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MODELING OF FREEZE DRYING BEHAVIORS OF STRAWBERRIES BY USING ARTIFICIAL NEURAL NETWORK

Tayfun MENLİK*, Volkan KIRMACI and Hüseyin USTA***
* Gazi University, Faculty of Technical Education, Mechanical Education Department, Teknikokullar, 06503 Ankara, Turkey
** Bartın University, Faculty of Engineering, Mechanical Engineering Department, 74100 Bartın, Turkey

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Abstract: The freeze drying process is based on different parameters, such as drying time, pressure, sample thickness, chamber temperature, sample temperature and relative humidity. Hence, the determination of the drying behaviors, such as *MC* and *MR*, of the freeze drying process are too complex. In this paper, to simplify this complex process, the use of artificial neural networks has been proposed. An artificial neural networks model has been developed for the prediction of drying behaviors, such as *MC* and *MR*, of strawberries in the freeze drying process. The back-propagation learning algorithm with variant which is Levenberg–Marquardt (LM) and Fermi transfer function have been used in the network. In addition, the statistical validity of the developed model has been determined by using the coefficient of determination (R^2), the root means square error (*RMSE*) and the mean absolute percentage error (*MAPE*). R^2, *RMSE* and *MAPE* have been determined for *MC* and *MR* as 0.999, 0.001924, 0.152284 and 0.999, 1.87E-05, 0.13393, respectively.
Keywords: Strawberry, Drying, Freeze drying, Modeling, ANN.

ÇİLEKLERIN DONDURARAK KURUTMA DAVRANIŞLARININ YAPAY SINIR AĞLARI KULLANILARAK MODELLENMESI

Özet: Dondurarak kurutma işlemi, kurutma süresi, basınç, ürün kalınlığı, kurutma odası sıcaklığı, ürün sıcaklığı ve bağıl nem gibi farklı parametrelere bağlıdır. *MC* ve *MR* gibi dondurarak kurutma davranışlarının belirlenmesi oldukça karmaşıktır. Bu çalışmada, bu karmaşıklığı gidermek için yapay sinir ağlarının kullanılması amaçlanmıştır. Dondurarak kurutma işleminde çileklerin *MC* ve *MR* gibi kurutma davranışlarının tahmin edilerek belirlenebilmesi için yapay sinir ağı modeli geliştirildi. Ağ modellinde geri besleme yayılımlı öğrenme algoritması, Levenberg–Marquardt (LM), ve Fermi transfer fonksiyonu kullanılmıştır. Ayrıca R^2, *RMSE* ve *MAPE* kullanılarak geliştirilen modelin doğruluğu belirlenmiştir. *MC* ve *MR* için R^2, *RMSE* ve *MAPE* sırasıyla, 0.999, 0.001924, 0.152284 ve 0.999, 1.87E-05, 0.13393 olarak belirlenmiştir.
Keywords: Çilek, Kurutma, Dondurarak kurutma, Modelleme, YSA.

NOMENCLATURE

CT	chamber temperature [^oC]
Dt	drying time [min]
M	moisture content [g water/g dry matter]
M_e	equilibrium moisture content [g water/g dry matter]
M_0	initial moisture content [g water/g dry matter]
MC_{db}	moisture contents (dry basis) [g water/g dry matter]
MR	moisture ratio [dimensionless]
MR_{exp}	experimental moisture ratio
MR_{ANN}	predicted moisture ratio
MAPE	mean absolute percentage error
N	number of observations
R^2	coefficient of determination
RMSE	root mean square error
P	pressure, mbar
RH	relative humidity fraction
ST	sample temperature [^oC]
Sth	sample thicknesses [mm]
T_C	chamber temperatures
T_S	sample temperatures
V_{min}	the minimum value in all the values for related variable
V_{max}	the maximum value in all the values for related variable

INTRODUCTION

The freeze drying process is a well-known and established technology for some time and a lot has been done regarding the research and development. Energy consumption, product quality and thermal and physical parameters during the drying process are some areas of interest (Claussen et al., 2007). Freeze drying, also known as lyophilization, is a separation process widely used in biotechnology, fine chemicals, food, and pharmaceutical industries (Liapis ve Bruttini, 1995; Liapis et al., 1996; Sadikoglu ve Liapis, 1997).

The drying time required for the freeze drying process is substantially long when compared with the conventional evaporative drying methods. The intensive energy requirement during freezing, primary and secondary drying steps along with labor and overhead costs make the freeze drying a very expensive separation process (Sadikoglu et al., 2006). Currently, freeze drying has become an important industrial process for drying of high-value products such as foodstuffs, pharmaceuticals, and so on (Marques ve Freire, 2005).

Few studies have been published on numerical solutions based on linear and nonlinear regression for the modeling of drying of strawberries (Kırmacı et al. 2008; Doymaz, 2008; Zhang et al., 2006; Kavak Akpinar ve Bicer, 2006). However, there is not any studying as yet which is based on artificial neural network (ANN) approach. ANNs are widely used in the energy systems and predicting the energy consumption (Sözen ve Arcaklıoğlu, 2007; Sözen et al., 2007; Sözen et al., 2008; Sözen et al., 2009).

