Alejandro R. Lespinard*, Javier R. Arballo, Francisco J. Taus and Rodolfo H. Mascheroni

Multi-Objective Optimization of the Pasteurization Process of Pumpkin Cubes Packaged in Glass Jars

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Abstract: The influence of particle size (PZ) and processing temperature (PT) on quality attributes and processing time of pumpkin cubes packaged in glass jars were evaluated during their pasteurization. Second-order polynomial models were developed for the following responses: texture retention (TR), total colour change (TCC) and heating time (HT), using multiple linear regression for a range of operating conditions (20–30 mm and 85–100°C for PZ and PT, respectively). A combination of the polynomial models with the methodology of desirability function was used for optimization of the pumpkin pasteurization process. The obtained optimal conditions were 20 mm and 100°C for PZ and PT, respectively; in order to obtain TR of 82.21%, TCC of 7.54 and HT of 44.97 min. However, these optimal conditions change to 100°C and 21 mm and the responses obtained are TR of 73.60%, TCC of 7.52 and HT of 39.66 min, when the processing time is prioritized.

Keywords: pasteurization, pumpkin cubes, glass containers, multiple response optimization, desirability function

1 Introduction

Pumpkin is a seasonal crop that has been used traditionally both as human and animal feed [1]. It is a good source of carotene, water-soluble vitamins, and amino acids, being relatively low in total solids [2, 3]. Fresh pumpkins have very short shelf-life since they are very sensitive to microbial spoilage, even at refrigerated conditions; thus they must be frozen or subjected to high temperature thermal processes (sterilization, pasteurization, dehydration, etc.). Pumpkin is usually thermally processed for the manufacture of preserves such as jam, jelly, beverages and other products. Among pumpkin preserves; one of the most representative is that based in pumpkin cubes canned in glass containers, using sucrose solution as covering liquid. Thus, the manufacturing of these types of preserves submitted to a thermal process, such as pasteurization, is a useful alternative to extend the shelf-life and conservation period. Pasteurization is one of the oldest known food preservation methods, based on the partial thermal degradation of microorganisms and denaturation of enzymes which present a potential risk for food spoilage [4]. Industrial processes of pasteurization have to ensure the prolongation of food lifetime, and at the same time preserve the product quality [5]. In pumpkin, thermal processing also improves the bio-availability of beta-carotene, since it breaks down the cellulose structure of plant cell. However, sensory properties of pumpkin, including nutrients, color and texture deteriorate during the process [6]. As the requirements for microbial safety, food acceptability and product quality are conflicting, an optimal thermal process of food always requires commitment between the beneficial and the destructive influences of heat on the food. Factors typically considered in optimization routines may include the minimum degradation of nutrients and organoleptic attributes that could be tolerated in terms of product marketability and, most importantly, the primary constraint of meeting the required lethality [7]. Other factors of the economic type, as energy consumption and process time, can also be considered with purpose of finding the best processing conditions. To optimize is to select the best alternative of a specific group of alternatives for a determined process, and for it is required, a relation that describes the potential alternatives of the process, and a criterion to decide which of the alternatives is the best one [8]. In this sense, polynomial regression (PR) has the ability to

***Corresponding author: Alejandro R. Lespinard,** Centro de Investigaciones y Transferencia (CIT Villa María), CONICET – Instituto de Ciencias Básicas y Aplicadas, Universidad Nacional de Villa María. Av. Arturo Jauretche 1555, (5900), Villa María, Córdoba, Argentina, E-mail: alelespinard@yahoo.com.ar
Javier R. Arballo, Centro de Investigación y Desarrollo en Criotecnología de Alimentos (CIDCA), CONICET La Plata – Universidad Nacional de La Plata, 47 y 116, (B1900AJJ), La Plata, Argentina; Depto. Ing. Química – Facultad de Ingeniería, UNLP, La Plata, Argentina
Francisco J. Taus, Depto. Ing. Química – Facultad de Ingeniería, UNLP, La Plata, Argentina
Rodolfo H. Mascheroni, Centro de Investigación y Desarrollo en Criotecnología de Alimentos (CIDCA), CONICET La Plata – Universidad Nacional de La Plata, 47 y 116, (B1900AJJ), La Plata, Argentina; Depto. Ing. Química – Facultad de Ingeniería, UNLP, La Plata, Argentina

