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An analytical model for cooking automation in industrial steam ovens

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ABSTRACT

This paper presents an analytical model for the prediction of cooking time of meat products in industrial steam ovens. To achieve this aim, the paper first develops a mathematical model for cooking meat, which is numerically solved and validated on the basis of the outcomes of an appropriate experimental campaign. Numerical simulations are then performed setting different values of sample sizes, with the aim to derive a parameterised model able to analytically reproduce the time–temperature curves of meat samples. As input the model developed requires an appropriate "translation" parameter, describing the shape of the time–temperature curve as a function of the sample size and diameter; as output it gives an estimate of the cooking time. The "translation" parameter is provided as a result of the numerical simulations for a wide range of sample size and length. The analytical model is validated by comparing the predicted cooking time with experimental cooking data related to time–temperature curves of seven meat samples. The comparison shows that the average percentage deviation between experimental results and model predictions is about 4.6%, proving good performance of the model developed. The model can be successfully used to estimate the meat cooking time starting from typical values of meat parameters, and, due to its simplicity, it appears to be suitable for direct implementation as a tool to monitor and automate the industrial meat cooking treatments by means of computer control.

1. Introduction

Food products are usually subjected to cooking treatment involving chemical, rheological and structural changes, before they are eaten (Thorvaldsson and Janestad, 1999). Meat products, in particular, become edible and more digestible when subjected to cooking (Rodriguez-Estrada et al., 1997). According to Frentz (1982), such products can be either dry-air or wet-air cooked, although new processes, such as water cooking, have recently emerged as promising techniques for cooking meat (Drummond and Sun, 2006).

With the increasing production of meat food products, efficient control of the cooking process is a relevant issue for the food industry, which directly affects the products' safety and quality. Time–temperature control, in particular, is commonly recognized as a key point in the cooking process of meat products (Cheng and Sun, 2004); high cooking temperatures can shorten cooking time, but can also cause greater cooking loss and lower texture quality (Bejerholm and Aaslyng, 2004).

Cooking treatments of meat products have been widely investigated in literature. However, most studies have focused on assessing the effects of such treatments and related conditions on the products' quality and texture (García-Segovia et al., 2007; Rodriguez-Estrada et al., 1997; Zhang et al., 2006). Conversely, only few works have dealt with modelling the meat cooking treatments and defining predictive models for the cooking time. Mathematical models based on heat transfer have successfully been applied to food products for thermal process calculation and optimization by Teixeira et al. (1969a,b) and Teixeira and Manson (1982). More recently, a model to predict heat, moisture and fat transfer for the deep-fat frying of beef meatballs at 159 ± 1 °C was proposed by Ateba and Mittal (1994). Thorvaldsson and Janestad (1999), developed and validated a model describing the simultaneous heat, water and vapour diffusion to predict the diffusion of water inside food products during heat processing. The model accurately predicts water diffusion and is useful for industrial applications, but is mainly general in nature, and does not precisely focus on cooking treatments of meat products. Sebastian et al. (2005), proposed and experimentally validated a complex model which reproduces the drying and smoking processes of meat, with a particular focus on a traditional smoked product from France. A mathematical model for heat and mass transfer for hamburger patties was proposed by Ou and Mittal (2006), but the model is mainly aimed at predicting and avoiding, microbial activation during the cooking process in order to preserve product quality.

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Nomenclature

$T = T(x,y,z,t)$ temperature of meat along x, y and z axes as a function of time t (°C)
$T_S = T_S(x,y,z)$ surface temperature (°C)
$\overline{T}_S$ average surface temperature (°C)
T_∞ oven chamber temperature (°C)
T_0 initial temperature of meat samples (°C)
ΔT discrete temperature interval (=0.5 °C)
Δt discrete time interval (=30 s)
$\overline{T}_t$ average temperature of sample at time t
$\overline{T}_{t+\Delta t}$ average temperature of sample at time $t + \Delta t$
T_i temperature values at time t_i
t time (s)
t_i time values
θ' dimensionless temperature
Fo Fourier number
δ translation parameter
τ logarithm of time ($\log_{10}(t)$)
n normal unit vector

Thermodynamic parameters of meat
k thermal conductivity (W m^{-1} °C^{-1})
ρ density (kg m^{-3})
c_p specific heat (J kg^{-1} °C^{-1})
h global heat transfer coefficient (W m^{-2} °C^{-1})
$\overline{h}$ average global heat transfer coefficient during time interval Δt (W m^{-2} °C^{-1})
α thermal diffusivity (m^2 s^{-1})

