Computers and Electronics in Agriculture 145 (2018) 341–348

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Multi-objective optimization of convective drying of apple cubes

Radosław Winiczenko[a], Krzysztof Górnicki[a,*], Agnieszka Kaleta[a], Alex Martynenko[b], Monika Janaszek-Mańkowska[a], Jędrzej Trajer[a]

[a] Warsaw University of Life Sciences, Department of Fundamental Engineering, Nowoursynowska 164, Warsaw 02-787, Poland
[b] Nova Scotia Agricultural College, Department of Engineering, Truro, NS B2N 5E3, Canada

ARTICLE INFO

Keywords:
Apple
Drying
Modelling
Artificial neural network
Genetic algorithm
Pareto

ABSTRACT

The effect of drying temperature and air velocity on apple quality parameters, such as color difference (CD), volume ratio (VR) and water absorption capacity (WAC) in convective drying was experimentally studied. Optimization of drying conditions was carried out in the range of air temperatures from 50 to 70 °C and air velocity from 0.01 to 6 $\mathrm{m\,s^{-1}}$. A novel algorithm of multi-objective optimization, based on artificial neural network (ANN), genetic algorithm (GA) and Pareto optimization was developed. Three optimization objectives included simultaneous minimization of CD, maximization of VR and maximization of WAC. Objective functions for CD, VR and WAC were developed by using ANN training on the experimental dataset of apple drying at 50, 60 and 70 °C. Pareto optimal set was developed with elitist non-dominated sorting genetic algorithm (NSGA II). Unique Pareto optimal solution within specified constraints was found at air temperature 65 °C and velocity 1 $\mathrm{m\,s^{-1}}$. This mode of apple drying resulted in CD = 5.24, VR = 49.66% and WAC = 0.488. Experimental verification showed that maximum error of modelling did not exceed 3.24%.

1. Introduction

Drying process is one of the well-known methods for preservation of fruits and vegetables. This process prevents occurrence of unpleasant changes such as microbial spoilage and enzymatic reaction by removing water from food products. Moreover, drying decreases the mass and volume of products, reduces the cost of packaging, storage and transportation (Pasban et al., 2017). Drying with traditional methods is very time consuming and results in energy wastage and quality deterioration (Karim and Hawlader, 2005). Theoretical and experimental studies have been conducted to uncover the actual physical phenomena of heat and mass transfer during drying. Most of the studies investigated the drying kinetics at tissue or bulk level (Hazervazifeh et al., 2016; Zarein et al., 2015). Khan et al. (2018) investigated the intracellular water transport phenomena for two different food materials: potato, as a low porous material (Khan et al., 2017), and Granny Smith apple as a highly porous food material.

Dried products are popular ingredients of convenient food and usually require rehydration during their use. Rehydration is a complex phenomenon, which includes at least two simultaneous processes: water imbibition and swelling of biopolymers resulting in increasing of dried material mass and volume, as well as leaching of solubles (sugars, acids, minerals, vitamins) into surrounding water (Witrowa-Rajchert and Lewicki, 2006). Drying technology and properties of dried material significantly affect rehydration. Thus rehydration characteristics reflect changes of raw material during drying (Lewicki, 1998).

The key issue of drying is the proper selection of process parameters in order to obtain acceptable quality of the final product (Jokiniemi and Ahokas, 2014). Therefore optimization of drying conditions is necessary in order to preserve the best qualities of raw material. The majority of optimization studies in food engineering refer to single-objective optimization, using response-surface methodology (RSM) (Yazgi and Degirmencioglu, 2007; Balasubramani et al., 2013; Rouissi et al., 2013). RSM has been successfully adopted as an effective tool for optimization of drying parameters. Multi-objective optimization (MOO) has been rarely implemented in the food industry, probably due to mathematical complexity (Abakarov et al., 2009). Only a few researchers proposed multi-objective strategies for analyzing food processes such as drying (Nazghelichi et al., 2011), thermal processing (Sendín et al., 2010), bulk-grain handling (Thakur et al., 2010), baking (Hadiyanto et al., 2009) or roasting (Goñi and Salvadori, 2012). One of the earliest studies of MOO for optimization of flow pattern in a multi-effect evaporator system was published by Nishitani and Kunugita (1979). Another interesting application of MOO for evaporator was described by Sharma et al. (2012).

MOO is defined as finding a vector of decision variables satisfying constraints to give acceptable values to all objective functions (Coello and Christiansen, 2000). Mathematically, in MOO, a vector $X^* = [x_1^*,$

* Corresponding author.
E-mail address: krzysztof_gornicki@sggw.pl (K. Górnicki).

https://doi.org/10.1016/j.compag.2018.01.006
Received 17 July 2017; Received in revised form 5 January 2018; Accepted 6 January 2018
0168-1699/

Nomenclature

T	drying temperature, °C
v	drying air velocity, $m\ s^{-1}$
M	mass, g
V	volume, m^3
S	dry matter content, %
L	lightness in CIELab and CIELCh color space, –
C	chroma in CIELCh color space, –
h	hue angle in CIELCh color space, –

Subscripts

0	initial reference
d	dried reference
r	rehydrated reference
T	tested reference
S	standard reference