find a unique equation that can predict the evolution of process variables in a specific range of work. This ability can be used combined with other techniques to find optimal operating conditions in the food industry. The desirability function method (DFM) [9] has the capacity to represent all the process variables in one measure and it allows to work with a large number of factors and responses at the same time. In this manner, PR and DFM result a useful tool to optimize a wide range of industrial processes, allowing a fast and consistent identification of the optimal operating zones without needing a strict experimental design [10]. Several authors have presented optimization theories and techniques, and discussed their relevance and implementation in the food industry. However, most optimization studies reported in food engineering refer to single-objective optimization. Only a few researchers proposed multi-response strategies in the analysis of different food processes: bulk-grain handling [11]; thermal processing [12–17]; conventional drying [18–20]; osmotic dehydration [10, 21–28]; baking [29–33]; roasting [34, 35]. Pasteurization process requires optimization with the purpose of simultaneously diminish costs and undesired effects on the quality in the resulting product. Particularly, in foods packed in transparent glass containers, as pumpkin cubes, visual quality (colour, texture and overall appearance) of the products is the main quality index that costumers count on [36]. On the other hand, in solid-liquid food mixtures, parameters of the product such particle size, shape, concentration and density, are important for the establishment of thermal process [37]. While the optimization considering a single factor (e.g., maximization of the retention of a quality factor) has received considerable attention in research of canned foods, the possibilities of dealing with several factors (including factors of the economic type, as processing time) for packaged food in glass container have up to now not been addressed. At the same time, although thermal processing is widely used for food preservation, only processing of foods packaged in cans or plastic containers and continuous aseptic processing (without containers) have been mostly studied. Almost no attention has been devoted to food processing in glass containers [38]. Furthermore, there is a lack of studies concerning the optimization of thermal processing of preserves of pumpkin cubes immersed in liquid medium.

In agreement with the expressed so far, the objectives of the present study were the following:

(i) To evaluate the influence of particle size and processing temperature on the quality attributes (texture and colour) and processing costs (heating time) during the pasteurization process of pumpkin cubes packaged in glass jar.
(ii) To obtain optimal processing conditions, by maximizing the texture retention (TR) and minimizing the total colour change (TCC) and the heating time (HT) through PR and DFM.

2 Materials and methods

2.1 Sample preparation

Fresh pumpkins (*Cucurbita moschata Duchesne ex Poiret*) obtained from a local market (La Plata, Argentina) were selected for the preparation of the preserves. The selection criteria of the products were based on the same maturity level, peel colour (pale orange), shape and size. Samples were washed with tap water to remove superficial dirt. Afterwards, they were manually peeled and cut into cubes of three sizes (20, 25 and 30 mm). These cubes were pretreated by inmersion in an aqueous solution of calcium hydroxide (2.5% w/w) for 8 h, in order to increase the firmness and to maintain its shape during the thermal processing. These were then washed with water to remove calcium hydroxide adhered to the surface. In addition, the cubes were blanched in a water bath at 100°C for 5 min and then in cold water to stop the cooking process. After the above pretreatments, those cubes were placed in cylindrical glass containers of 660 cm^3 (13.7 cm height and 8.8 cm in diameter) and submitted to pasteurization process. The amount of pumpkin cubes in each container was calculated considering 45% of porosity. As covering liquid a 50° Brix sucrose syrup (containing 0.2% citric acid) was added, completing 90% of the total volume of the container. This solution used as covering liquid ensures that the product has a pH less than 4.5.

2.2 Thermal processing

Pasteurization process consisted of two stages: (a) heating and (b) cooling. In the first stage, jars were placed into a thermostatized water bath at different temperatures (85, 90 and 100°C). Then the jars were placed in a cooling bath which was at a temperature difference of 40°C lower than the temperature of the heating bath. Higher temperature differences were not employed to avoid rupture of the glass containers. Equivalent processes were specifically designed by determining the processing time needed to reach, at the cold spot, a sterilization value (*F-value*) of 5 min (eq. (1)), as recommended by Ref. [39] for foods with pH lower than 4.5.

$$F = \int_{t_0}^{t_f} 10^{(T_c - 93.3)/8.3} \mathrm{d}t \tag{1}$$

Where T_c is the cold spot temperature, t_O and t_f are initial and final time of the process, respectively.

Temperatures within the water baths and in the cold spot of the packaged food in the containers (determined in exploratory runs) were measured, each 15 sec, using Type T – copper-constantan – (Cu-CuNi) thermocouples. To this end, the metallic lids of the containers were drilled in the centre to let the passage of the thermocouple. A high-temperature resistant seal was used to secure hermeticity around the thermocouple in the lid. Thermal histories were measured and registered using a multichannel data acquisition system (AS-TC, Keithley, Cleveland, USA). Experiments were performed by triplicate for each condition.

2.3 Evaluation of quality indexes

All the quality parameters considered were measured in ten different samples for each experimental condition tested (unprocessed and processed at three different processing temperatures and particle sizes). That means 180 samples were used for the determination of each quality parameter. The results were presented as percentage of relative variation with regard the unprocessed sample.

2.3.1 Texture

The firmness of the pumpkin cubes was evaluated - in terms of maximum force (*F*) (N) – by a compression test, using the texture analyzer TA.XA2i (Stable Micro Systems Ltd., Godalming, Surrey, UK) with an aluminium compression plate P50 (50 mm of diameter). Texture analysis was carried out under the following instrument parameters: pre-test speed 2 mm/s; test speed 0.5 mm/s; post-test speed 2 mm/s; strain 30% of sample height; trigger force 0.5 N; data acquisition rate 25 pps.

