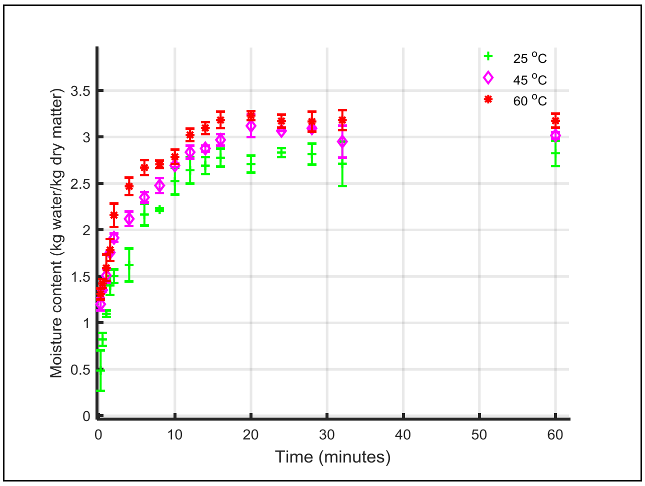
$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(M_{exp,i} - M_{pred,i})^2\right]^{1/2} \tag{13}$$

where, $M_{pred,i}$ is expressing the approximated moisture content, $M_{exp,i}$ expresses the experimental moisture content, N is the number of experimental input-output values. The best model describing the rehydration behavior was chosen as the one with the lowest RMSE [34]. In addition, some statistical information criterion can be used to assess the designed models to discuss the number of the parameters and the modeling performance. However, the number of the parameters are here used in limited number and so the designed models are not too large models to discuss such as deep neural networks. Therefore, the RMSE criterion is determined to discuss the performance of the models.

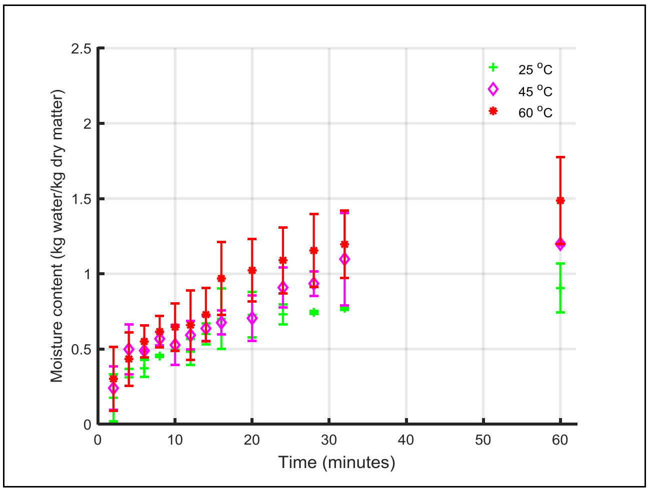
4 Computational results and discussions

4.1 Distribution models

Rehydration behavior of damson plums dried by vacuum drying and freeze drying methods were determined and the results are illustrated in Figure 2. It was observed that the rehydration curves of the samples obtained from both drying processes followed a similar trend, i.e., the amount of water absorbed increased with increasing time (Figure 2). However, the rapid initial water absorption period was continued by relatively slower rate in subsequent stages. Rehydration rate of the freeze-dried samples began to stabilize after almost 30 min Figure 2(a), while the rehydration rate of the vacuum-dried samples began to stabilize in approximately 360 min. Figure 2(b).



(a): Freeze-dried.



(b): Vacuum-dried.

Figure 2. Rehydration behavior of damson plums at different temperature values.