$x_2^*,\ldots x_n^*$] should be found so as to optimize objective function $F(x) = [f_1(x), f_2(x),\ldots, f_n(x)]^T$ subject to m inequality $g_i(x) \le 0$ ($i = 1$ to m) and p equality constraints $h_j(x) = 0$ ($j = 1$ to p) where $X^* \in R^n$ is decision vector and $F(x) \in R^k$ is the vector of objective functions, both of which must be minimized (Shojaeefard et al., 2013). To solve MOO problems various optimization methods have been proposed which generally use two different approaches. The conventional approach is to combine two or more objectives into a single objective by weighted sum method (desirability criteria) or to reduce the problem to single-objective optimization by the conversion of other objectives into constraints. In case of desirability criteria the major concern is choosing weight for each objective. Both methods result in a single solution rather than a set of solutions, which can be evaluated for each particular drying scenario. For the sake of flexibility in the decision-making, a set of solutions considering the multiple objectives, would be preferable (Udayakumar et al., 2014). Usually MOO gives no single solution optimal with respect to all objectives, but rather a set of optimal solutions known as Pareto optimal solution. Pareto optimal solution is one, which is not dominated by any other solution in the solution space, where improvement of one objective requires a certain sacrifice of other(s) (Censor, 1977). A set of all these non-dominated solutions are called Pareto optimal set, and their representation in the objectives space is called Pareto front. The major goal in MOO is to find the Pareto front, which consists of Pareto optimum solutions (Shojaeefard et al., 2013).

To define Pareto optimal set, the concept of dominant must be introduced. Assuming that x_1 and x_2 are vectors in n-dimensional space and f is a cost function, x_1 dominates x_2 if the following conditions are satisfied:

$$f_1(x_1) < f_1(x_2) \quad \text{and} \quad f_2(x_1) \leqslant f_2(x_2) \tag{1}$$

or

$$f_1(x_1) < f_1(x_2) \quad \text{and} \quad f_2(x_1) < f_2(x_2) \tag{2}$$

A solution is Pareto optimal if no other solution dominates it with respect to the cost function. Once the set of solutions is found, it is easy to select single optimal solution, particularly suitable for chosen drying scenario.

Developing of Pareto optimal solutions usually requires preliminary knowledge of cost functions, in our case relationships between drying variables and quality parameters. Highly nonlinear nature of these relationships could be managed by introducing of relational models, such as artificial neural networks (ANN) (Gautam et al., 2006). This approach was successfully used for numerous drying applications (Farkas et al., 2000; Erenturk et al., 2004; Aghbashlo et al., 2015), however it has not been used for multi-objective optimization. Mohamed et al. (2013) by performing a comparative analysis of RSM and ANN stated that both methodologies complemented each other in interpreting the results, whether in pointing out synergistic interactions among the input variables via ANOVA, or in classifying the importance of each component. Additionally, ANN is unrestricted to the order of the model, and therefore, the approach is more dynamic in simulating the true behavior of nonlinear dataset.

Genetic Algorithms (GA) is a powerful optimization tool especially in irregular experimental regions. Several strategies based on genetic algorithms have been developed for MOO, including weight-based GA (Hajela et al., 1992), non-dominated sorting GA (Srinivas and Deb, 1994), distance–based Pareto GA (Osyczka and Kundu, 1995), random-weighted GA (Murata, 1997), Pareto-archived evolution strategy (Knowles and Corne, 2000) and elitist non-dominated sorting GA (NSGA II) (Deb, 2001; Deb et al., 2002; Dedieu et al., 2003). One way to find the Pareto front is to run a genetic algorithm for many different combinations of the cost function weights. Each optimal solution is one of the Pareto front. However, this approach requires too many runs to estimate the Pareto set (Haupt and Haupt, 2004). The computational efficiency of GA could be significantly improved by introducing ANN relational models, establishing relationship between drying variables and quality parameters. In this research we have chosen two drying variables (air temperature and velocity) and three quality parameters of apples (color, shrinkage and water absorption capacity).

The aim of the present work was to develop and verify novel approach to multi-objective optimization (MOO) based on ANN modelling of product quality parameters and non-dominated sorting genetic algorithm (NSGA II) to determine Pareto optimal set of drying conditions required for quality drying of apple cubes. It is a novel approach to multi-objective optimization. In literature to drying process optimizing authors used only RSM (Erbay and Icier, 2009; Sturm et al., 2012; Gupta et al., 2013; Aghilinategh et al., 2015).

To achieve this goal the four-steps approach was used: (1) collect data from drying experiments, (2) apply ANN modelling to find functional relationships between process variables (T, v) and quality characteristics CD, VR and WAC of dried material, (3) use NSGA II to find Pareto front and (4) apply constraints to find unique Pareto solution(s).

2. Materials and methods

2.1. Sample preparation

Fresh, high-quality apples (var. Ligol) were purchased from a local store in Warsaw, Poland. Just before drying experiments apples were peeled and the outer cortex was cut into cubes with thickness of 10 ± 1 mm. The initial moisture content of fresh apple samples was about 85% w.b. (5.66 d.b.).

2.2. Experimental procedures

The effect of drying temperature (T) and drying air velocity (v) on quality parameters of apple cubes was evaluated. The following techniques were used for drying of the raw material: natural convection with $v = 0.01\ m\ s^{-1}$ (KWC-100, PREMED, Marki, Poland), forced convection with $v = \{0.5\ m\ s^{-1}, 2\ m\ s^{-1}\}$ (constructed in the Department of Fundamental Engineering, Warsaw University of Life Sciences, Warsaw, Poland) and fluidized bed drying with $v = 6\ m\ s^{-1}$ (constructed in the Department of Fundamental Engineering, Warsaw University of Life Sciences, Warsaw, Poland) (Górnicki and Kaleta, 2007; Kaleta and Górnicki, 2010; Kaleta et al., 2013). Drying experiments were carried out at 50, 60 and 70 °C in three replications until the constant mass of dried material was reached. The equilibrium moisture content of dried samples was about 9% w.b. (0.098 d.b.). Samples