Each reported value corresponded to the mean of ten measurements, for unprocessed as well as processed samples. Results were presented as percent texture retention (eq. (2)).

$$TR(\%) = \frac{F_t}{F_0} 100 \tag{2}$$

Where F_O and F_t are the maximum compression force of the samples before and after pasteurization, respectively.

2.3.2 Colour

CIE-Lab scale [40] was used to describe the spatial 3D colour representation determined with a Minolta colorimeter CR 300 Series (Osaka, Japan) with a measuring area of 8 mm diameter and provided with a 10° standard observer and a D65 standard illuminant. The instrument was calibrated with a standard white plate (Y = 93.2, × = 0.3133, y = 0.3192). The colour measurements were taken by placing the colorimeter at several points on the cubes surface. The L^*: lightness; a^*: redness and b^*: yellowness parameters were determined for unprocessed samples and thermally treated samples.

The total colour change (*TCC*) in cubes during the pasteurization process, was calculated using eq. (3) for each processing condition:

$$TCC = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \tag{3}$$

Where ΔL^*, Δa^* and Δb^* are the differences between the values of L^*, a^* and b^* of the pasteurized and non-pasteurized pumpkin cubes.

2.4 Optimization problem

An optimization process means to find, by an efficient and systematic way, a set of independent variables -also known as decision variables- that minimize or maximize a determined criterion or objective function of interest, previously defined. The objective function is also usually subjected to a number of specific restrictions, derived from the process itself [41, 42].

This work is focused on the optimization of pasteurization applied to canned solid–liquid food mixtures (pumpkin cubes in liquid medium) by minimizing the total colour change (TCC) and the heating time (HT), and maximizing the texture retention (TR). The main restriction of this multiple response optimization problem was to achieve sterilization value (*F*) of 5 min, at the coldest point. Additional restrictions were also included to establish the operating limits of the water bath temperature ($\leq$100°C).

The polynomial regression and desirability function methods were used as mathematical tools to formulate the optimization problem. These techniques are detailed following.

2.4.1 Polynomial regression

With the aim to predict the evolution of pasteurization and to evaluate the relative influence of each operating factor (process temperature – PT and particle size – PZ) on the overall product quality (TR and TCC) and processing costs (HT), a second order polynomial model was developed for the three process responses (TR, TCC and HT) using multiple linear regressions. The model proposed for each variable is described as follows:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j \quad (4)$$

Where y is the predicted value of TR, TCC or HT, β_O independent term, β_{i} linear coefficients, β_{ii} the quadratic effects terms, β_{ij} the interaction effects and x are the operating variables (PT and PZ). The coefficients were obtained by fitting the experimental data applying multiple linear regressions using a code developed in Matlab 7.2 (Mathworks, Natick, MA, USA).

2.4.2 Desirability function method

This methodology consists in obtaining a function that converts a multi-response problem into a simple response case, known as simultaneous desirability function [43]. In this method each response value (TR, TCC and HT), obtained from polynomial regression is converted into a desirability dimensionless value d_{i}. These values vary between 0 and 1, from an unacceptable response to an optimal one, respectively. If the response should be maximized, d_i is defined as:

$$\begin{gathered} d_i = 0 \qquad y_i < L_i \quad ; \quad d_i = 1 \qquad y_i > T_i \\ d_i = \left[\frac{y_i - L_i}{T_i - L_i}\right]^{\theta_1} \qquad L_i \le y_i \le T_i \end{gathered} \quad (5)$$

and if the response is to be minimized, the individual desirability function (d_i) is calculated as follows:

$$\begin{gathered} d_i = 1 \qquad y_i < T_i \quad ; \quad d_i = 0 \qquad y_i > U_i \\ d_i = \left[\frac{U_i - y_i}{U_i - T_i}\right]^{\theta_2} \qquad T_i \le y_i \le U_i \end{gathered} \quad (6)$$

where y_i is the predicted response of the fitting model, L_i and U_i represent acceptable minimal or maximal y_i values, respectively, and T_i is the goal value corresponding to the maximal, minimal or target value depending on specified constraints for each response. The d_i values are affected by the user-defined factors (θ_1, θ_2) that weigh the influence of the goal value and of the minimal or maximal limits. To achieve the representing values of the optimal processing conditions, just one global desirability function (D) is obtained, which is calculated by the geometric mean of $n$converted responses:

$$D = \left(d_1^{v_1} \cdot d_2^{v_2} \cdot \ldots \cdot d_n^{v_n}\right)^{1/\sum_{i=1}^{n} v_i} = \left(\prod_{i=1}^{n} d_i^{v_i}\right)^{1/\sum_{i=1}^{n} v_i} \quad (7)$$

where v_i is the relative importance assigned to each d_i converted response, which might typically be an integer in the range of 1–3, with 3 indicating the greatest importance and 1 indicating the least. Moreover, it can be observed that if any response is unacceptable ($d_i = 0$), the total function equals zero, giving a major coherence to the obtained function. A high value of D indicates the best process factors combinations, which is considered as the system optimal solution. The optimal values for each process factor are determined from individual desirability functions values that maximize D [44].

