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Model-based multi-objective optimization of beef roasting

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ABSTRACT

A validated mathematical model has been used to perform multi-objective optimization of beef roasting, considering the minimization of both cooking time and weight loss. Simulations were performed using irregular geometrics models of beef *semitendinosus* muscle and constant oven temperature. Minimum temperature of 72 °C at the coldest point was imposed as a constraint. From model results a compromise situation was encountered, since no operative condition lead simultaneously to optimal values of both objectives, i.e., an increase in oven temperature leads to a decrease in cooking time, between −0.25 and −0.325 min/°C, and an increase in weight loss, between 0.175 and 0.275%/°C. In this sense, not one, but a set of optimal solutions was found in the Pareto sense. Experimental cooking tests were performed, which are in good agreement with model simulations. Furthermore, energy consumption for each optimal solution obtained in the optimization problem was estimated, being lower using low oven temperatures.

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1. Introduction

The market of processed foods is becoming more exigent every year. This compels the food processors, responsible for the design and operation of processes, to optimize them paying attention to different objectives: to diminish the operational costs (for instance process time and energy consumption) and to increase the overall performance, while maintaining high quality standards and satisfying safety restrictions.

The search for the optimum solution demands a deep knowledge of the mechanisms involved in the different stages of transformation. Some processes have been studied thoroughly while others still deserve more profound studies. Among these last group lays the cooking of meat products in convective ovens.

Focusing on the physical mechanisms, beef roasting implies heat transfer from the surrounding oven ambient to the food, what increases the temperature of the product. Additionally, significant weight loss is often observed during the process, which is generally attributed only to water loss, neglecting other food components losses (i.e. proteins, lipids). The weight loss determines the global yield of the cooking procedure and affects specific quality attributes, such as texture and juiciness.

Both practical experience and literature (Bengtsson et al., 1976; Burfoot and Self, 1989) suggest that the choice of the optimum cooking conditions is not necessarily direct or trivial, since a conflict among the different objectives can be found. For instance, given specific beef doneness, a higher oven temperature will reduce the process time, yet it will decrease yield (high weight loss). Otherwise, a lower oven temperature will provide lower weight loss values, however demanding a greater cooking time. This particular type of behavior justifies the development of a multi-objective optimization strategy.

Although many efforts have been done regarding modelling and simulation in food engineering, few researches have been done to exploit these validated models through mathematical optimization (Banga et al., 2003). Hence, any attempt to perform process optimization can improve its knowledge and provide a helpful decision tool. Until now, beef roasting optimization has been addressed by few authors. Townsend et al. (1989a,b) used a cooking model to optimize the process with different combinations of oven temperature–time. Powell et al. (2000) optimized the cooking of *semitendinosus* muscle focusing on texture and collagen denaturalization. Given the high volumes consumption and the safety considerations due to ground meat, mathematical modeling and optimization of hamburgers contact-cooking has been thoroughly studied focusing on cooking loss or different texture attributes (Banga et al., 2001; Erdoğdu et al., 2005; Zorrilla et al., 2000, 2003; Zorrilla and Singh, 2000, 2003).

Most optimization studies reported in food engineering refer to single-objective optimization. Only a few researchers propose multi-objective strategies in the analysis of different food processes: bulk-grain handling (Thakur et al., 2010); thermal processing (Erdoğdu and Balaban, 2003; Chen and Ramaswamy, 2002a,b; Noronha et al., 1996; Sendín et al., 2010); drying (Kiranoudis and Markatos, 2000; Olmos et al., 2002; Trelea et al., 1997); baking

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Nomenclature

a_w	water activity
c	moisture content, dry basis
C_P	specific heat of beef ($J\,kg^{-1}\,K^{-1}$)
h	convective heat transfer coefficient ($W\,m^{-2}\,K^{-1}$)
k	thermal conductivity of beef ($W\,m^{-1}\,K^{-1}$)
k_g	mass transfer coefficient ($kg\,Pa^{-1}\,m^{-2}\,s^{-1}$)
K_W	parameters of Eq. (4) (kg dry solid s^{-1})
m_s	dry solid mass (kg)
P_{sat}	water vapor pressure (Pa)
RH	oven relative humidity
T	temperature (K or °C)
WHC	water holding capacity of beef, dry basis

Greek symbols

ε	beef emissivity
λ	latent heat of water evaporation ($J\,kg^{-1}$)
ρ	beef density ($kg\,m^{-3}$)
σ	Stefan–Boltzmann constant ($5.67 \times 10^{-8}\ W\,m^{-2}\,K^{-4}$)

Subscripts

C	core
o	oven
s	surface

(Hadiyanto et al., 2007, 2008a,b, 2009; Purlis, 2011); roasting (Białobrzewski et al., 2009).

In this context, the aim of this work is to analyze the behavior of cooking times and weight losses as a function of constant oven temperature (provided by a previous developed roasting model) and to formulate a multi-objective optimization problem to minimize both quantities. We intend for these predicted trends of cooking time and weight loss to be used as a reference guide in the food engineering field. Additionally a simple procedure was performed in order to estimate the energy consumption of the oven.

2. Material and methods

2.1. Modeling of beef roasting

In a previous work, we have developed a mathematical model of beef roasting (Goñi, 2010; Goñi and Salvadori, 2010). Such model will be employed in this research to propose and solve the multi-objective optimization problem. Table 1 presents a summary of its principal equations. Briefly, the mathematical model considers conductive heat transfer inside the sample and assumes that weight loss occurs by two well-differentiated mechanisms: superficial evaporation, depending on the water activity on the food surface and the relative humidity of the oven ambient; and dripping, i.e., direct liquid water loss from the surface, associated to the denaturalization of proteins and the shrinkage of meat fibers network (Godsalve et al., 1977). It is worth to note that this model assumes that the evaporation front remains in the surface. At any time, the cumulative evaporative loss is predicted by time and surface integration of instant evaporative mass flux, and the cumulative dripping loss is estimated as the difference of liquid water content between the initial value and volume average moisture content, evaluated at time t. Finally, the total weight loss is obtained by summing both evaporative and dripping losses. Thermophysical properties of beef and the transfer coefficients were computed according to published data; WHC and K_W parameters were obtained in earlier studies using beef *semitendinosus* muscle samples. The roasting model was successfully validated: cooking experiments of beef *semitendinosus* muscle, performed in a domestic electric oven, show that model predictions were in good agreement with the experimental results. The average absolute relative error was 3.91% for cooking time prediction, and 7.96% for total weight loss prediction (or equivalently 3.02% for final weight prediction) (Goñi, 2010; Goñi and Salvadori, 2010).

