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Comparison of Regression Analysis and Artificial Neural Networks in Predicting Carrot Drying Kinetics

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Abstract: *In this study, the single layer drying kinetics of carrots were investigated for different drying conditions and different sample thicknesses. Drying curves were obtained using drying data. Four different drying models found in the literature were applied to the system in order to express the drying kinetics. Comparison of the models was made by finding r, r^2, χ2, and SSR values. In addition, artificial neural network models were applied to estimate the moisture content and compared with the selected models. Artificial neural networks gave the highest r and r^2 and the lowest χ2, and SSR values compared to the other four models. Accordingly, artificial neural networks gave the best result with a very high accuracy in estimating carrot drying kinetic.*
Keywords*: Carrot drying, artificial neural networks, mathematical modeling.*

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I. INTRODUCTION

Carrots are widely used in human nutrition as fresh and dried. When carrots containing 80-90% moisture are dried, their volume decreases fivefold, while their storage life can be extended considerably. Carrots processed and dried in this way are used in powdered soups and condiments.

Dried carrots are used in dehydrated soups and in the form of powder in pastries and sauces. Since a fresh carrot has a water content close to 80–90% (Prakasha, Jhab, & Datta, 2004) its volume is reduced fivefold and its shelf life extended significantly when it is dried. These advantages make dried carrots an easy product to transport and store. Several studies have been conducted related to carrot drying. Prakasha et al. (2004) investigated the drying characteristics of carrots using a solar cabinet drier, fluidized bed drier, and microwave oven drier. Cui, Xu, and Sun (2004) studied the kinetics of microwave–vacuum drying of thin layer carrot slices by introducing a theoretical model. Litvin, Mannheim, and Miltz (1998) dried carrot slices by combining freeze drying with a short microwave treatment and air or vacuum drying.

Tein, Lin, Durance, and Scaman (1998) addressed a comparison study between vacuum microwave drying of carrot slices and air drying and freeze drying on the basis of rehydration potential, color, density, nutritional value, and textural properties. Doymaz (2004) investigated the effects of air temperature, air-flow rate and sample thickness on drying kinetics of carrot cubes.

Drying behavior of different materials has been proposed in the literature by various researchers on both theoretical and application grounds during the past 60 years. There have been many studies for modeling of drying behavior and determining the drying kinetics of various vegetables and fruits such as onion (Sarsavadia, Sawhney, Pangavhane, & Singh, 1999), grape (Dincer, 1996), potato (Diamante & Munro, 1993), pistachio (Midilli, 2001), kiwifruits (Maskan, 2001), red pepper (Akpinar, Bicer, & Yildiz, 2003), rosehip (Erenturk, Gulaboglu, & Gultekin, 2004a, 2004b) and Echinacea roots (Erenturk, Erenturk, & Tabil, 2004).

Dynamic modeling of the drying characteristics of agricultural products, using artificial intelligence methods including genetic algorithms and neural networks has gained momentum, because learning ability of the neural network is suitable for identifying plant and fruit responses, which are complex processes to which mathematical approaches are not easily applied.

Studies to identify nonlinear and difficult-to-define system behavior with aid of neural networks were conducted on grain drying by Farkas, Reme´nyi, and Biro´ (2000a, 2000b) Trelea, Courtois, and Trystram (1997). Kaminski, Strumillo, and Tomczak (1998) also used an artificial neural network for modeling of moisture content and quality index for vitamin C in sliced potatoes and green peas.

The aim of this study is to examine the effect of parameters on carrot drying and to apply regression analysis methods to express drying kinetics using the obtained data, as well as to estimate moisture content using artificial neural networks and to compare the results obtained from analysis methods and artificial neural networks.

II. MATERIAL AND METHOD

The drying of carrots was carried out in a convective type dryer. Drying experiments were carried out at four different drying air temperatures of 60-70-80-90ºC, three different air velocities of 0.5-1.0-1.5 m/s, and also at three different material thicknesses of 0.5-1 cm. During the experiments, weight reductions were determined as a function of time. Then, moisture contents were calculated using these data, converted to dimensionless moisture content (MR) and time (MR) graphs were drawn for different parameters.