2.4.3 Optimization algorithm

With the aim to obtain the predictive polynomial equations for each product, to calculate the desirability function and to plot the desirability surfaces, the algorithm developed by Ref. [10] coded in Matlab 7.2 was applied. Mathematical and graphic functions were employed in the code Matlab to obtain the polynomial coefficients and the predictive 3D-surfaces. This methodology is described in detail in Ref. [10], where a complete block diagram of the optimization solution-algorithm is shown.

2.5 Statistical analysis

The mathematical models were evaluated for each response by means of multiple linear regression analysis. Multiple linear regression was used to fit data to explanatory models for texture retention (TR), total colour change (TCC) and heating time (HT), in function of particle size (PZ) and processing temperature (PT). The analysis of variance (ANOVA) of the polynomial models was carried out to evaluate the significant effect of each factor on responses. The model adequacies were checked by R^2, R^2 *adjusted*, prediction error sum of squares (PRESS) and relative mean error (RME) [45]. Then, methodology of desired function was used to optimize the pasteurization process of pumpkin cubes. All statistical analysis were carried out using Statgraphics 5.1 (StatPoint Technologies Inc., Warrenton, VA, USA).

3 Results and discussion

3.1 Temperature profiles

Equivalent processes were designed by determining the heating time needed to reach at the cold spot a final sterilized value (*F*-value) equal to 5 min. For this purpose, several experiments, for each process condition, were carried out varying the length of first stage (heating). As an example, in Figure 1 the measured temperatures for the coldest point of the container filled with cubes of 20 mm during thermal processing at 90°C are shown. The temperatures, at the heating bath, cooling bath and the evolution of sterility value (*F-value*) are also shown in the same figure. The figure shows that the microbial inactivation of the process (*F-value*) occurs mainly (85%) during the heating period, which is much longer than cooling stage. Similar behaviours were found for the other conditions tested. In the same way, heating period accounts for more than 90% (91–97.4%) of total process time in all cases. For this reason, the heating time (HT) was considered as one of the objective functions, and has to be minimized in order to reduce the processing costs.

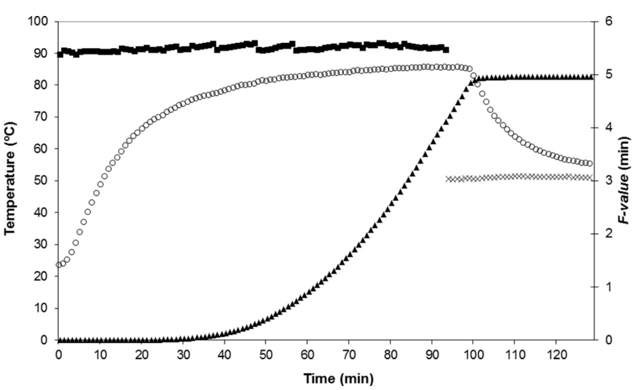

Figure 1: Experimental time-temperature curves for (■) heating bath, (x) cooling bath, (O) pumpkin cube of 20 mm and (▲) *F*-value during pasteurization at 90°C.

The HT values obtained for each process condition are presented in the Table 1. Moreover, the conditions of the entire set of experiments and their respective responses are also detailed in the same table.

3.2 Optimization of the process

3.2.1 Fitting polynomial models

Three fitted models were obtained for TR, TCC and HT, using the polynomial approach coded in Matlab 7.2. To visualize the combined effects of the two factors (PT and PZ) on each response, the 3D response surfaces and contour plots were generated for TR, TCC and HT of the fitted models using Matlab graphical functions (Figure 2).

These models were obtained as a result of fitting eq. (4) to experimental data shown in Table 1. The models were tested for adequacy and fitness by analysis of variance (ANOVA). The values of *F*-values, *p*-levels, R^2, R^2 *adjusted*, prediction error sum of squares (*PRESS*) and relative mean error (*RME*) are presented in Table 2. For the model to be significant, that is, not generated by noise, *P-model* values should be less than 0.05 [43]. As it can be seen, the three quadratic models were significant (*P-model* < 0.05). Morevover, the *F-values* obtained imply that the model is significant. On the other hand, R^2, R^2*adjusted*, prediction error sum of squares (*PRESS*) and

Table 1: Complete set of pasteurizations and experimental responses.