2.2. Optimization problem

To optimize 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, defined previously. The objective function is also usually subject to a number of specific restrictions, derived from the process itself (Banga et al., 2003, 2008).

When there is only one optimization criterion (single-objective), there exists a unique optimal solution. However, a process with different simultaneous objectives (for example energy consumption, process time, and global yield), presents a much more complex and difficult to solve optimization problem. In an ideal case, in which there are no conflicts between the different objectives that are to be optimized, it would be possible to find only one set of decision variables that lead to the global optimum solution. Nonetheless, in practice, most applications of interest in food engineering present conflicting objectives: the values of each objective function cannot be improved without deteriorating at least one of the other objective functions. Hence, to optimize a multi-objective problem is equivalent to obtaining a complete set of solutions involving optimal trade-off among the objectives (Deb, 2001; Sendín et al., 2010), the so-called Pareto optimal, non-inferior or non-dominated solution. So, when solving a multi-objective optimization problem it is desirable to obtain multiple Pareto optimal solutions, which have a wide range of values of the objectives. Ultimately, the user will select among all the solutions the one that represents the best alternative, referring to additional information on the problem or their own preferences (Sendín et al., 2010).

This work is focused in the optimization of beef roasting, and seeks to minimize simultaneously the cooking time (t_c), and the total weight loss. Values of both objective functions are actually provided by the cooking model. The main restriction of this

Table 1
Summary of equations of the beef cooking model.

Eq. No.	Description	
(1)	Energy balance	$\rho C_P \frac{\partial T}{\partial t} = \nabla(k\nabla T)$
(2)	Evaporative mass flux at surface	$j_{evap} = k_g(a_w P_{sat}(T_s) - RH P_{sat}(T_o))$
(3)	Boundary condition of the energy balance	$-nk\nabla T = h(T_s - T_o) + \varepsilon\sigma(T_s^4 - T_o^4) + \lambda j_{evap}$
(4)	Local water content variation	$m_s \frac{dc}{dt} = -K_W(c - WHC(T))$

multi-objective optimization problem was that the temperature at the coldest point (T_C) must reach at least 72 °C. Additional restrictions were also included to establish the operative limits of the oven temperature (ranging between 150 and 230 °C).

The multi-objective optimization problem was solved using the ε-Constraint method (Deb, 2001), which optimizes a single-objective problem, incorporating the other ones as an additional constraint. In this sense, in this work the weight loss was considered the objective to be minimized, and the cooking time was treated as an additional constraint. It is worth noting that "time" is both a decision variable and an objective, so considering it as a constraint automatically determines the feasible search space.

Then, the multi-objective optimization problem was formulated according to:

$$\min_{(t,T_o)} \quad WL$$

Subject to :

$$\begin{cases} 0 \leqslant t \leqslant t^* \\ 150 \leqslant T_o \leqslant 230 \\ 72 \leqslant T_C \end{cases} \tag{5}$$

Eq. (5) was repeatedly solved for different cooking times values (t^*). These t^* values are arbitrarily selected from the interval [t_1, t_2], being t_1 and t_2 the minimum and maximum cooking times for each sample.

Additional equality restrictions describing beef roasting (i.e. heat and mass balances, initial and boundary conditions) complete the formulation of the optimization problem, which was solved by means of a gradient based method coded in MATLAB(R) (The Math Works Inc., USA). A similar methodology was successfully used by Olmos et al. (2002) for optimizing the quality of rice during drying.

The roasting optimization was carried out using six samples of beef *semitendinosus* muscle. Their shape was considered to be 3D irregular, and were constructed according to a procedure previously developed (Goñi et al., 2007, 2008). Table 2 provides the initial characteristics (weight, size) of the samples; the width and height of them were measured at the half of the length. Fig. 1 shows a beef sample and the constructed 3D irregular geometric model. Numerical solutions of the roasting model were obtained using the finite element method in COMSOL™ Multiphysics (COMSOL AB, Sweden). A mesh consisting of ca. 6400 (in average) deformed tetrahedrons was used for each sample. The solver is an implicit variable time-stepping scheme combined with Newton's method to solve the resulting non-linear equation system. The initial temperature and water content were fixed at 4 °C and 75% (wet basis), respectively, for the whole set of numerical simulations.

Table 2
Weight and characteristic dimensions of beef raw samples used to perform the multi-objective optimization.

Sample	Raw weight (kg)	Raw sample characteristic dimensions (cm)		
		Height	Width	Length
#1	1.0799	8.2	10.6	17.7
#2	0.9718	7.7	10.5	17.5
#3	0.7795	6.7	11.2	14.3
#4	0.7406	7.3	10.0	15.7
#5	0.6325	6.5	8.5	14.0
#6	0.4900	5.7	9.0	13.0

2.3. Experimental validation

In order to analyze the roasting model prediction capability considering constant oven temperature, additional cooking test were performed. For this aim, half pieces of *semitendinosus* muscle samples of similar initial weight were cooked at low and high oven temperature respectively, near to the operative limits considered in the optimization problem (150 and 230 °C). Cooking of each sample was performed in a domestic electrical oven (ARISTON FM87-FC, Italy), using the forced convection heating mode. The oven was preheated and once the oven temperature reach the selected value, the meat sample was placed on the central region of the oven. Meat (surface and core) and oven temperature profiles were measured using T-type thermocouples (Omega, USA) connected to a data logger (Keithley-DASTC, USA). The cooking was finished when the core temperature reached 72 °C. The weight and characteristic dimension (height, width, and length) of the samples were measured before and after cooking. Details of the experimental tests are summarized in Table 3: two large pieces (near 0.9 kg) and two small ones (near 0.6 kg) were used. It is worth to note that oven temperature represents an average value once the oven reaches the regime; initially, opening the oven door produces a decrease of temperature, and then it is maintained near a constant value.