Poonnoy et al. (2007) presented a ANN approach for predicting the temperature and the moisture content in tomato slices undergoing microwave-vacuum drying. Hussain and Rahman (2002) developed a model consisting of hybrid neural network including a polynomial–based regression model and a standard neural network for the prediction of porosity in eleven various fruits and vegetables. ANNs were used for rapid determination of the drying kinetics (k and n) used in Page equation in drying potato slices by Islam, Sablani and Mujumdar (Islam et al., 2003). Cubillos and Reyes (2003) also used ANN approach for modeling the drying of carrots.The progress of neurobiology has allowed researchers to build mathematical models of neurons to simulate neural behavior. ANN approach has become a well known way for evaluating the computation methods in last decades. ANN technique has also been adapted for a large number of applications in different scientific areas, such as the prediction of the energy consumption and the modeling of the energy systems (Doymaz, 2008; Zhang et al., 2006; Kavak Akpinar ve Bicer, 2006). In the field of drying, ANNs can be a good alternative to conventional empirical and semi-empirical modeling based on polynomial and linear regressions. The objective of this study is to develop and test an ANN model for determining the drying behaviors, such as moisture content and moisture ratio, of strawberry during the freeze drying process.

ARTIFICIAL NEURAL-NETWORKS

During the last 15 years there has been a substantial increase in the interest on ANNs. ANNs have been successfully employed in solving complex problems in the various fields as followings (Sözen ve Akçayol, 2004; Sözen ve Arcaklıoğlu, 2007; Sözen et al., 2008; Poonnoy et al., 2007);

- Function approximation
- Pattern association and pattern recognition
- Associative memories
- Generation of new meaningful pattern.

The ANNs are good for some tasks while lacking in some others. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. They can learn from experiments and are able to deal with nonlinear problems. Furthermore, they exhibit robustness and fault tolerance. The tasks that ANNs cannot handle effectively are those requiring high accuracy and precision, as in logic and arithmetic (Sharma et al., 1999; Sözen et al., 2007). Artificial Neural Network is a system loosely modeled on the human brain. A biological neuron is shown in Fig. 1. In a brain, there is a flow of coded information from the synapses towards the axon. The axon of each neuron transmits information to a number of other neurons. The neuron receives information at the synapses from a large number of other neurons (Yücesu et al., 2007).

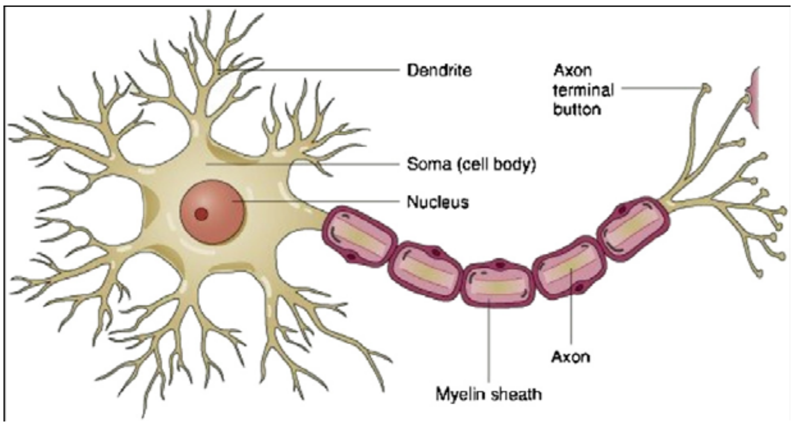

Figure 1. A simplified model of a biological neuron.

ANN has been developed as a generalization of mathematical models of human cognition and neural biology. In ANN, the available data set is partitioned into two parts, one corresponding to training and the other corresponding to validation of the model. The purpose of training is to determine the set of connection weights and nodal thresholds that cause the ANN to estimate outputs that are sufficiently close to target values. The weights and biases are assigned small random values initially. During training, these are adjusted based on the error or the difference between ANN output and target responses. This adjustment can be continued recursively until a weight space is found, which results in the smallest and overall prediction error. The performance of a trained ANN can be fairly evaluated by subjecting it to the new patterns that it has not seen during training. The performance of the network can be determined by computing the percentage error between predicted and desired values (Satish ve Setty, 2005).

The ANN consists of an input layer, an output layer and a number of hidden layers. At each node in a layer the information is received, stored, processed and communicated further to nodes in the next layer. All the weights are initialized to small random numeric values at the beginning of training. These weights are updated or modified iteratively using the generalized delta rule or steepest-gradient descent principle. There are different learning algorithms. A popular algorithm is the back propagation algorithm, which has different variants. Back-propagation training algorithms that employ gradient descent and gradient descent with momentum are often too slow for practical problems because they require small learning rates for stable learning. In addition, success in the algorithms depends on the user dependent parameters learning rate and the momentum constant. An ANN with a back-propagation algorithm learns by changing the weights and these changes are stored as knowledge (Jang et al., 1997). The prediction performance of the developed ANN model is determined by using different error analysis method. In general, these methods are the coefficient of determination (R^2), the root means square error (RMSE) and the mean absolute percentage error (MAPE). The higher values of the R^2, the lowest values of the RMSE and the MAPE are indications of better performance of the developed ANN model. These parameters can be calculated as follows:

$$R^2 = 1 - \left[\frac{\Sigma\left(MR_{exp,i} - MR_{ANN,i}\right)^2}{\Sigma\left(MR_{ANN}\right)^2} \right] \tag{1}$$

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

$$MAPE = \frac{MR_{ANN} - MR_{exp}}{MR_{ANN}} * 100 \tag{3}$$

Input and output layers are normalized in the (-1, 1) or (0, 1) range.

$$V_N = \frac{V_R - V_{min}}{V_{max} - V_{min}} \tag{4}$$

where, V_R is the actual value, V_{min} and V_{max} are the minimum and the maximum values in the data set, respectively.

