Artificial Intelligence Techniques for Food Drying Technology

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Abstract: Applications of artificial intelligence techniques, such as artificial neural networks, fuzzy logic, genetic algorithms and neural-fuzzy systems, in engineering have gained momentum in past decade. Main applications of these techniques in engineering are estimation, optimization and control process. In this paper, some of the applications are studied and both simulation and real-time experimental results are given. Artificial neural networks and genetic algorithms are very useful for estimation and optimization process for drying technologies. However, fuzzy logic is also capable of both classification and control of the drying process. Estimation, optimization and control applications of artificial intelligence methods are given in detail for different types of food drying applications. Echinacea angustifolia and carrot are selected as application examples. A fuzzy logic based control approach is employed to control a convective type drier. Estimation and optimization applications of artificial neural networks and genetic algorithms are compared with non-linear regression analysis. In addition, fuzzy control is also compared with a classical control technique to conclude the robustness of the fuzzy control in terms of classical control. According to the results, it is observed that artificial intelligence techniques have several advantages such as: decreasing computation time, increasing stability and accuracy. Moreover these techniques could be applicable for different type processes with simple changes in configuration.

Introduction

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 and b) and Echinacea roots (Erenturk, Erenturk, & Tabil, 2004c).

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, Reményi, & Biró (2000a and b) and Trelea, Courtois, & Trystram (1997). Kaminski, Strumillo, & 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.

On the other hand, the genetic algorithm is one of the search methods and optimization techniques for an optimal value of a complex objective function by simulation of the biological evolutionary process based, as in genetics, on crossover and mutation. Morimoto, De Baerdemaeker, & Hashimoto (1997a) developed an artificial neural network-genetic algorithm intelligence approach for optimal control of fruit-storage process. Morimoto, Purwanto, Suzuki, & Hashimoto (1997b) used genetic algorithm for optimization of heat treatment for fruit during storage. Hashimoto (1997) introduced applications of artificial neural networks and genetic algorithms to agricultural systems.

Fuzzy set theory is a theory about vagueness and uncertainty. This theory provides an approximate, and yet effective, means of describing the behavior of systems that are too complex or ill-defined to permit precise mathematical analysis. Fuzzy controllers were developed to imitate the performance of human expert operators by encoding their knowledge in the form of linguistic rules. The fuzzy control is also nonlinear and adaptive in nature, which gives it a robust performance under parameter variations. Fuzzy control systems provide control through a set of membership functions quantified from ambiguous terms in control rules. As fuzzy control can be implemented by a small number of rules, it has a short initial development period. The number of the rules is determined by required accuracy.

After the invention of fuzzy logic by Zadeh, the fuzzy modeling and fuzzy identification of systems has found numerous practical applications in control, prediction and inference. In many cases, reducing to design time and costs the fuzzy logic approach allows the designer to handle efficiently very complex closed-loop control problems. Fuzzy control also supports nonlinear design techniques that are now being exploited in motor and temperature control applications. A fuzzy logic based controller adjusts the system input to get a desired output by just looking at the output without any requirement mathematical model of to be controlled system. For this reason fuzzy logic based controller systems differ from classical control systems and it is possible to get desired control actions for complex, uncertain, and non-linear systems by using fuzzy logic controller (FLC) without the requirement of their mathematical models and parameter estimation.

In this study, applications of artificial intelligence techniques, such as artificial neural networks, genetic algorithms and fuzzy logic, for food drying technologies are studied. Estimation, optimization and control applications of artificial intelligence methods are given in detail for different types of food drying applications. Echinacea angustifolia and carrot are selected as application examples. A fuzzy logic based control approach is employed to control a convective type drier. Estimation and optimization applications of artificial neural networks and genetic algorithms are compared with non-linear regression analysis. In addition, fuzzy control is also compared with a classical control technique to conclude the robustness of the fuzzy control in terms of classical control.