For each cooked sample, the corresponding cooking simulation was done, according to the following procedure (for further details the reader should be referred to Goñi and Salvadori, 2010):

- A 3D irregular domain was constructed from sample.
- The convective heat and mass transfer coefficient were estimated from the experimental cooking conditions.
- The initial sample temperature and water content were experimentally determined.
- The experimental oven temperature profile recorded during the cooking tests was used.

The simulated cooking time and total weight loss were determined when core temperature reached 72 °C.

2.4. Consumption of energy during roasting

In addition to cooking time and weight loss, which were actually considered in the optimization problem, the oven energy consumption during roasting was estimated. Such issue is of great

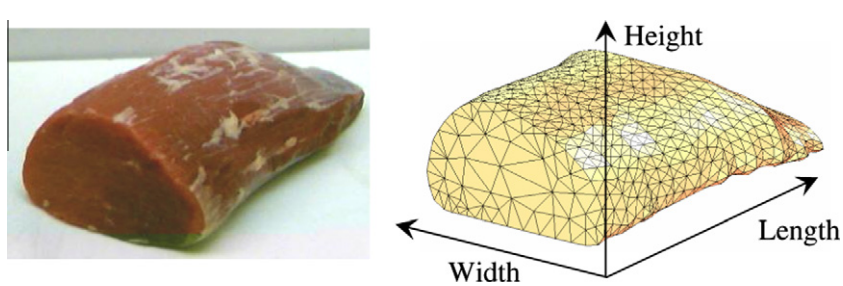

Fig. 1. (a) Image of whole raw sample of *semitendinosus* muscle, and (b) constructed 3D irregular geometric model (which is already meshed). Direction of length, width and height characteristic dimensions are indicated.

Table 3
Experimental and simulated results of the cooking tests.

Sample	#7	#8	#9	#10
Initial weight (kg)	0.9128	0.8865	0.6048	0.6374
Initial water content (dry basis)	2.83	2.89	2.91	2.97
Initial temperature (°C)	10.19	12.62	13.81	10.05
Oven temperature, at regime (°C)	155.23	229.26	156.06	230.05
Initial and (final) dimensions (cm)				
Height	7.8 (8.9)	7.3 (8.4)	7.0 (7.6)	7.4 (8.1)
Width	11.1 (9.6)	11.5 (9.2)	9.5 (8.2)	10.3 (8.3)
Length	16.5 (13.1)	15.6 (12.1)	12.6 (10.9)	13.5 (10.7)
Cooking time (min)				
Experimental	101.50	75.50	92.50	66.50
Simulated	96.00	70.50	85.50	64.00
Total weight loss (%)				
Experimental	24.04	34.74	26.17	32.19
Simulated	21.09	34.99	25.52	36.53

importance, since, along with the yield, is a determinant issue in the economic balance. In order to estimate the consumption of energy, the relationship between effective electric power and oven temperature must be considered. The effective power consumption was estimated as the nominal power (P_N) of the oven multiplied by a factor of use (f), which depends on the selected oven temperature.

The nominal power was measured with the oven empty at the maximum temperature, using a clamp tester (SEW ST-300, Taiwan). Since the circuit is mainly resistive, the power was estimated equal to electric current multiplied by the supplied voltage. Experimental oven temperature profiles measured during beef roasting in earlier studies (Goñi, 2010; Goñi and Salvadori, 2010) and the ones obtained in the current work, were used to estimate f values, according to the following procedure: (i) the oven temperature profile obtained after reaching a regimen state was considered; (ii) the factor of use was defined as the ratio between the heating time (when the oven temperature increases) respect to the total regimen time. Then, for each combination of oven temperature – cooking time obtained in the multi-objective optimization problem, the energy consumption was calculated as the effective power ($P_N \times f$) multiplied by the cooking time:

$$E = P_N \times f \times t \tag{6}$$

3. Results and discussion

Table 3 shows the experimental cooking time and total weight loss for the four tested samples used in the additional experimental validation tests. As can be seen from these results, an increase of the oven temperature produces a reduction of the cooking time and an increase of the total weight loss. This situation shows that the optimization objectives are in conflict with each other. Variation of characteristic dimensions was similar to results previously found (Goñi and Salvadori, 2010): in all cases the height of cooked samples was greater than raw ones, while width and length were smaller.

Regarding surface temperature profiles, the sample #8 cooked at high temperature (see Table 3) exhibits an increase above 100 °C, reaching values close to 112 °C. In this sense, the cooking model can not predict these values, since it assumes that the surface remains near 100 °C and a constant drying rate is established. It is worth to note that in all cases the surface thermocouple was inserted in the top region of the samples. On the other hand, the behavior of the liquid water expelled from meat by dripping was similar to the one found in earlier studies (Goñi and Salvadori, 2010): liquid water expelled from meat by dripping remains "adsorbed" to the surface until large droplets were formed, then water flow down to lower regions of the beef. This behavior determines that a great proportion of the sample surface remains wet, avoiding or limiting the development of a dehydrated surface layer. Fig. 2 shows an image of an axial cut for the samples near 0.9 kg of initial weight. As it can be seen, a crust was observed in the top region of the sample cooked at high temperature, while at low temperature the crust formation was much less evident. A similar behavior was observed for the smaller samples used in this work. Since the major fraction of meat surface remains wet during all the cooking process, the cooking model can be applied. In this sense, Table 3 shows predicted cooking times and weight losses. In all cases the simulated cooking times were shorter than the experimental ones, with an average under-prediction of 5 min (absolute average relative deviation for cooking time was 5.84%). Regarding weight loss, the absolute average relative deviation was 7.24% (or equivalently 2.81% for final weight prediction), which correspond to 14.6 g in average.