In order to express the drying kinetics, 4 mathematical models (Newton, Page, Modified Page, Henderson and Pabis) found in the literature were applied to the experimental data. Comparison of the models was made by finding r^2, r, $\chi 2$, and SSR values. In addition, a forward artificial neural network working independently of the models was used to estimate the moisture content of carrots. Many network configurations were tried and the 4-25-1 structure was selected because it gave the least error. The selected artificial neural network structure is given in Figure 1.

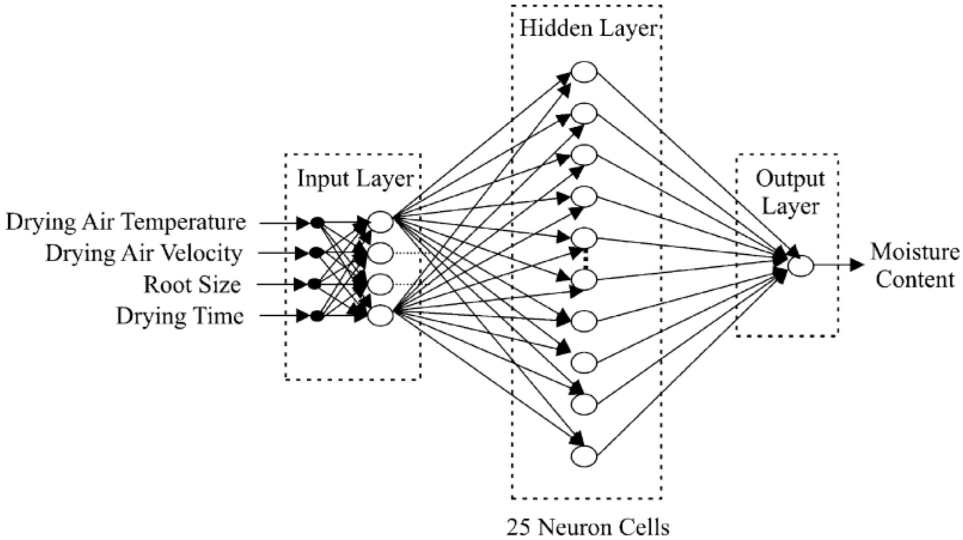

Fig. 1. Selected neural network structure.

Backpropagation algorithm was used in learning and testing the network. MATLAB computer program was used to solve this algorithm.

III. RESULTS AND DISCUSSION

The effects of material thickness, air temperature, and air speed on carrot drying are given in Figure 2, Figure 3, and Figure 4. Table 1 shows the statistical results of the regression and artificial neural network models applied to the drying curves obtained experimentally. According to Table 1, although the Modified Page equation gave the highest r and r^2 and the lowest $\chi 2$ and SSR values among the regression models tested, it was determined that the applied artificial neural network model gave higher r^2 and r, and lower $\chi 2$ and SSR values than the regression models. As a result, the artificial neural network gave better results than the regression methods in estimating the moisture content of carrots.

Table 1. Statistical results of the mathematical models and the neural network model proposed

Model Name	Equation	r	r^2	$\chi 2$	SSR
Newton	$MR = \exp(-kt)$	0.9892	0.9785	2.45E-3	2.644
Page	$MR = \exp(-kt^n)$	0.9966	0.9932	2.61E-3	2.815
Modified Page	$MR = \exp(-(kt)^n)$	0.9985	0.9971	2.52E-3	2.725
Henderson &Pabis	$MR = a.\exp(-kt)$	0.9876	0.9753	2.90E-3	3.132
ANN		0.9999	0.9998	1.89E-5	2.039E-3