The high rate of rehydration in freeze-dried samples could be due to the numerous surface capillaries and intercellular spaces formed during freeze drying processing. Since the equilibrium was reached quickly due to the rapid filling of the free capillaries and cracks on the sample surface with water, the rehydration rate was stabilized in a short time and the sample regained a considerable percentage of its original moisture content. In vacuum-dried samples, moisture transfer was mostly realized by diffusion mechanism since capillaries and intercellular spaces were less than freeze-dried samples. The rate of hydration by diffusion depends on the difference between the saturated moisture content and the moisture content at a given hydration time, and this driving force decreases as the water absorption process progresses, thereby causing a reduced hydration rate [10]. In addition, the effect of temperature on rehydration was investigated and it was determined that the rate of rehydration increased at increasing temperatures (Figure 2). In different studies, it has been emphasized that the increase in water absorption rate is caused by the increasing water diffusion rate due to the increase in temperature [35].

In order to formulate rehydration kinetics of damson plums, experimental data were fitted to four empirical models and model coefficients and RMSE values were given in Table 2 and Table 3 for freeze dried and vacuum dried samples, respectively. Wiebull model was chosen as the best model for describing the rehydration behavior having the lowest RMSE values for all conditions (Table 2 and Table 3). Similarly, different studies are available in the literature showing that the Weibull model well describes the rehydration behavior in dried products [13, 17-19]. The rate constant k_1 found in the Peleg equation is related to the water absorption rate of the system, and $1/k_1$ is higher for the systems with faster initial rates. As seen in Table 2 and Table 3, k_1 shows the same trend for both freeze-dried and vacuum-dried samples, with the fastest initial rehydration rate at 60°C and the slowest rate at 20°C. It was determined that the value of the scale parameter of the Weibull model (β) decreased significantly when the rehydration temperature increased to 60°C, where temperature has no linear influence on the shape parameter α (Table 2 and Table 3).

Table 2. Kinetic model coefficients and RMSE values for freeze-dried samples.

Temperature/Model	25°C		45°C		60°C	
	Coefficients	RMSE	Coefficients	RMSE	Coefficients	RMSE
Weibull	α=0.641; β=3.706; M_e= 2.88; R^2= 0.988	0.1060	α=0.396; β=3.587; M_e= 3.414; R^2= 0.988	0.0976	α= 0.464; β= 1.913; M_e= 3.241; R^2= 0.983	0.1213
Peleg	k_1=0.722; k_2=0.347; M_e=2.975; R^2= 0.980	0.1309	k_1=0.345; k_2=0.337; M_e=3.058; R^2= 0.938	0.2183	k_1=0.281; k_2=0.326; M_e=3.162; R^2= 0.953	0.1944
First-order	K=0.338; M_e=2.697; R^2= 0.952	0.2024	K=0.666; M_e=2.844; R^2= 0.862	0.3269	K=0.745; M_e=2.976; R^2= 0.897	0.2877
Exponential association	H=0.372; M_e=2.680; R^2= 0.942	0.2233	H=0.726; M_e=2.833; R^2= 0.849	0.3420	H=0.796; M_e=2.969; R^2= 0.886	0.3033

Table 3. Kinetic model coefficients and RMSE values for vacuum-dried samples.

Temperature/Model	25°C		45°C		60°C	
	Coefficients	RMSE	Coefficients	RMSE	Coefficients	RMSE
Weibull	α=0.483; β=408.2; M_e=3.007; R^2= 0.976	0.0775	α=0.467; β=494.2; M_e=3.723; R^2= 0.985	0.0699	α= 0.5867; β= 46.92; M_e= 2.036; R^2= 0.970	0.0985
Peleg	k_1=20.18; k_2=0.566; M_e=1.809; R^2= 0.937	0.1215	k_1=16.82; k_2=0.481; M_e=2.123; R^2= 0.946	0.1301	k_1=10.76; k_2=0.5173; M_e=1.976; R^2= 0.967	0.0999
First-order	K=0.026; M_e=1.54 R^2= 0.884	0.1653	K=0.027; M_e=1.797 R^2= 0.900	0.1778	K=0.042; M_e=1.725 R^2= 0.938	0.1367
Exponential association	H=0.029; M_e=1.514 R^2= 0.869	0.1757	H=0.294; M_e=1.778 R^2= 0.887	0.1891	H=0.045; M_e=1.715 R^2= 0.931	0.1447

Table 4. RMSE performance values of the designed models on testing data.