Process temperature (°C)	Particle size (mm)	HT (min)	TR (%)	TCC
85	20	164.00 ± 7.25	53.10 ± 9.60	9.63 ± 1.92
85	25	121.00 ± 5.75	31.59 ± 6.94	11.23 ± 1.33
85	30	142.50 ± 8.20	27.23 ± 2.73	13.75 ± 2.88
90	20	97.50 ± 7.92	72.88 ± 16.62	7.55 ± 0.91
90	25	68.50 ± 6.24	39.32 ± 14.30	8.08 ± 1.07
90	30	82.00 ± 5.63	19.44 ± 5.86	12.99 ± 2.60
100	20	38.00 ± 3.81	81.00 ± 9.34	7.59 ± 0.92
100	25	45.00 ± 4.02	44.59 ± 7.53	8.58 ± 0.61
100	30	46.50 ± 3.50	31.80 ± 6.75	11.27 ± 2.28

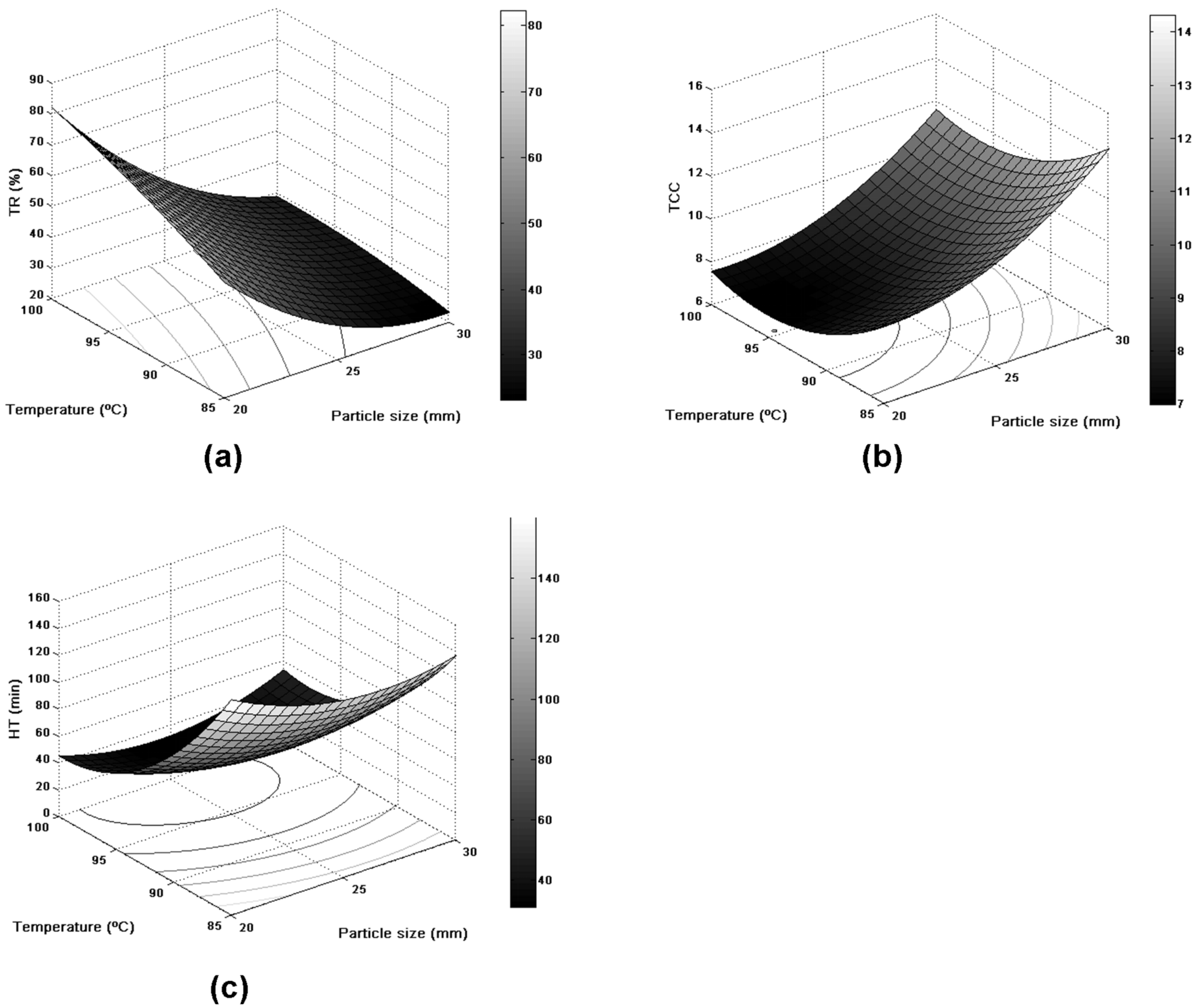

Figure 2: Predictive surfaces for (a) texture retention (TR), (b) total colour change (TCC) and (c) process time (HT).

Table 2: Statistical results of fitted quadratic models.