EXPERIMENTAL SET-UP

A freeze drying experimental set-up (FDES) shown in Fig. 2 has been used in the experiments from which data were obtained. FDES consists mainly of a drying chamber, a condensing unit, a vacuum pump, a weighing system and the measurement equipments (Kırmacı, 2008). The description of the equipment used in measurement system is given Table 1.

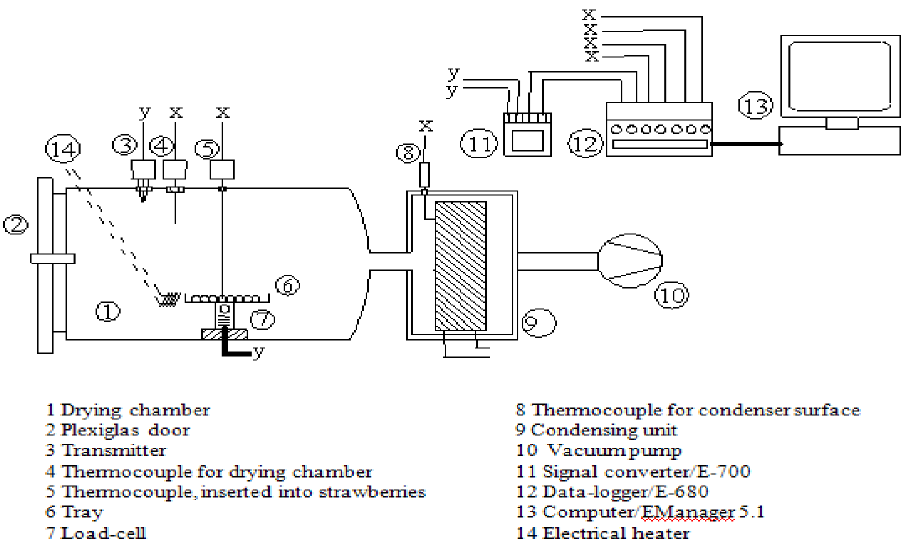

Figure 2. Experimental set-up of the freeze drying.

Table 1. Description of measurement and control equipments.

Equipment		Properties	Accuracy
Temperature sensor	Elimko	Input Pt-100 R/T Type, Scale -70 +100 ^{0}C, Feed 24 V-DC Output 4-20mA	±0.002 ^{0}C
Temperature sensor		J Type	±0.1 ^{0}C
Data-logger	E-680/Elimko	A/D Conversion 16 bit, D/A Conversion 12 bit, Input Scan Time 0.2–9.9 Seconds/channel, Display Scan Time 2–9.9 Seconds/channel, Input Types T/C, R/T, mA, mV, V	Class 0.5
Load-cell		Capacity 1000 g	0.01 g
Converter	E-700/Elimko	Output Signal 0–20 mA, 4–20 mA, Output Resolution For 0–20 mA 1/4000,	Class 0.5 (0.2 for linear outputs)
Pressure Transmitters		Range: 1x10^{-3} mbar~ 2x10^{-3} mbar, Feed: 10.5 - 42 V-DC, Output: 4 – 20 mA.	±0.075 %
Humidity &Temperature Transmitter	E-RHT-10 Elimko	*Humidity* Range 0-100 % RH Response Time 4 sec. Reproducibility ± 0.1 % RH	± 2 %
		Temperature Range -40 ÷ 120 ºC Response Time 30 sec. Reproducibility ± 0.1 ºC	± 1 %

The drying chamber is a cylindrical enclosure with a Plexiglas door (transparent) permitting visual observation of the strawberries during the freeze drying. Condensing unit protecting the vacuum pump against the humidity coming from samples is a vapor compression refrigeration system. The vacuum in the drying chamber has been achieved by hybrid vacuum pump with 2x10^{-3} mbar pressure, 5.6 m^3/h pumping flow rate and 0.37 kW power. The temperatures have been measured by different type of thermocouples. The thermocouples have been connected to a data-logger and to a personal computer to record the temperatures continuously. The weight loss of the samples has been followed by a load-cell located in the center of the the drying chamber. The pressure variations of the drying chamber have been measured by pressure transmitters.

The outputs of the load-cell and the transmitter have been connected to a signal converter, then to a data-logger and to a personal computer to record continuously the chamber pressure and the weight loss of the sample data using a software, EManager 5.1/ELİMKO. The heating which is necessary for sublimation has been provided by a 1 kW-electrical heater placed at a 4 cm-distance from the side of a sample tray. A stainless steel (0.5 mm of thickness and bore diameter of 9 mm) sample tray with dimensions of 200x200 mm has been placed onto the load-cell. Initially, fresh strawberries have been obtained from the market. After elimination of unripe and rotten fruits, part of the strawberries has been cut into 5 mm and 7 mm thick slices. The sliced strawberries have been dried in an oven at 70 ± 3 °C. During the drying period, weight measurement has been made once every half an hour. At the end of two consecutive attempts, the absolute dry weight has been considered to be achieved with the condition that the weight changed less than 1%. Initial moisture contents (dry basis) of the strawberries have been calculated with the following equation. (Kırmacı, 2008).

$$MC_{db} = \frac{M_i - M_d}{M_d} \quad (5)$$

Then, sliced strawberries have been frozen at -30 °C in a deep-freezer (UĞUR deep-freezer, UDD 300-BK). Then, 5 mm thick sliced frozen samples have been placed on sample tray in drying chamber. After this, drying chamber has been vacuumed rapidly from 920 mbar to 7 mbar in 30 s and the decrease in the pressure continued during the process.