Model/Case	Freeze 25 °C	Freeze 45 °C	Freeze 60 °C	Vacuum 25 °C	Vacuum 45 °C	Vacuum 60 °C
Chebyshev Network Model	0.1618 R^2=0.927	0.0521 R^2=0.914	0.0792 R^2=0.911	0.0460 R^2=0.813	0.0523 R^2=0.891	0.0495 R^2=0.851
Enhanced Chebyshev Network Model	0.0263 R^2=0.986	0.0261 R^2=0.981	0.0164 R^2=0.9344	0.0429 R^2=0.879	0.0320 R^2=0.964	0.0430 R^2=0.916

4.2 Chebyshev network modeling

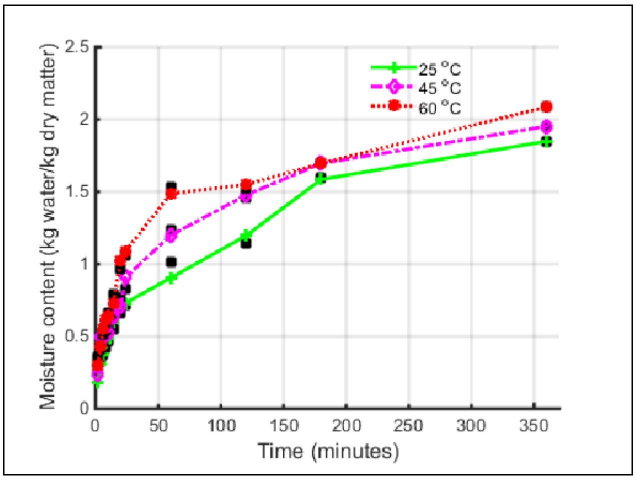
In order to evaluate the performance of the nonlinear mathematical models, the collected data is randomly split into two parts such as training and testing. 75% of the collected data is used for training, 25% of the collected data is used for testing. The training data is used to optimize the parameters of the models, but the testing data is used to evaluate the performance of the trained model. The idea behind performance measurement for the testing data is a possible usage of the designed model for the future implementations. Note that the optimized parameters are accepted to be the best parameters of the designed models using the training data. Therefore, the performance values for the training part are not counted as a general performance of the models. Instead, the performance values for the testing data which is not already used for the model construction can be accepted as an ultimate performance for the used data. Therefore, in the following results, training performances are plotted in the Figures, but their performance values are not tabled. Then, the training and testing error bar plots are shown. As an important result of the modeling process, RMSE values are given to discuss in Table 4 for the testing data. The obtained results are presented both for the modeling of rehydration kinetics of vacuum-dried and freeze-dried damson plums. Table 2, 3 and 4 show that enhanced Chebyshev network model was found to be the best performing model of the rehydration kinetics for the vacuum-dried and freeze-dried damson plums. To exemplify the designed feature extraction matrices, two of them are given as

$$F_1 = \begin{bmatrix} -0.0021 & 0.0008 \\ 0.0122 & -0.0068 \\ -0.0004 & 0.0011 \end{bmatrix} \quad V_1 = \begin{bmatrix} 0.645 & -0.2708 \\ -0.2138 & 0.0956 \\ 1.1318 & -0.5778 \end{bmatrix}$$