Statistical parameter	HT	TR	TCC
Fitted model	Quadratic	Quadratic	Quadratic
F-model	22.16	14.99	14.06
P-model	0.0142	0.0248	0.0271
R^2	0.9736	0.9615	0.9590
R^2 *adjusted*	0.9296	0.8973	0.8908
PRESS	432.25	134.41	1.78
RME	9.23%	4.02%	0.45%

Source: *TR*. texture retention; *TCC*. total colour change; *HT*. heating time

relative mean error (*RME*) were calculated to check the model adequacy for each response. Regression analyses for different models indicated that the fitted quadratic models accounted for more than 95% of the variation in the experimental data, which were highly significant ($R^2 > 0.95$). However, a large value of R^2 does not always imply that the regression model is good one. Adding a variable to the model will always increase R^2, regardless of whether the additional variable is statistically significant or not [46]. For this reason, R^2*adjusted* were calculated, presenting values close to 0.9. According to Eren and Kaymak-Ertekin [47], when R^2 *adjusted* present high values and did not differ dramatically with R^2, as in the present study, indicates that non-significant terms have not been included in the model. Aditionally, all fitted models present *RME* lower than 10%. This means that the fitted models can predict the evolution of responses as function of temperature and particle size with sufficient accuracy. These results show that obtained quadratic models are adequate to predict the response variables.

When the individual effect of each equation term (linear, quadratic and interaction) was analysed, it is clear, from Table 3, that linear terms of particle size and temperature affect significantly ($P \leq 0.1$) TR and TCC while HT is affected significantly ($P \leq 0.1$) by linear and quadratic terms of temperature. In this sense, the quadratic effect of temperature on HT, within the particle size range analysed, is apparent from the surface shape shown in Figure 2(c). On the other hand, the heating time dependence with the particle size was not proven statistically ($P > 0.1$).

The interaction effect of particle size and temperature (x_1, x_2) was not significant ($P > 0.1$) for the different objective functions analysed.

Figure 2a shows the response surface and contour plot of the texture retention as function of process temperature and particle size. In this plot it is observed that the TR increases when the heating temperature increases and particle size decreases. These results can be explained by the fact that equivalent thermal processes were applied, i.e. low temperatures involved long processing times and high temperatures reduced considerably the thermal treatment time. For instance, a heating time of 164 min at 85°C achieves a TR of 53.10% whereas 38 min at 100°C produced a TR of 81%, for cubes of 20 mm. With regard to particle size, smaller particles are less exposed to the heating fluid, because the bed in the jars is more compact. This fact could explain the higher texture retention achieved by smallest cubes after the pasteurization process. For instance, a treatment at 100°C achieves a TR of 31.80% for cubes of 30 mm whereas for cubes of 20 mm a TR of 81% is obtained. In order to obtain high TR, the pasteurization must be carried out at high temperature and with small particle size.

Similarly, Figure 2(b) shows the response surface and contour plot for TCC as a function of temperature and particle size. The samples became darker and lost redness, yellowness and vivid characteristic during thermal process. Carotenoids is the main group of colouring substances in pumpkin, and responsible for its orange colour [48]. These colour alterations may be explained by carotenoids degradation, through enzymatic and nonenzymatic browning reactions as stated by Ref. [49]. It is seen that at higher temperatures, shorter processing times, TCC decreases for the same particle size. It is evident that these conditions favor less thermal degradation of color of pumpkin. On the other hand, the increases of TCC with the particle size could be explained by the fact that heating of the particle surface is more gradual for smaller particles, because the bed is more compact. As expected, the estimated heating times were shorter at higher temperatures (see Figure 2(c)). With regard to particle size, the longest heating time was achieved for the smallest cubes (20 mm) during treatment at 85°C. This fact could be attributed to that the arrangement cubes of 20 mm in the jar is more compact, which restricts convective movement of the fluid between the particles.

3.2.2 Multiple optimisation – desirability function

Desirability function method can be applied to different foods and processing systems with the aim of optimizing different factors. In the case of food pasteurization, texture, taste, colour, process time, costs, etc., alone or in combination, can be used for this purpose. In our study, the optimal conditions for pasteurization of pumpkin cubes were found using desirability function method coded in Matlab 7.2 according to the following main criteria: maximize TR and minimise TCC and HT. The second-order polynomial models obtained by polynomial regression were used for each response (TR, TCC and HT) to determine graphical optimal zones and the exact

Table 3: Analysis of variance of polynomial fitted models for response variables during pasteurization of pumpkin cubes.

Factors		HT		TR		TCC	
		Coefficients	*P*-value	Coefficients	*P*-value	Coefficients	*P*-value
constant	β_0	6,145.2700	–	−270.8843	–	234.9117	–
$x_{1(\text{particle size})}$	β_1	−53.5405	0.4035	−10.7684	0.0043	−1.4310	0.0060
$x_{2(\text{temperature})}$	β_2	−110.4520	0.0023	9.8200	0.0700	−4.4736	0.0411
x_1^2	β_{11}	0.6746	0.1408	0.3630	0.1510	0.0467	0.1223
x_2^2	β_{22}	0.5334	0.0538	−0.0304	0.7730	0.0240	0.1198
x_1x_2	β_{12}	0.2057	0.2814	−0.1273	0.2424	−0.0050	0.6531

Source: *TR*. texture retention; *TCC*. total colour change; *HT*. heating time.

optimal conditions for preserves of pumpkin cubes during the pasteurization. Values of desirability function were calculated according to eqs (4)–(6). Individual and total desirability surfaces (Figures 3 and 4, respectively) were obtained using Matlab graphical functions according to desirability function values calculated from different particle sizes (20, 25 and 30 mm) and processing temperatures (85, 90 and 100°).