Mathematical Model of Food Drying Process

The flow of moisture from the agricultural material to its surroundings can be considered as analogous to the heat transfer from a body immersed in cold fluid. Comparing the drying phenomenon with Newton's law of cooling, the drying rate will be approximately proportional to the difference in moisture content between the material being dried and equilibrium moisture content at the drying air state. Hence:

$$\text{Drying rate} = \frac{M_{t+dt} - M_t}{dt} \tag{1}$$

Similarly, the moisture ratios of Echinacea and carrot are obtained from:

$$MR = \frac{M - M_e}{M_0 - M_e} \tag{2}$$

As proposed by earlier authors and given in Table 1, the drying curves obtained were processed for drying rates to find the most suitable model among the four different expressions (Akpinar et al, 2003).

Model no:	Model name:	Model equation:
1	Newton	$MR = \exp(-kt)$
2	Page	$MR = \exp(-kt^n)$
3	Modified Page	$MR = \exp(-(kt)^n)$
4	Henderson and Pabis	$MR = a.\exp(-kt)$

Table 1: Thin layer drying curve models considered.

The correlation coefficient (r) was one of the primary criteria for selecting the best equation to define the drying curves. In addition to r, the coefficient of determination (r^2), reduced Chi-Square (χ^2), and sum of squares of the difference between the data and fit values (SSR) were used to determine the quality of the fit. The best results of the proposed criteria were obtained by using the modified Page equation (Madamba et al., 1996; Panchariya et al., 2002) as shown in Eq. (3):

$$MR = \exp(-(kt)^n) \tag{3}$$

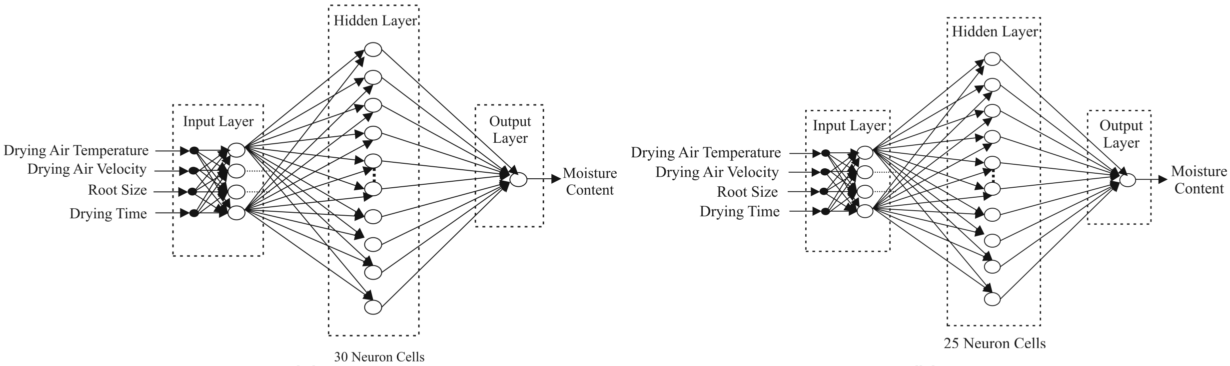
The dependence of the drying rate constant, k, and drying parameter, n, on the drying air variables was modeled as an Arrhenius-type equation. This dependence of both constants on the variables can be expressed in the following form:

$$k = a_0 V^{a_1} d^{a_2} \exp(-\frac{a_3}{T}) \tag{4}$$

$$n = b_0 V^{b_1} d^{b_2} \exp(-\frac{b_3}{T}) \quad (5)$$

Artificial intelligence techniques for food drying process

The selected structure of the applied neural network, with its four inputs and single output, is shown in Figure 1. There is no feedback from the output to the inputs. Since the physical structure of a thin layer dryer consists of three main parts (the input variables, the drying bed itself and the output variables) a three layer feed-forward neural network was chosen for modeling purposes (Farkas et al., 2000a). In the hidden layer, 30 hidden neurons were used for Echinacea and 25 hidden neurons were used for carrot. For training, the classical back-propagation algorithm was used (Farkas et al., 2000b) for the both cases. In this study, a logarithmic sigmoid activation function was used.