Drying of strawberry samples started with an initial moisture content of around 91 % (db) and continued drying until no further changes in their mass have been observed, e.g. to the final moisture content of about 9 % (db) in the drying chamber. The mass variations of the samples in the drying chamber have been measured at intervals of 30 min. All procedure described above has been repeated for 7 mm thick sliced samples. The experiments have been replicated three times and the average of the moisture content values that found at each test has been used. The drying data from the drying tests have been then used for determining the moisture ratio (MR) by Eq. (6) (Kırmacı, 2008).

$$MR = \frac{M - M_e}{M_o - M_e} \quad (6)$$

APPLICATION OF ANN

Freeze drying is a complex and a difficult process when compared to the conventional evaporative drying methods. Because the drying behaviors, such as moisture content and moisture ratio, of the product in the freeze-drying process are based on more parameters, and also the determination of the drying behaviors are complex. The drying behaviors, *MC* and *MR*, depend on drying time, pressure, sample thickness, chamber temperature, sample temperature and relative humidity in the freeze-drying process. The values of these parameters have been obtained from the experiments and used to train the network. Inputs for network are drying time (Dt), pressure (P), sample thicknesses (Sth), chamber temperature (CT), sample temperatures (ST) and relative humidity (RH), and the outputs are moisture ratio (MR) and moisture content (MC). There are 376 received patterns from the experiments. All patterns have not been used in training the ANN. Some of them have been excluded at the training stage and have been used in the test. Some of the sample patterns used for training the network are shown in Table 2.

Table 2. Some of the experimental samples for input and output data.

***Dt* (min)**	***P* (mbar)**	***Sth* (mm)**	***CT* (°C)**	***ST* (°C)**	***RH***	***MR***	***MC***
30	7	5	22	-21.2	22	0.887854	9.259048
60	7	5	22.1	-18.1	22	0.770228	8.032381
120	8	5	21.6	-12.3	23	0.578082	6.028571
210	8	5	22.6	-7.1	22	0.350868	3.659048
240	7	5	23.2	-5.4	21	0.285479	2.977143
300	7	5	23.5	-1.1	20	0.173699	1.811429
330	7	5	23.8	3.9	18	0.135708	1.415238
450	7	5	28.2	22.8	12	0.0579	0.60381
480	11	5	27.5	25.9	11	0.041461	0.432381
540	7	5	28.7	29.6	9	0.011689	0.121905
60	6	7	22.3	-13.9	22	0.847695	8.676966
90	6	7	22.3	-12.5	22	0.77854	7.969101
150	6	7	22.1	-9.4	21	0.612102	6.265449
210	6	7	25.1	-6.2	20	0.464599	4.755618
360	6	7	26.6	8.3	18	0.24506	2.508427
390	6	7	26.6	10.9	18	0.212267	2.172753
480	5	7	28.4	22	15	0.105379	1.078652
510	5	7	28.5	23.9	14	0.070801	0.724719
540	18	7	30.1	27.4	14	0.05461	0.558989
570	5	7	30.1	28	10	0.042536	0.435393
600	5	7	30.2	28.8	9	0.024698	0.252809
690	6	7	30.4	30	9	0.01331	0.136236
720	5	7	30.4	30	9	0.010977	0.11236

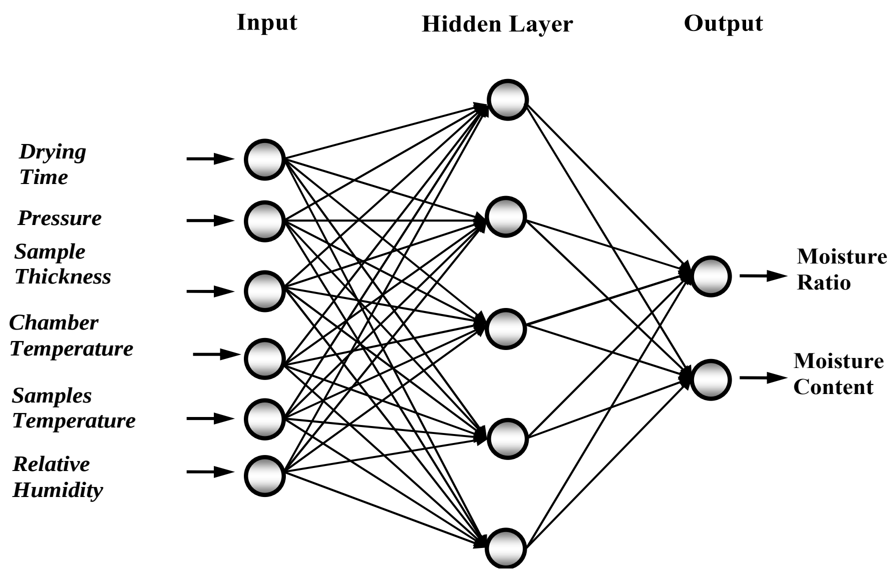

Figure 3. Selected ANN structure with one hidden layer with five neurons.

The back-propagation learning algorithm has been used in feed-forward work with single hidden layer having five neurons. Variant of the algorithm used in the study is Levenberg–Marquardt (LM). LM method is in fact an approximation of the Newton's method. The selected ANN structure with one hidden layer having five neurons is shown in Fig. 3.The FERMI transfer function has been used.