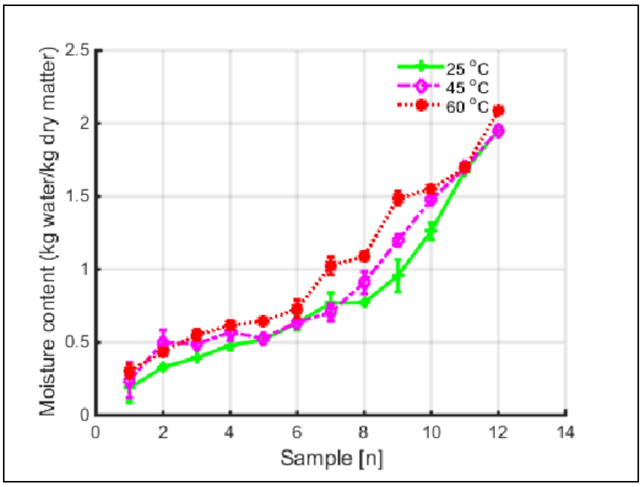
for freeze-dried (F_1) and vacuum-dried (V_1) at 25°C degrees, respectively.

Figure 3 shows the modeling results of rehydration kinetics for the vacuum-dried damson plums using enhanced Chebyshev network. Figure 3(a) shows the modeling results of the training part with randomly selected twelve data points according to their time values. It is seen that the training results are very good for all temperatures with small modeling errors. The error values of the training part are given in Figure 3(b) as sample values. When they are observed in detail, the training error vales are large for 25 °C and 60 °C experiments. In fact, it can be validated from Figure 3(a) since the rehydration values are not smooth for 25 °C and 60 °C experiments. However, the variations on the training data can support better training or learning of the model for the testing part which is seen in testing RMSE values of the enhanced Chebyshev polynomial model. There is obtained better RMSE values for 25°C and 60°C experiments. The corresponding testing errors are shown in Figure 3(c).

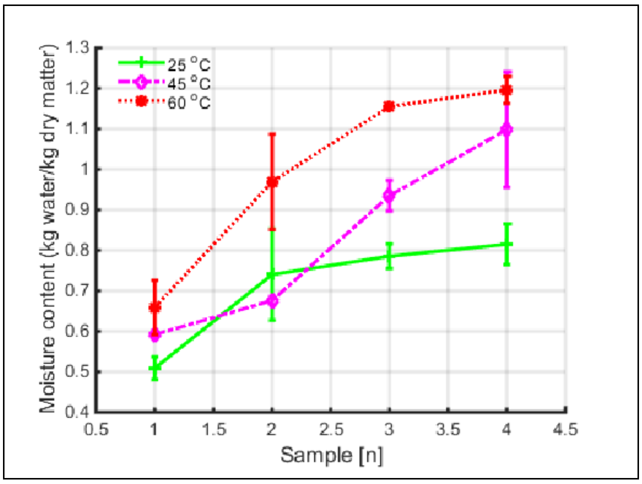
To compare the prediction performance of designed models, the freeze-dried damson plums with same random data indices are used for training and testing as in vacuum-dried samples. Then, there is obtained that the performance of a models is not permanent for all the temperatures. Therefore, by considering the sum of the performances for all temperatures, enhanced Chebyshev network model results are plotted for this experiment too. The modeling results, training errors and testing errors are shown in Figure 4, respectively.



(a): Modeling results for the training data.

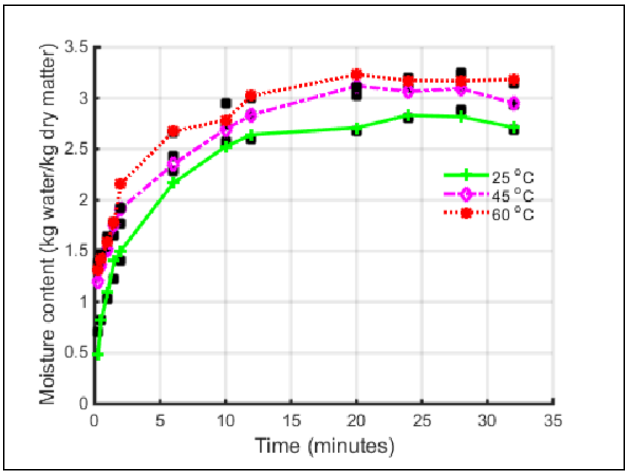


(b): Training errors (randomly selected twelve data points).