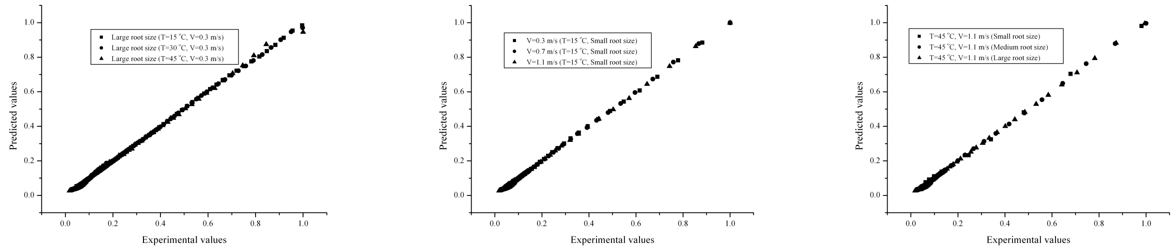
(a) (b)

Figure 1: Neural network structure for a) Echinacea and b) carrot.

Higher r, r^2, χ^2 and SSR values were obtained by using the neural network compared with that of modified Page model. The results have shown that the indicators for goodness of fit of the proposed neural network model are better than the values obtained by the modified Page model. These results are shown in Table 2. Therefore, the proposed neural network model was selected to represent the thin layer drying behavior of E. angustifolia because of the higher values of r and r^2, and the lower values of χ^2 and SSR than that by the modified Page model. It can be clearly seen from Table 2 that the accuracy of the neural network model provided a better fit and better results. The performance of the neural network model for E. angustifolia is illustrated in Fig.2a, 2b and 2c for different drying air temperatures, drying air flow rates and root sizes. Detailed information for this case could be found in (Erenturk, Erenturk, & Tabil, 2004c)

Model name	Model constants		Correlation coefficient (r)	Coefficient of determination (r^2)	χ^2	SSR
Newton	k=0.004		0.9862	0.9726	1.27E-3	0.348
Page	k=0.014	n=0.790	0.9938	0.9876	3.78E-4	0.089
Modified Page	k=0.004	n=0.790	0.9965	0.9930	3.29E-4	0.089
Henderson &Pabis	k=0.004	a=0.915	0.9896	0.9793	9.64E-4	0.262
NNET	-	-	0.9994	0.9989	3.96E-05	0.0109

Table 2: Results of statistical analyses on the modeling of moisture contents and drying time.



(a) (b) (c)

Figure 2: The performance of the neural network model for E. angustifolia for a) root sizes b) drying air flow and c) different drying air temperatures.

Similiar to the previous case, the drying rate k and the drying parameter n of the modified Page model for carrot were best described by Arrhenius-type model and shown below:

$$k = 42.66V^{0.3123}d^{-0.8437}\exp\left(-\frac{2386.6}{T}\right) \qquad (r=0.987)$$

$$n = 5.48V^{-0.0846}d^{-0.1066}\exp\left(-\frac{452.5}{T}\right) \qquad (r=0.954)$$

Above expressions can be used to estimate the moisture content of carrot at any instant during drying, because the regression coefficient, r, is found with acceptable accuracy. The accuracy of the established model was evaluated by comparing the computed moisture ratio under any particular drying conditions with the observed moisture ratio.

During both regression routines and determination of the dependence of the drying rate constant, k, and drying parameter, n, on the drying air variables, the proposed GA approach in (Erenturk, Erenturk, 2007d) was employed for all experimental runs. After the step by step procedure described in (Erenturk, Erenturk, 2007d), the following relationship between drying variables and drying characteristics was obtained.

$$k = 26.64V^{0.4199}d^{-0.8362}\exp\left(-\frac{2223.1}{T}\right) \qquad (r=0.996)$$

$$n = 5.29V^{-0.0856}d^{-0.1023}\exp\left(-\frac{443.4}{T}\right) \qquad (r=0.962)$$

Regarding above r, r^2, χ^2 and SSR values determined by using regression analysis and the mathematical model optimized by applying GA were listed in Table 3. The accuracy of the mathematical model optimized by using GA was observed more satisfactory than that of regression analysis.