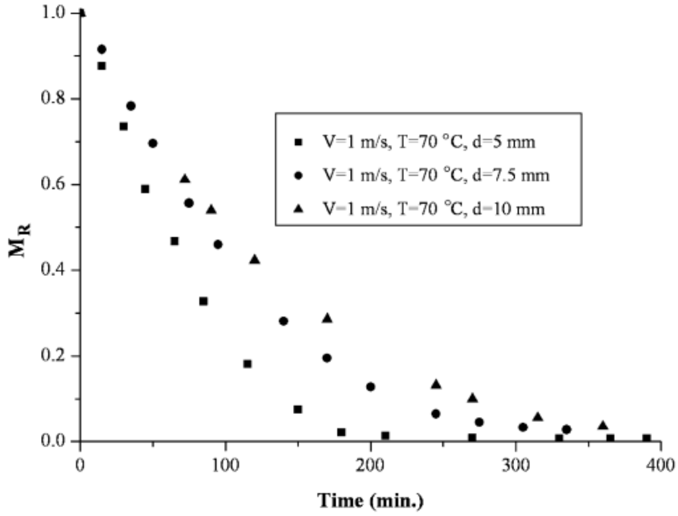

Fig. 2. Effect of thickness on drying time.

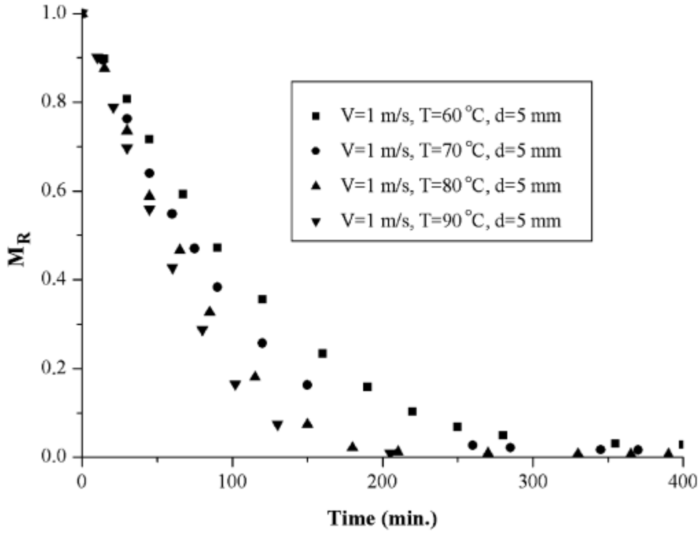

Fig. 3. Relationship between air temperature and drying time.

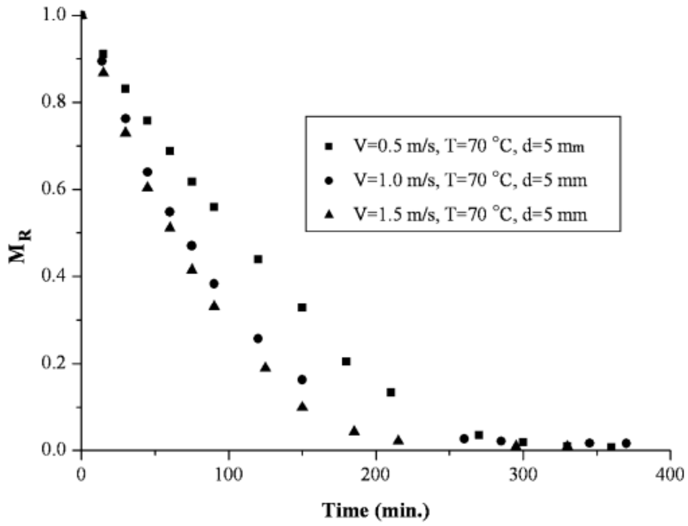

Fig. 4. Effect of air velocity on drying time.

IV. CONCLUDING REMARKS

In this study, thin layer drying kinetic of carrot was investigated experimentally. A comparative study was performed among a regression analysis and multilayer feed-forward neural network to estimate dynamic drying behavior of carrot. Among the four mathematical drying models considered, the modified Page model was found to be more suitable for predicting drying of carrot. However, when the ANN was used, higher r and r^2, and lower χ2 and SSR values were obtained than that of the modified Page model. In addition, the neural network model provided better than 0.05% accuracy in the estimation of moisture content. It also demonstrated that the neural network model proposed not only minimized χ2, and SSR, but also removed dependence on the mathematical model. As a result, the neural network model introduced here was successful in predicting the experimental drying kinetics. This shows the importance of the artificial neural networks in estimating the drying curves of foodstuff. The neural network model is not complex because the estimation is realized by simple arithmetic operations. The applications of the artificial neural networks can be used for the on-line state estimation and control of drying processes in industrial operations successfully.

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