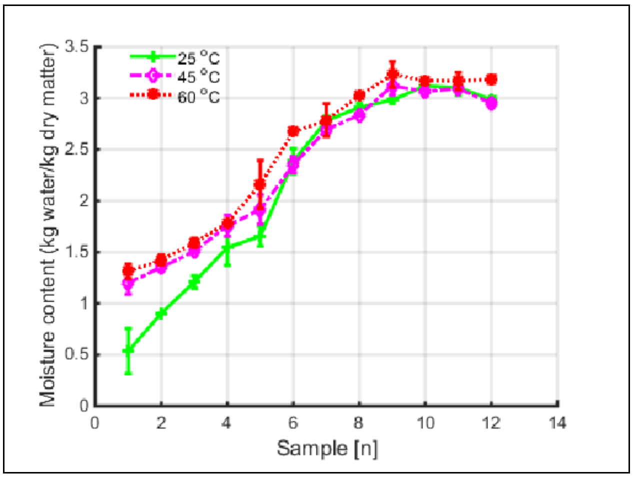


(c): Testing errors (randomly selected four data points).

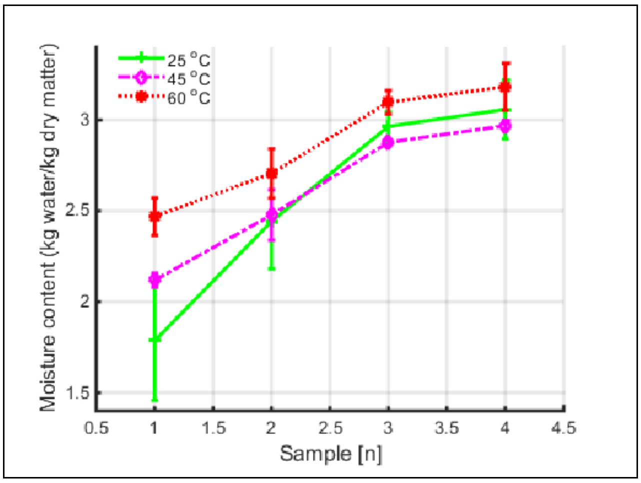
Figure 3. Modeling results of vacuum-dried damson plums using enhanced Chebyshev network.



(a): Modeling results for the training data.



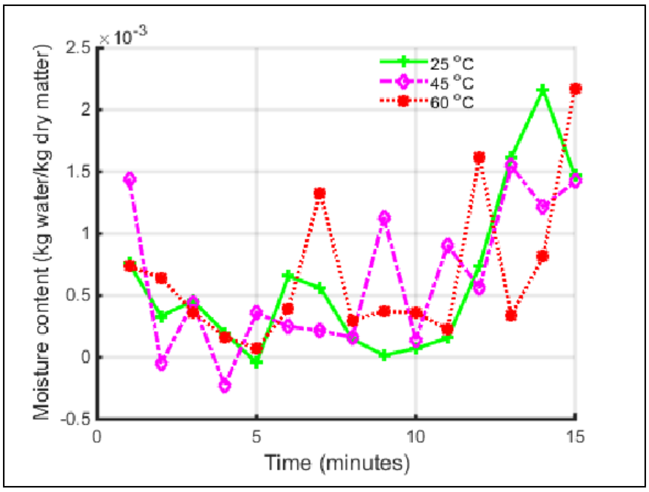
(b): Training errors (randomly selected twelve data points).