Model name	Correlation coefficient (r)	Coefficient of determination (r^2)	χ^2	SSR
Newton	0.9964	0.9928	2.36E-3	2.553
Page	0.9938	0.9876	2.62E-3	2.825
Modified Page	0.9991	0.9981	2.45E-3	2.698
Henderson &Pabis	0.9976	0.9917	2.42E-3	2.611
Modified Page before optimization	0.9985	0.9971	2.52E-3	2.725

Table 3: Statistical results of the mathematical models optimized by using GA

Another AI technique suitable for drying process is fuzzy logic. Fuzzy controllers were developed to imitate the performance of human expert operators by encoding their knowledge in the form of linguistic rules. Since the fuzzy control is also nonlinear and adaptive in nature, these properties give FC a robust performance under parameter variations. Fuzzy control systems provide control through a set of membership functions quantified from ambiguous terms in control rules. As fuzzy control can be implemented by a small number of rules, it has a short initial development period. The number of the rules is determined by required accuracy. A fuzzy logic based controller adjusts the system input to get a desired output by just looking at the output without any requirement mathematical model of to be controlled system. For this reason fuzzy logic based controller systems differ from classical control systems and it is possible to get desired control actions for complex, uncertain, and non-linear systems by using fuzzy logic controller (FLC) without the requirement of their mathematical models and parameter estimation. For this purpose, a fuzzy logic based control approach is employed to control a convective type drier. Simulation result is illustrated in Fig. 3. Fuzzy control (FC) is also compared with a classical control technique to conclude the robustness of the fuzzy control in terms of classical control. Comparison results are given in Table 4. According to the results, it is observed that artificial intelligence techniques have several advantages such as: decreasing computation time, increasing stability and accuracy.

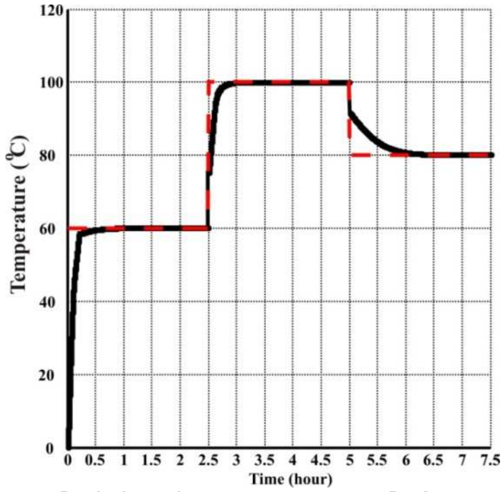


Figure 3: Fuzzy logic based temperature control of a convective drier.

Controller type	Overshoot (%)	Rise time (h)	Steady state error (°C)
Fuzzy control	-	0.28	1.23
PID	1.22	0.61	3.52

Table 4: Performance evaluation of controllers.

Conclusions

In this study, applications of artificial intelligence techniques for food drying processes are presented. In order to estimate the drying behavior of different type foods, a feed-forward artificial neural network (ANN) structure is designed and applied to Echinacea and carrot. It is observed that ANN based estimation is more accurate than that of nonlinear regression analysis. In addition, for more complex operation, such as Arrhenius-type modeling, GA based optimization technique is applied and more reliable results are observed. Fuzzy logic based control of a convective drier is also given and compared with a classical PID-type control technique to conclude the robustness of the fuzzy control in terms of classical control. According to the results, it is observed that artificial intelligence techniques have several advantages such as: decreasing computation time, increasing stability and accuracy. Moreover these techniques could be applicable for different type processes with simple changes in configuration.

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