From individual desirability function for texture retention (dTR) (Figure 3(a)) it can be seen that its maximum value was achieved at maximum temperature and minimum particle size. It is apparent from Figure 3(a) that PZ had a strong influence on the TR, which decreases rapidly as the particle size increases. When individual desirability function for TCC (dTCC) is analysed from Figure 3(b), a plateau zone (in the shape of semi-ellipse) corresponding to maximum dTCC can be appreciated in the range of temperature from 91 to 100°C and particle size from 20 to 24 mm. In a similar manner, dHT also presents an optimal zone located from 96.25 to 100°C and from 21.5 to 27.5 mm for temperature and particle size, respectively (see Figure 3(c)).

From total desirability plot (see Figure 4), it can be seen that a optimal condition is located in maximum temperature level (100°C) and minimum particle size level (20 mm). For these conditions the total desirability function has a value of 0.98, this high value close to unit indicates that individual functions exhibit similar trends, with optimal values close to one (this is more apparent for TR and TCC). The combinations of factors that lead to a

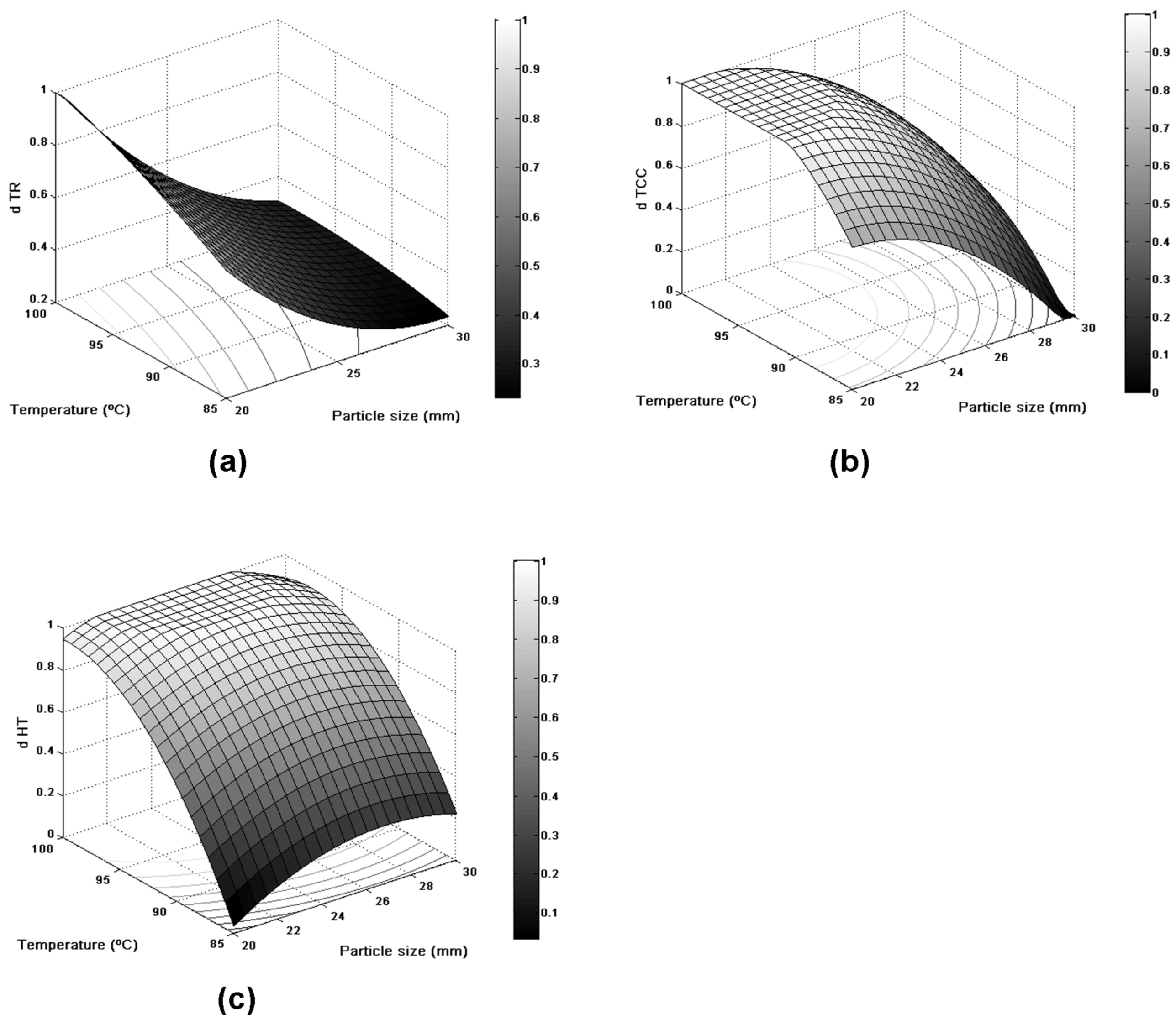

Figure 3: Individual desirability surfaces and contours for TR, TCC and HT.