The said transfer function used is:

$$F(z) = \frac{1}{1+e^{-4(z-0.5)}} \quad (7)$$

where z is the weighted sum of the input.

ANN has been modeled by ''Pithiya" computer software. In the training, we used five neurons in single hidden layer to define the output accurately. When the network training was successfully completed, the network was compared with test data which was excluded at the training stage.

For MC and MR, the new formula of the outputs as the algorithm LM with 5 neurons is given in Eq. 8 and Eq. 9. Eq. 8 and Eq. 9 can be used to the prediction of the drying behaviors, MC and MR respectively, of the strawberries in the freeze-drying process, where drying parameters are known.

$$f_{MC} = \frac{1}{1+e^{-4*(2.486126*F_1+2.447821*F_2+1.369536*F_3-1.754223*F_4+0,613741*F_5-0.5)}} \quad (8)$$

$$f_{MR} = \frac{1}{1+e^{-4*(2.475604*F_1+2.439838*F_2+1.46377*F_3-1.743172*F_4+0,616945*F_5-0.5)}} \quad (9)$$

In Eqs. F_1, F_2, F_3, F_4 and F_5 are calculated according to Eq. 10.

$$f_i = \frac{1}{1+e^{-4*(E_i-0.5)}} \quad (10)$$

where E_1, E_2, E_3, E_4 and E_5 are defined in Eq. 11. The drying parameters are used in this Eq. Thus, Eq. 8 and Eq. 9 are dependent upon the drying parameters of strawberries in freeze-drying process as seen in Eq. 11.

$$\begin{aligned} E_i &= C_{1i} * \mathrm{Dt} + C_{2i} * \mathrm{P} + C_{3i} * \mathrm{Sth} \\ &+ C_{4i} * \mathrm{CT} + C_{5i} * \mathrm{ST} + C_{6i} * \mathrm{RH} \end{aligned} \quad (11)$$

The list of the constants used in Eq. 11 are given in Table 3

Table 3. Constants used in Eq. 11 from LM algorithm with 5 neurons.

i	Constants					
	C_{1i}	C_{2i}	C_{3i}	C_{4i}	C_{5i}	C_{6i}
1	-0.10614	-1.43658	-0.15363	0.389487	-0.10009	0.244947
2	-1.33065	-1.7689	1.338695	0.534378	1.001098	-1.79272
3	-0.93947	0.864681	0.285122	0.169074	0.357673	-2.61356
4	1.823256	-0.1978	-0.40132	-0.49219	-0.18877	-0.39804
5	-0.80843	0.748596	-3.41779	0.628079	-0.90633	1.939439

Inputs and outputs are normalized in the (0, 1) range by using Eq. 4. The V_{min} and V_{max} values for normalization are given in Table 4.

Table 4. Values for normalization.

Parameters	V_{min}	V_{max}
Sample thickness	5	7
Pressure	5	18
Chamber temperature	21.6	32
Sample temperature	-28.3	32
Drying time	0	780
MC/MR	0.00968037	1

RESULTS AND DISCUSSION

In this paper, a model has been developed by using ANN with 5 neurons in the one hidden layer for the prediction of drying behaviors, such as MC and MR. In the developed model, Mc and MR have been used for outputs and Dt, P, Sth, TC, ST and RH have been used for inputs.

The performance of the ANN model for MC and MR are shown in Figs. 4–7 and Figs. 8–11. For both parameters, the statistical values, such as R^2, $RMSE$ and $MAPE$, of training, are given in Table 5.

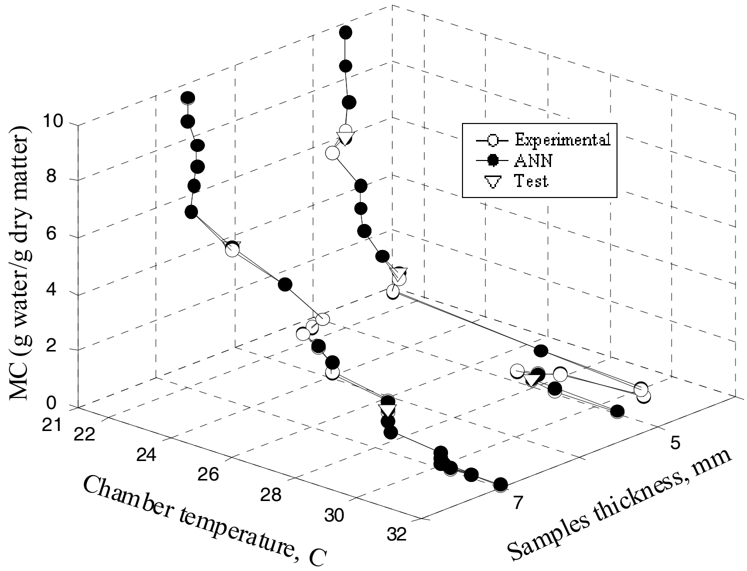

Figure 4. The variation of MC with sample thickness and chamber temperature.