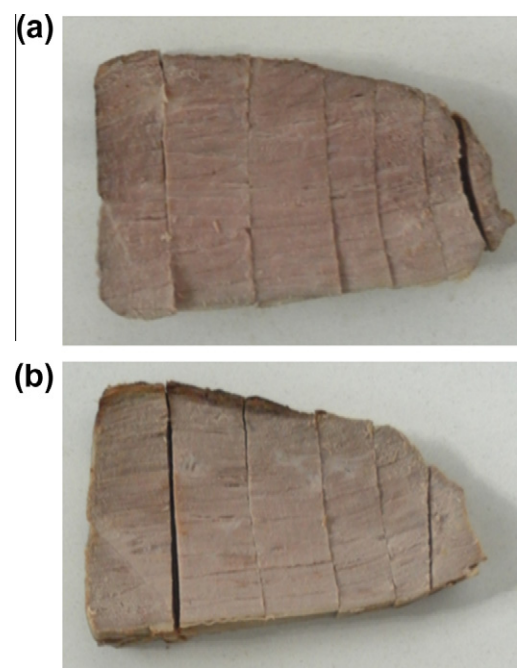

Fig. 2. Image of a cut along axial axis of the cooked samples (at the half of width): (a) sample #7, oven temperature 155.23 °C; (b) sample #8, oven temperature 229.26 °C. Vertical (perpendicular to axial axis) cuts corresponded to the ones used to perform geometric modeling.

Since it has been demonstrated that the roasting model provides satisfactory predictions of cooking time and weight loss, it is used to perform cooking optimization. Before solving the stated optimization problem, a preliminary sensitivity analysis was performed to examine the behavior of the simulated cooking times and weight losses respect to oven temperature, using samples indicated in Table 2. With this aim, cooking simulations were done for each sample considering different values of constant oven temperature, between 150 and 230 °C (with a 10 °C step). For each case the cooking time (when the coldest point reached 72 °C), and the weight loss were calculated. Fig. 3 shows the obtained cooking times and weight losses, as a function of oven temperature. The simulated cooking time ranged between 49 min (minimum) and 106 min (maximum), which correspond to the smallest sample cooked at the highest temperature and to the largest sample at the lowest oven temperature, respectively. For these two cases, the total weight losses were 39.3% and 21.7%. The variation of the cooking time with temperature is more noticeable at lower oven temperatures: when the sample surface reaches 100 °C, water evaporation limits the heating rate and the energy transfer is reduced to a problem of imposed temperature (Skjöldebrand and Hallström, 1980). In these conditions the surface remains moist and a constant drying rate period is established. Besides, if evaporation is low or moderate, dripping losses can be observed. On the other hand, high evaporation rates can produce a displacement of the evaporation front toward the core of the sample and generation of a dehydrated surface crust. In these conditions, the water arriving from inside the product will evaporate entirely in an inner evaporation front and dripping will be not observed (Hung et al., 1978).

Fig. 4a shows simulated total weight loss vs. time, for one sample, at different oven temperatures. After an initial stage, the total weight loss augments linearly with time; also, it is clear that an increment in the oven temperature reduces the cooking time and increases the weight loss. Fig. 4b shows the variation of the total weight loss and the contribution of the evaporative one. During the first minutes of cooking, the weight loss can be exclusively attributed to evaporation; the dripping losses start to show once inner temperature is sufficient to induce protein denaturalization. The shape of the weight loss curves obtained from the cooking model (Fig. 4), match consistently with those obtained experimentally by Bengtsson et al. (1976), for cooking of *semimembranosus* bovine muscle in an experimental oven with a low energy transfer rate.

The results obtained with the cooking model agreed well with the trends observed in the experimental tests, clearly showing that the optimization objectives are in conflict with each other. Increasing the oven temperature from 150 to 230 °C reduces the cooking time 20–26 min (equivalent to −0.25/−0.325 min/°C) and increases the weight loss 14–22% (equivalent to 0.175/0.275%/°C), depending on the initial size of the beef sample. This opposite behavior predicted by the model agrees other works published