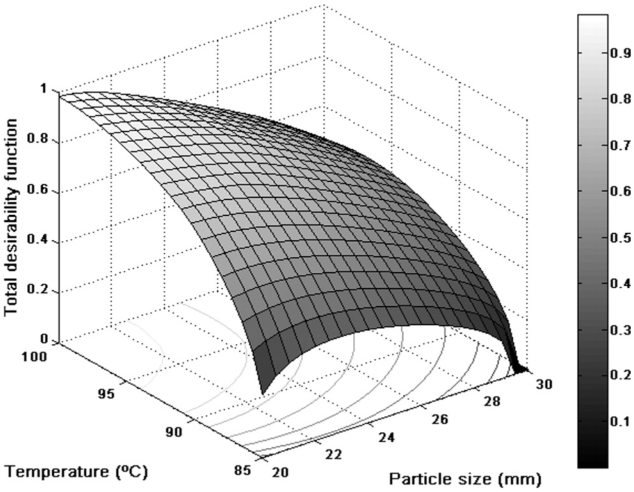

Figure 4: Total desirability surfaces and contours for pasteurization optimization of pumpkin cubes packaged in glass jar.

product with the highest quality (maximize TR and minimize TCC) in the shortest possible processing time (minimize HT), considering different relative importances (v_i) assigned to each dependent variable, are presented in Table 4. It is apparent from Table 4 that when equal importances were assigned to the three variables the optimal condition was 20 mm and 100°C for PZ and PT, respectively. Thereby, the values obtained for the three responses were: TR of 82.21%, TCC of 7.54 and HT of 44.97 min. As can be observed in the same table, when a major importance was assignated to quality retention (TR or TCC), variations in optimal conditions were not found.

Table 4: Optimized operating conditions for pasteurization of pumpkin cubes.

Operating conditions		Optimized responses			
Process temperature (°C)	Particle size (mm)	TR (%)	TCC	HT(min)	D_{max}
Goal		max	min	min	
θi		1	1	1	
100	20	$v_{TR}=3$	$v_{TCC}=3$	$v_{HT}=3$	
		82.21	7.54	44.97	0.98
100	20	$v_{TR}=3$	$v_{TCC}=1$	$v_{HT}=1$	
		82.21	7.54	44.97	0.99
100	20	$v_{TR}=1$	$v_{TCC}=3$	$v_{HT}=1$	
		82.21	7.54	44.97	0.99
100	21	$v_{TR}=1$	$v_{TCC}=1$	$v_{HT}=3$	
		73.60	7.52	39.66	0.97

Note: v_i is the relative importance assigned to each process variable. θi, goal-weight factor.

On the other hand, practically no difference was found between the TCC values obtained for different criteria to assign the importance to each response. Nevertheless when a major importance is assigned to heating time the optimal particle size is increased to 21 mm, whereas the processing temperature is maintained (100°C). An important observation is that at these optimal conditions (21 mm and 100°C) the HT was reduced (11.8%) from 44.97 to 39.66 min, however TR was negatively affected decreasing (10.47%) from 82.21 to 73.60%. Therefore the final decision of the optimal conditions depends on considerations of costs and effects in the sensory characteristics of the product [21]. In order to evaluate the goodness of the surface response model for total desirability function, predicted optimized conditions and experimental results obtained for particle size = 20 mm and heating temperature = 100°C were compared; the models predicted the following responses: TR = 82.21%; TCC = 7.54 and HT = 44.97 min. Moreover, experimental responses obtained were the following: TR = 81.00%; TCC = 7.59 and HT = 38.00 min. A fact that is interesting to observe is that predicted heating time was higher than experimental value, which proves that the model is conservative and ensures the microbiological safety of the product. Predicted and experimental results were not statistically different at 5% significance level.

4 Conclusions

In this work, polynomial regression and desirability function methodologies were successfully applied to determine the optimum operating conditions that yield maximum texture retention and minimum total change colour and heating time in pasteurization of pumpkin cubes. The analysis of variance showed significance from all second-order polynomial models developed for the three responses. The optimal conditions for maximum texture retention (TR) and minimum total colour change (TCC) and heating time (HT) correspond to process temperature of 100ºC and particle size of 20 mm in order to obtain TR of 82.21%, TCC of 7.54 and HT of 44.97 min. However, when the heating time is prioritized the optimal condition changes to 100°C and 21 mm and the responses obtained are TR of 73.60%, TCC of 7.52 and HT of 39.66 min.

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