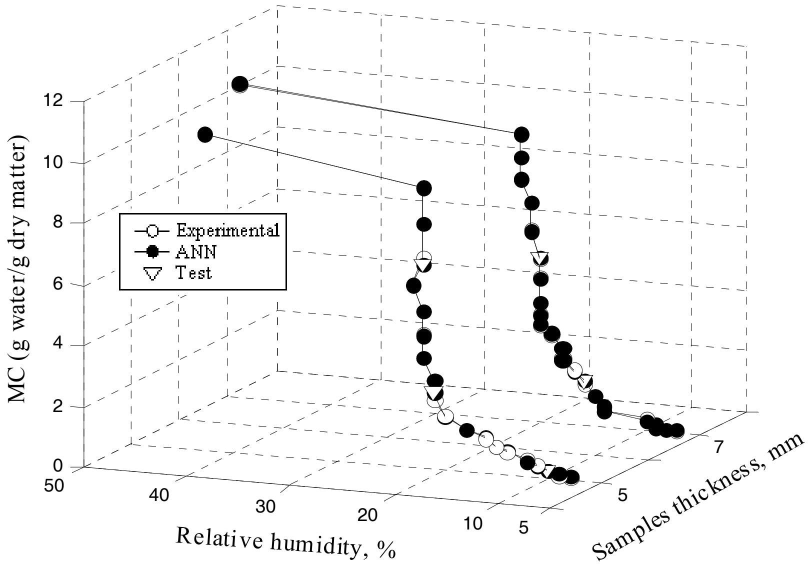

Figure 5. The variation of MC with sample thickness and relative humidity.

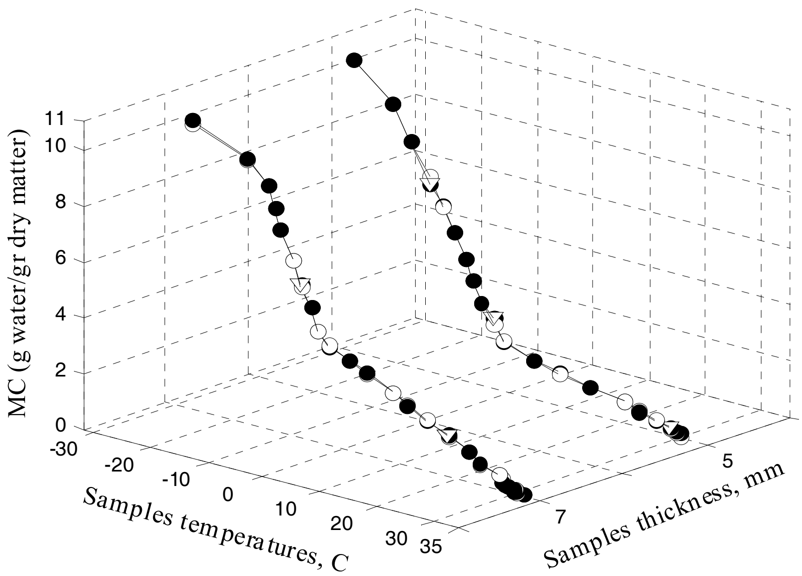

Figure 6. The variation of MC with sample thickness and samples temperature.

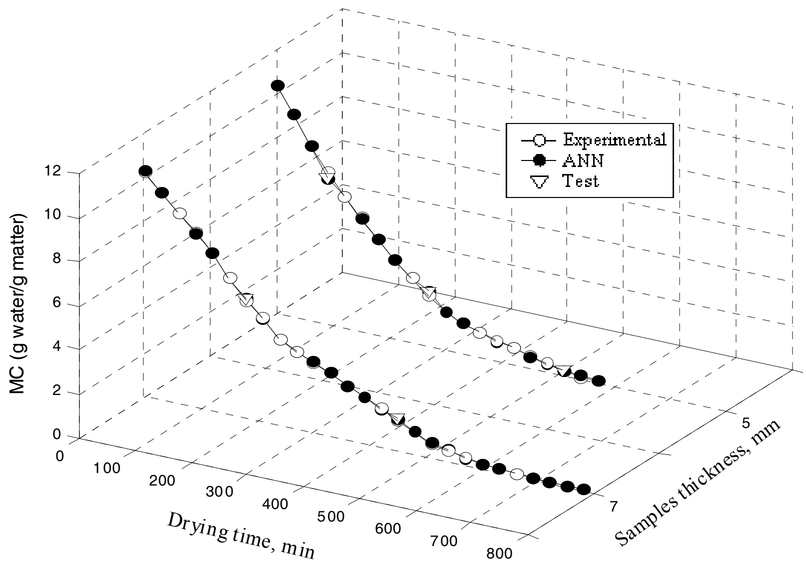

Figure 7. The variation of MC with sample thickness and drying time.

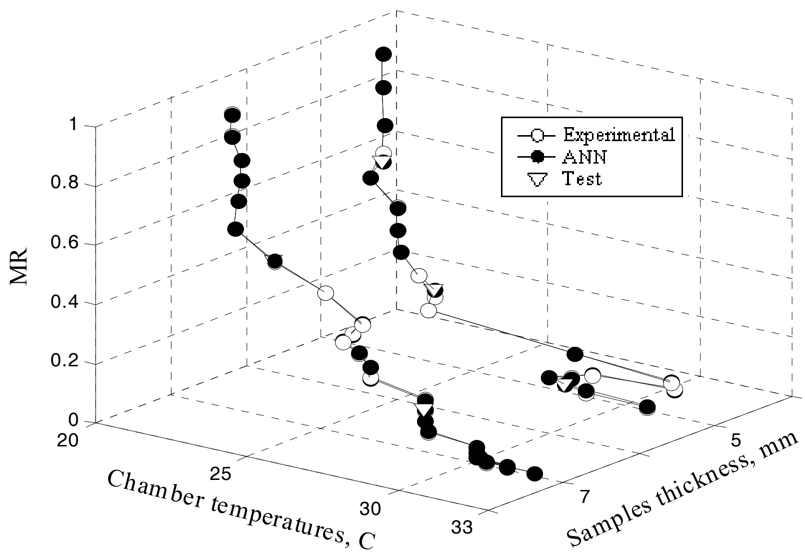

Figure 8. The variation of MR with sample thickness and chamber temperature.