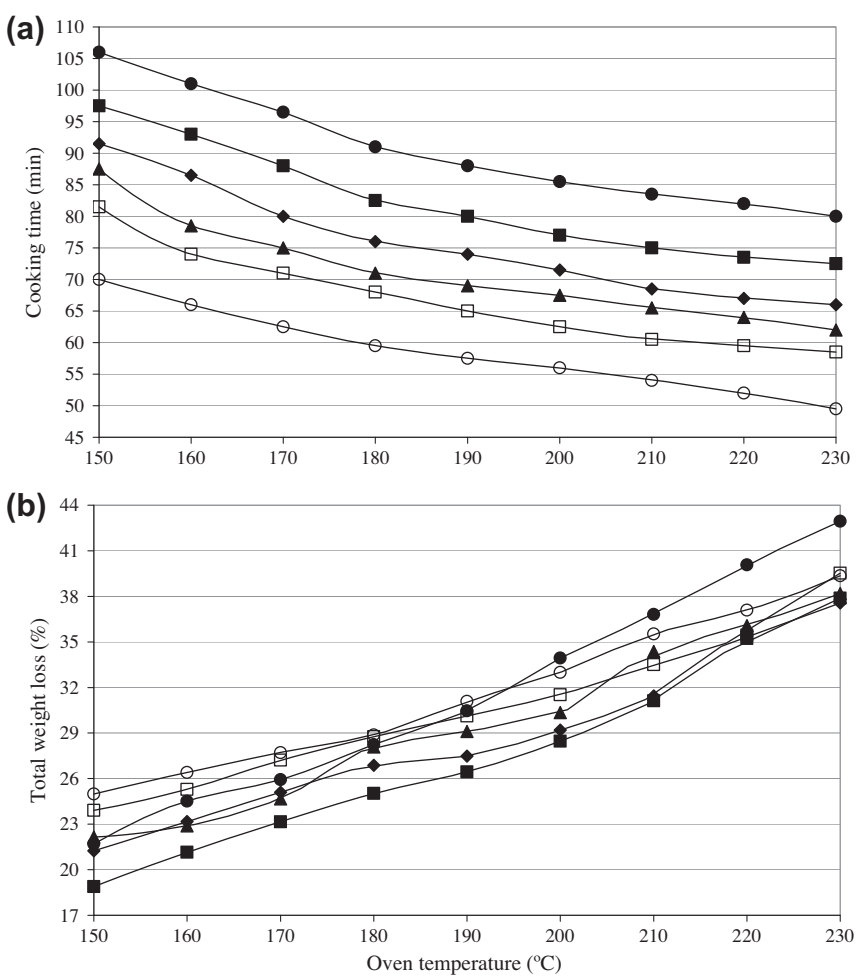

Fig. 3. Simulated values of (a) cooking time and (b) total weight loss (%), when coldest point reached 72 °C, T_o between 150 and 230 °C. Symbols correspond to samples of different initial weight (detailed in Table 2): (●) 1.0799 kg, (■) 0.9718 kg, (▲) 0.7795 kg, (♦) 0.7406 kg, (□) 0.6325 kg, (○) 0.49 kg. Lines correspond to interpolated values.

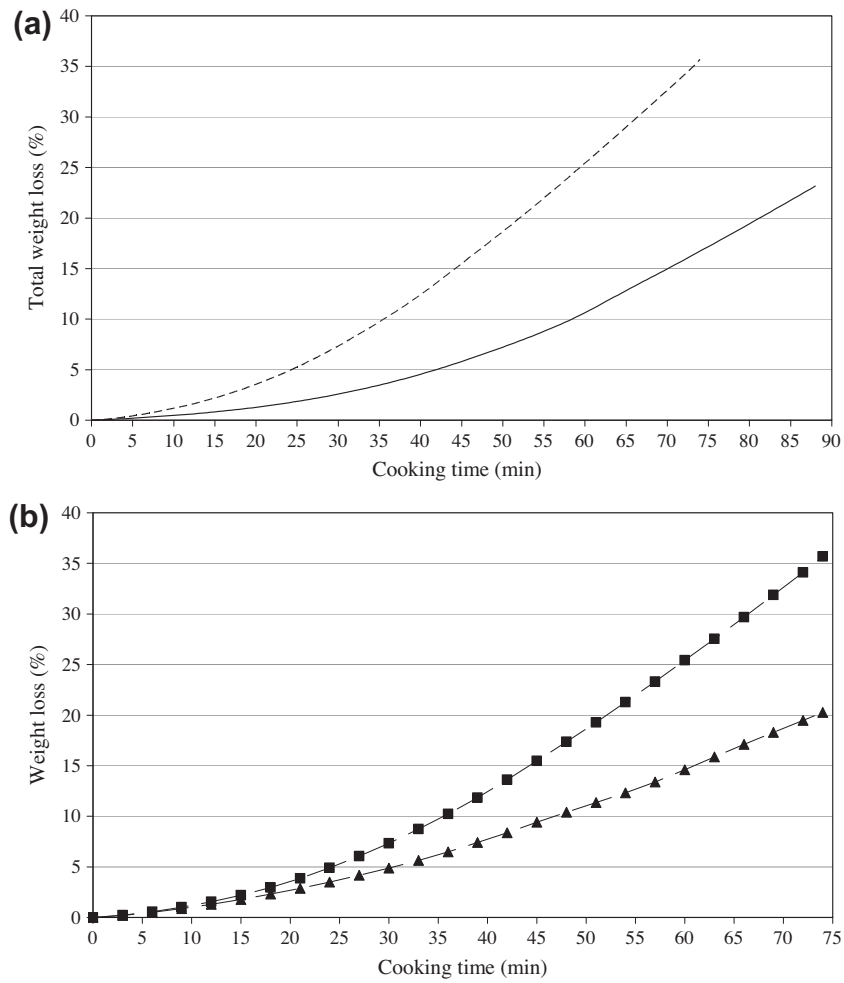

Fig. 4. (a) Simulated total weight loss (%), for the 0.9718 kg initial weight sample and end core temperature of 72 °C. Oven temperature: (---) 220 °C; (–) 170 °C. (b) Variation of (-■-) total weight loss and (-▲-) evaporative loss for the previous sample at 220 °C oven temperature.

Table 4
Experimental results of roasting of meat muscles showing a compromise situation between cooking time and weight loss.

Sample	Initial mass (kg), State	Temperature (°C)		Cooking time (min)	Total weight loss (%)	Average variation with oven temperature		Reference
		Oven	Final core			Cooking time (min/°C)	Total weight loss (%/°C)	
Beef	0.8–0.9, Unfrozen	175	70	80.0	24.0	−0.400	0.120	Bengtsson et al. (1976)
		225		60.0	30.0			
		175	40	39.0	12.0	−0.140	0.080	
		225		32.0	16.0			
Beef	0.6, Unfrozen	121	74	180.0	28.2	−1.446	0.032	Hung et al. (1978)
		177		99.0	30.0			
		121	67	150.0	21.3	−1.125	0.054	
		177		87.0	24.3			
		121	59	120.0	14.3	−0.804	0.079	
		177		75.0	18.7			
Pork	0.83–0.95, Frozen	93*	77	441.4	22.9	−1.091	0.071	Jones et al. (1980)
		121		183.1	16.7			
		149		140.8	18.5			
		163		131.4	19.6			
Beef	0.672–1.223, Unfrozen	120	62	100.0	16.4	−0.620	0.150	Mielche (1992)
		170		69.0	23.9			

* Data no included to calculate cooking time and weight loss variation.

by different authors, who have done experimental research regarding the cooking of meat muscles of different sizes in convective ovens. Table 4 resumes the information provided by them; different meat samples, oven temperature, and end core temperature are covered. Also, James and James (2004) indicated that low temperatures are necessary to reduce the weight loss during the cooking of big sized samples. On the other hand, Burfoot and Self (1989) found that an increase in oven temperature reduce both the

cooking time and the weight loss. Then, according to their results the objectives are not opposite. It is worth noting that the authors used a forced convection tunnel, different from the domestic-type oven used in all the other mentioned studies.