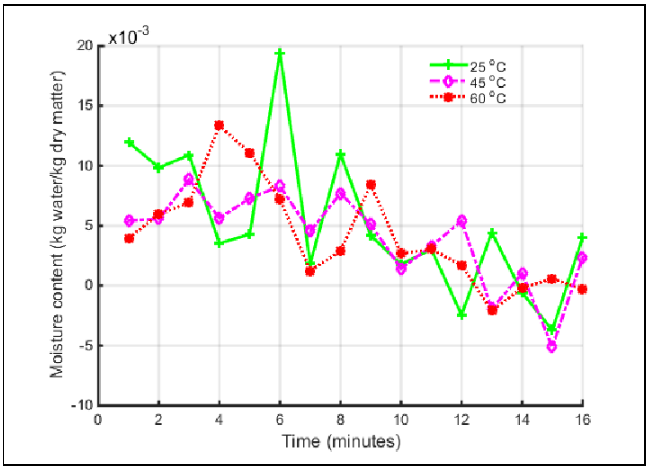
(c): Testing errors (randomly selected four data points).

Figure 4. Modeling results of freeze-dried damson plums using enhanced Chebyshev network model.

For the modeling of the rehydration kinetics for freeze-dried samples, the rehydration behavior is faster than the vacuum dried samples. To see that the rate of the rehydration for two drying conditions can be seen in Figure 5 by simply calculating $rate(t) = [y(t) - y(t-1)]/\Delta t$. However, there are obtained large RMSE vales at the 25 °C for all the models due to large change on the dynamics of the rehydration kinetics. In Figure 5(b) as well as the smooth change of the rehydration kinetics, this large change can be seen.



(a)



(b)

Figure 5. Rehydration rate of dried damson plums.
(a): Vacuum-dried. (b): Freeze-dried.

The RMSE value represents that the modeling error per each data point. Therefore, based on the RMSE performance values in Table 3 and Table 4, the percentage RMSE values are calculated by Eq. [14] and given in Table 5.

$$MSE\ \% \ = R\ \frac{\min(RMSE)}{\max(Data)} x100 \tag{14}$$

It is seen that percentage RMSE values are the best error percentages on each data point for the distribution and Chebyshev models. According to the Table 5, maximum and minimum percentage values are 2.32% and 0.51%, respectively for the Chebyshev networks, and the maximum and minimum percentage values are 4.79% and 3.13%, respectively for the distribution models. The Levenberg-Marquardt optimization-based Chebyshev models can represent the rehydration kinetics much better than the distribution models.

Table 5. Percentage RMSE (%) values at different temperatures.

Samples /Model	Chebyshev Models			Distribution Models		
	25 °C	45 °C	60 °C	25 °C	45 °C	60 °C
Vacuum-Dried	2.32	1.64	2.06	4.19	3.58	4.79
Freeze-Dried	0.93	0.84	0.51	3.74	3.13	3.75

5 Conclusion

This paper provided the modeling results of rehydration behavior of damson plums obtained by freeze drying and vacuum drying processes. The conventional kinetic models and Chebyshev network were employed to approximate the rehydration behavior at three different temperatures. The designed artificial models and featue extraction method were used to approximate the rehydration in training part and testing part of the data. Because of the rehydration process causes several changes in structure and composition of foods, it is necessary to optimize the rehydration conditions for each specific product. As a result, it was conducted that enhanced Chebyshev network was the most elegant model for modeling the rehydration behavior of the damson plums. The percentage RMSE values are acceptable for the future applications. In addition, its modeling performance is better than the conventional Chebyshev network and distribution models. It is thought that the experimental and modeling results of this study contribute the determining reconstitution properties of the damson plums also fruits having similar structure. Also, the obtained data can be used to optimize the drying conditions in the future to obtain the dried product with good rehydration properties.

5 Author contribution statement

In this paper, Hilal ISLEROGLU contributed to formation of the idea, conducting experiments, and examining the results; Selami BEYHAN contributed to the development of the artificial intelligence model, the development of software and the evaluation of the results.

6 Ethics committee approval and conflict of interest statement

There is no need to obtain an ethics committee approval for the article prepared. There is no conflict of interest with any person/institution in the article prepared.

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