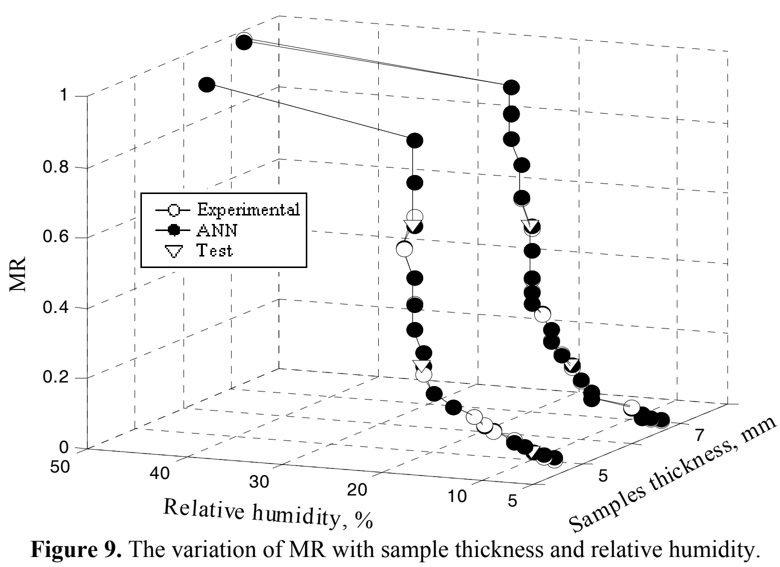

Figure 9. The variation of MR with sample thickness and relative humidity.

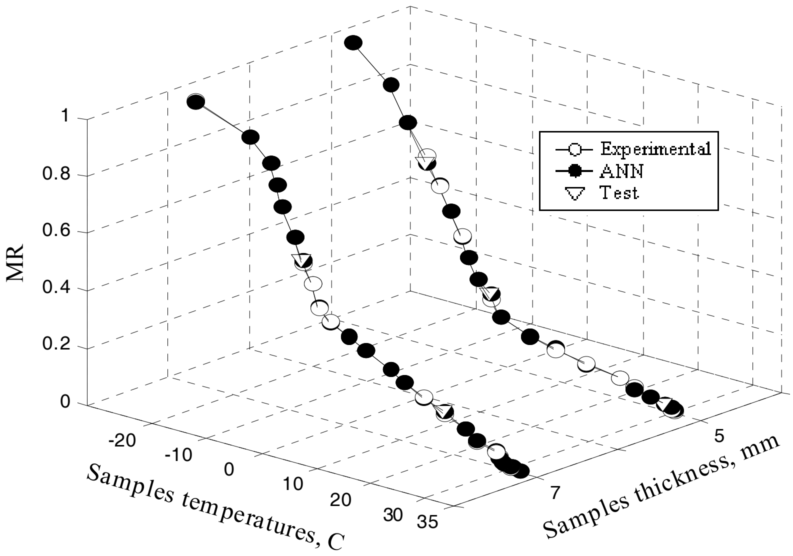

Figure 10. The variation of MR with sample thickness and samples temperature.

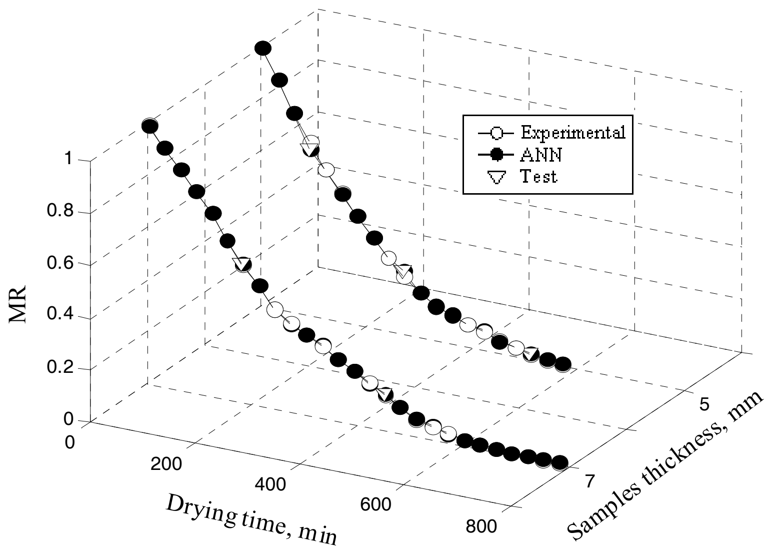

Figure 11. The variation of MR with sample thickness and drying time.

Table 5. Statistical values of MC and MR.

	R^2	*RMSE*	*MAPE*
MC	0.999	0.001924	0.152284
MR	0.999	1.87E-05	0.13393

For *MC* and *MR*, the coefficient of determination (R^2), the root means square error (*RMSE*) and the mean absolute percentage error (*MAPE*) are 0.999, 0.001924, 0.152284 and 0.999, 1.87E-05, 0.13393, respectively. Figs. 4-11 show the ability of the model to the prediction of the drying behaviors of the strawberries at the different parameters. The predicted *MC* and *MR* data are very close to the experimental data for all parameters. The performance of the ANN model for the prediction of the drying behaviors of the strawberries is shown in Fig. 12.