The analysis of the previous results indicates that it is not possible to select an oven temperature that has a favorable effect on both objectives: cooking time and weight loss. So, all the analyzed conditions are Pareto-optimal. In order to obtain different Pareto-optimal solutions in a systematic way, the multi-objective problem was solved as described previously. Fifty-one different time values (t^*) with a constant step between the minimum and the maximum ones were used for each sample. It means that 51 optimal solutions (combinations of oven temperature-cooking time) will be obtained for each sample. Using the complete 3D model, each run (for one particular value of t^*) requires several hours of calculation to arrive to an optimal solution. The convergence of the optimization algorithm was tested using different initial values, applying the complete 3D model and several selected values of t^*. Even using infeasible initial conditions (a cooking time greater than t^* and an oven temperature which produces $T_C < 72$ °C) the same optimal solution was found.

In order to improve this aspect and to reduce the computing time, an approximate procedure was proposed, according to the following steps: (i) the cooking times and weight losses data sets obtained for each sample (Fig. 3) were interpolated as a function of oven temperatures; (ii) the optimization problem was solved using only the oven temperature as a decision variable, while cooking time and weight loss were evaluated from the interpolated functions. For all cases, a piecewise cubic interpolation in MATLAB(R) (The Math Works Inc., USA) was used. Fig. 5 shows the results of the procedure for one sample; Fig. 5a shows the Pareto-optimal solutions in the decision space (time-oven temperature) while Fig. 5b shows the Pareto-optimal front in the objective space (time-weight loss). In this last case the conflict

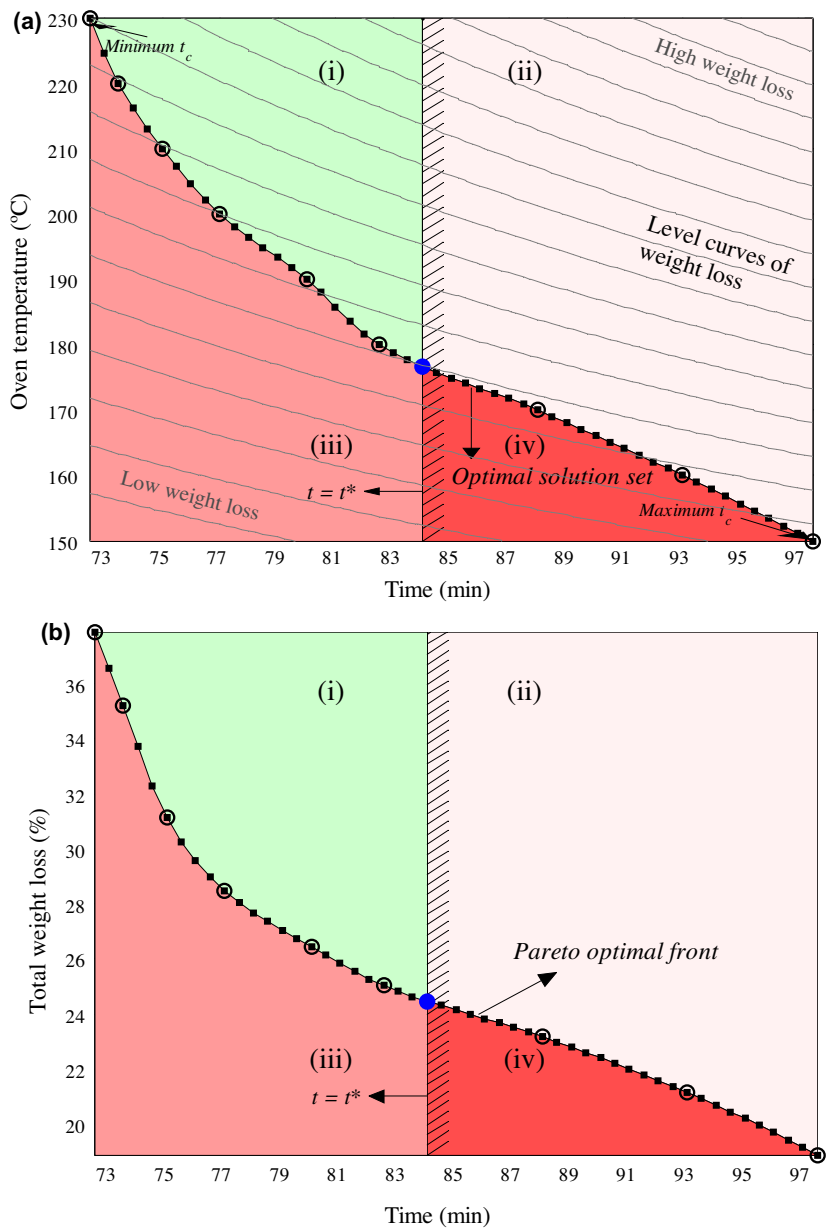

Fig. 5. Example of the optimization procedure, for the 0.9718 kg sample. (a) Decision and (b) objective space. (○) 3D model solutions used to perform interpolation; (■) solutions obtained from interpolated data. Four regions can be distinguished in both decision and objective spaces for a given t^* value: (i) feasible, $T_C > 72$ °C and $t < t^*$; (ii) infeasible, $T_C > 72$ °C and $t > t^*$; (iii) infeasible, $T_C < 72$ °C and $t < t^*$; (iv) infeasible, $T_C < 72$ °C and $t > t^*$. Also, level curves of weight loss are shown in the decision space.

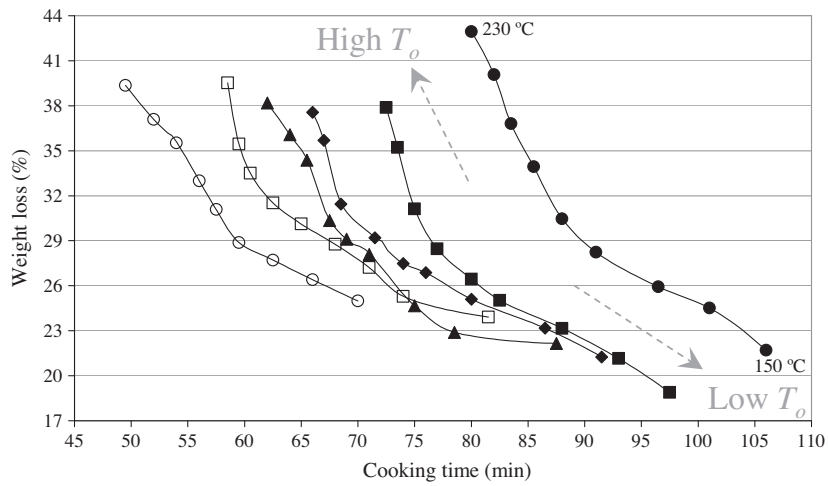

Fig. 6. Pareto optimal front of different initial weight samples: (●) 1.0799 kg, (■) 0.9718 kg, (▲) 0.7795 kg, (♦) 0.7406 kg, (□) 0.6325 kg, (○) 0.49 kg. Symbols correspond to 3D model solutions with T_o between 150 and 230 °C and ΔT = 10 °C. Lines correspond to intermediate optimal solutions obtained by using the interpolated values.

between the objectives can be clearly noticed: from any point placed on the Pareto Optimal front, there not exists a way to move away from this point that produces a decrement in both objectives, i.e., moving to the left, towards lower cooking times, weight loss increases and vice versa. On the other hand, moving below the Pareto optimal front (regions (iii–iv)) infeasible points are obtained, while moving above the Pareto optimal front (region (i–ii)), feasible but not optimal points are achieved. Fig. 5 also shows time constraint, which restricts the feasible space to the region (i). Fig. 6 shows the Pareto optimal front for the six samples tested in this work; as can be seen a similar trend is exhibited.

The usage of simple equations or data interpolation to approximate a set of optimal solutions reduces considerably the computational time, and the calculated Pareto-optimal front remains close enough to the real one. In this sense, the solutions obtained by interpolation were compared to those obtained with the 3D model, using one of the samples. For this, cooking times and weight loss values at intermediate temperatures were obtained (between 155 and 225 °C, ΔT = 10 °C). The difference between the simulated weight loss values and the interpolated ones was lower than 1%. A similar yet more sophisticated approach was successfully used by Chen and Ramaswamy (2002a,b). They developed an energy transfer model to obtain important information (process time, average quality retention, surface cooking value, energy consumption, etc.) during thermal processing with both constant and variable retort temperatures. Then, the obtained data was utilized to develop artificial neural networks (ANNs) as predictive models, than can handle the complex behavior of the system. The resulting ANNs were hence used to optimize the process using genetic algorithms. We have used a similar approach in previous studies: the simulated sets of cooking times and weight losses were adjusted to simple equations (such as quadratic polynomials) depending on the oven temperature. Then, these equations were used to carry out the optimization by means of the weighted sum method (Goñi, 2010; Goñi and Salvadori, 2011). Although this approximation is less complicated, in some regions it was unable to approach the Pareto-optimal front in a satisfactory way, since it is slightly non-convex and the weighted sum method requires the objective function to be convex. The use of the ε-Constraint eliminates these inconveniences, although the selection of the t^* values is still arbitrary.

3.1. Estimated energy consumption during roasting

First, the nominal power of the oven was estimated as 1.98 kW. Fig. 7 shows the thermal profile of the electric oven, obtained

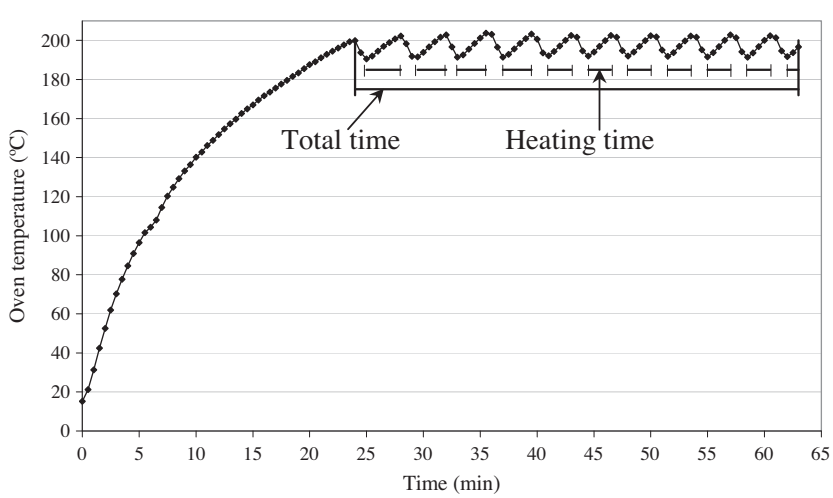

Fig. 7. Representation of the procedure employed to estimate de factor of use from an experimental oven profile. Regimen temperature was 197.3 °C.