Deviations between the experimental data and the data obtained from ANN in both testing and training are very small and negligible. As shown and seen from the Figs., the developed model can be used for the prediction of the freeze drying behaviors of the strawberries. From the statistical test results and correlation, it is understood that our developed model has been successful in the predicting *MC* and *MR* of the drying strawberries.

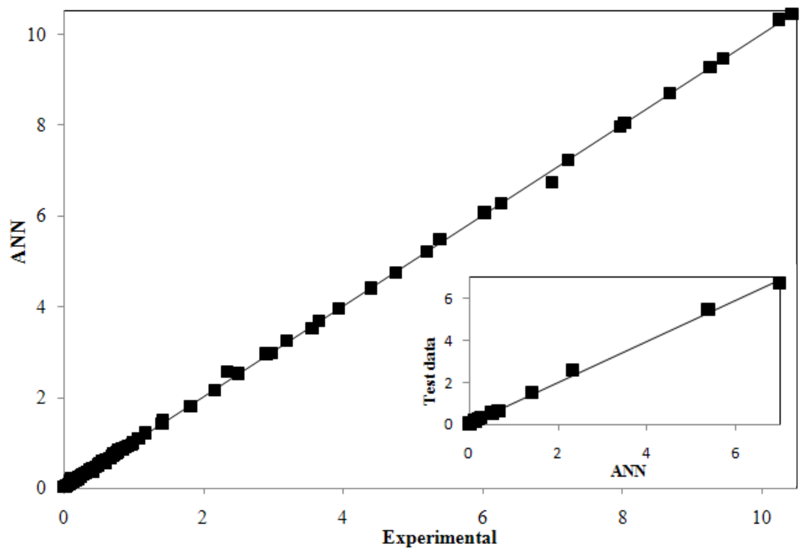

Figure 12. Comparison of the experimental data and the results obtained from developed ANN model for algorithm LM with five neurons in the single hidden layer.

CONCLUSIONS

In this study, an ANN model has been developed and tested and, the validation of it has been analyzed statically. The results indicate that the developed model is more suitable. This study confirms the ability of the developed ANN model to the prediction of the drying behaviors of strawberries in the freeze drying process based on different parameters. In addition, this study can especially be considered to be helpful in predicting the drying behaviors of strawberries in the freeze drying process.

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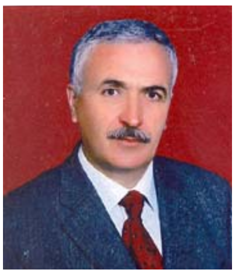
Tayfun MENLİK, 1974 yılında İstanbul'da doğmuştur. İlk ve orta öğrenimini İstanbul'da, yüksek öğrenimini Gazi Üniversitesi Teknik Eğitim Fakültesi Makina Eğitimi Bölümü Tesisat Eğitimi Anabilim Dalında tamamlamıştır. 1996-1997 M.E.B.'da öğretmen, 1997-2002 Gazi Üniversitesi Teknik Eğitim Fakültesi Makina Eğitimi Bölümü Tesisat Eğitimi Ana Bilim Dalında Araştırma Görevlisi, 2002-2007 aynı fakültede öğretim görevlisi olarak görev yapmıştır. Halen Gazi Üniversitesi Teknik Eğitim Fakültesi Makina Eğitimi Bölümü Tesisat Eğitimi Ana Bilim Dalında öğretim üyesi olarak görev yapmaktadır. Evli bir çocuk babasıdır.

Volkan KIRMACI, 1978 yılında İzmir'de doğmuştur. İlk ve orta öğrenimini İzmir'de, yüksek öğrenimini Gazi Üniversitesi Teknik Eğitim Fakültesi Makina Eğitimi Bölümü Tesisat Eğitimi Anabilim Dalında tamamlamıştır. 2000 yılında, Gazi Üniversitesi Teknik Eğitim Fakültesi Makina Eğitimi Bölümü Tesisat Eğitimi Ana Bilim Dalında Araştırma Görevlisi olarak göreve başlamış olup halen aynı göreve devam etmektedir. Yüksek Lisans eğitimini, 2002 yılında, Gazi Üniversitesi Fen Bilimleri Enstitüsü Makina Eğitimi Ana Bilim Dalında tamamlamıştır. 2008 yılında, Gazi Üniversitesi Fen Bilimleri Enstitüsü Makine Eğitimi Ana Bilim Dalında Doktora programına tamamlamıştır. (vkirmaci@gazi.edu.tr)



Hüseyin usta 1954 Ankara –Beypazarı- Karaşar doğumludur. Gazi Üniversitesi Teknik Eğitim Fakültesi (1976) ve Mühendislik Fakültesi (1982) mezunudur. 1991 yılında İngiltere'de 10 ay süreyle yabancı dil eğitimi almıştır. 1976 - 1986 yılları arası M.E.B.'de öğretmenlik yapmıştır. 1986 yılında Gazi Üniversitesi Teknik Eğitim Fakültesi'nde öğretim görevlisi olarak göreve başlamıştır. Halen ayni fakültede öğretim üyesi olarak görev yapmaktadır. Evli ve üç kız babasıdır.