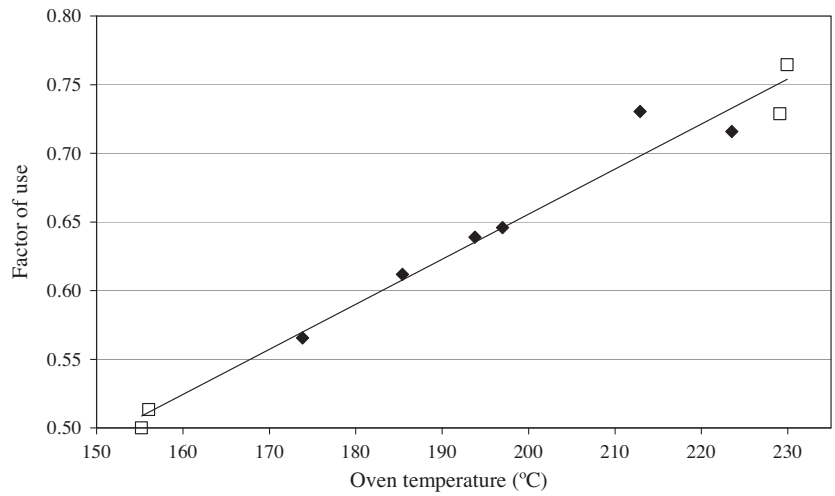

Fig. 8. Experimental (symbols) and fitted (–) values of the energy factor of use obtained at different oven temperature. Oven temperature profile from: (♦) Goñi and Salvadori (2010), (□) current work.

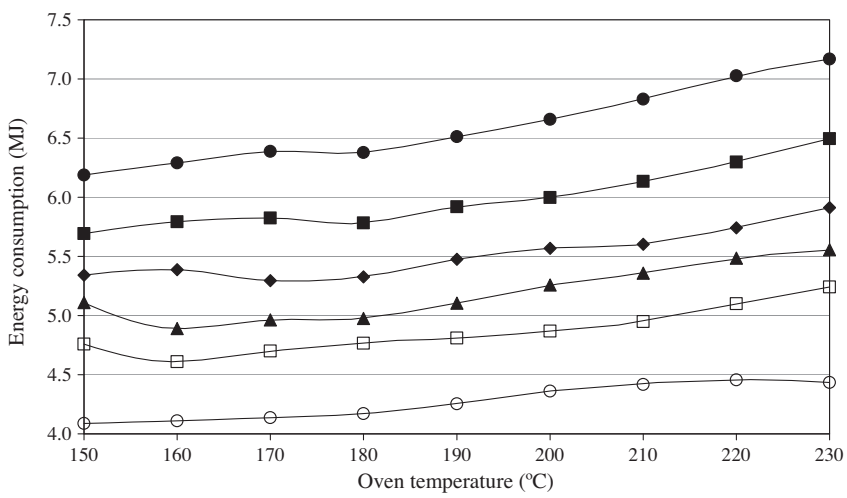

Fig. 9. Energy consumption for different initial weight samples: (●) 1.0799 kg, (■) 0.9718 kg, (▲) 0.7795 kg, (♦) 0.7406 kg, (□) 0.6325 kg, (○) 0.49 kg.

during a cooking experiment (Goñi and Salvadori, 2010), and illustrates the procedure applied to obtain the value of the energy factor of use. Fig. 8 shows the values of the usage factor for different oven temperatures. As it was expected, this factor is proportional to the oven temperature. For predictive purposes, the energy factor of use was expressed as a function of the oven temperature, using a linear relation (Eq. (7)), with an average absolute relative error of 1.53%.

$$f = 3.28 \times 10^{-3} T_O - 1.15 \times 10^{-3} \quad (7)$$

For all the optimal solutions obtained from the optimization problem (all the cooking time-oven temperature combinations), the energy consumption was estimated from the above-described relations. Fig. 9 shows the consumption of energy estimated for each sample. As it can be observed, lower consumption values were obtained for lower temperatures. Even if using high oven temperatures reduces the cooking time during which the power is used, the effective power is higher, producing an overall greater energy demand. It is worth to note that samples #3 and #4 have similar initial weight but different shape, so a noticeable difference between their cooking times and also energy consumptions is observed: sample #3, slightly heavier than sample #4 but with a more flat shape, requires less time and less energy to be cooked.

A similar approach was used by Townsend et al. (1989b) in order to estimate the energy consumption, which was considered to be proportional to the cooking time multiplied by the oven temperature. In this work, if the *y*-intercept of Eq. (7) is forced to 0, both approaches are identical. However, our approach allows the estimation of the actual energy consumption. If we consider a value that is different from the nominal power of the oven, the energy demand will be different, but the tendency will not be affected. It is worth mentioning that a fraction of the total power is used by the fan, which is on at all times, while another fraction can be used by the heating elements, which work intermittently. This may affect the energy consumption estimation; however the power required by the fan is considerably lower than that required by the heating elements, which makes the current approach acceptable.

4. Conclusions

A validated mathematical model has been exploited to perform multi-objective optimization of beef roasting, considering the minimization of both cooking time and weight loss. In all cases a compromise situation was encountered: an increase in the oven temperature led to a reduction in the cooking time and,

simultaneously, produces an increase in the weight loss. Experimental tests confirm such behavior and model predictions agreed well with the experimental ones. Using the full 3D model to perform optimization requires several hours to find a single optimal solution. Hence, a simplified procedure was developed, interpolating a subset of optimal solutions to estimate other intermediate solutions, which were acceptably predicted.

The trends of variations of both variables (cooking time and weight loss) predicted by the model are in good agreement with experimental published results. Because of the mentioned conflicting objectives, not one, but a set of optimal solutions was found in the Pareto sense, i.e., the improvement of one objective produces a deterioration in the other one. Thus the operator must select the best set of decision variables in an arbitrary way or from additional or higher level information. In this sense, oven energy consumption was analyzed, showing that it also depends on oven temperature and cooking time: it increases when oven temperature is higher. Besides, kinetics model of quality features as texture and color, among others, coupled to the roasting model, can be used to select an optimal solution.

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