Meat sample parameters
V volume (m^3)
S surface (m^2)
L length (m)
D diameter (m)

Most of the studies above are based on numerical models, which are recognized as powerful tools to describe phenomena of both heat and mass transfer occurring during cooking; such models are also commonly applied to cooking processes of several different kinds of food products (see, for instance, Chatterjee et al., 2007; Romano and Marra, 2008; among recent works). However, punctual assessment of the thermodynamic properties of foods and of parameters of the cooking system is required when applying numerical models (Rodrìguez-Fernàndez et al., 2007); with meat products such an estimate can be problematic, due to internal changes of meat properties during the cooking treatment (Pan and Singh, 2001).

In order to overcome this limit, this work develops and validates an analytical model for cooking meat in industrial electric steam ovens. The model is based on a properly defined "translation" parameter, which depends on the sample size and diameter, and is required as input. Numerical values for this parameter are provided, as a result of this study, for a wide range of samples size and diameters. Starting from this information, the model analytically derives the temperature–time trend of the sample during cooking and provides, as output, an accurate estimate of the cooking time. Due to its simplicity, the model can be usefully exploited as a tool to monitor and automate the industrial cooking treatments by means of computer control.

2. The resolutive approach

The approach followed to develop and validate the analytical model consists of several steps, as summarized in Fig. 1.

On the basis of the studies available, the first part of the approach deals with the development of a mathematical model, reproducing the cooking process of meat products in an electric steam oven. The model is then numerically solved, and the results validated by comparing them to data collected through an appropriate experimental campaign. Experimental data are also exploited to estimate the thermal parameters of the meat products examined.

Once validated, the model is exploited to numerically simulate the cooking process of meat products characterized by several combinations of shape, size and type. On the basis of simulation outcomes, in terms of time–temperature curves, an analytical model for the prediction of the cooking time is developed. The predictive model is finally validated through a second experimental campaign.

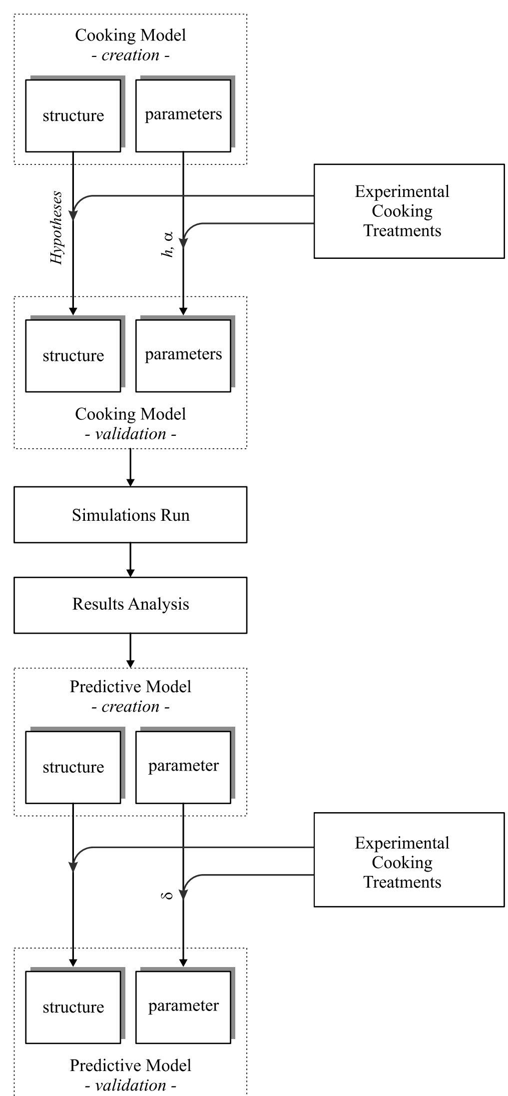

Fig. 1. Structure of the resolutive approach.

3. Materials and methods

3.1. Meat samples

Several beef and turkey samples were obtained from a local butcher in Parma, Italy. Lean pieces (i.e., less than 1% fat) were preferred in order to reduce the effects of fat on the thermal properties of the meat samples (Lyng et al., 2002). No minced meat was taken into consideration. The average surface temperature of the samples before starting the cooking treatment ranged from 8 to 10 °C.

3.2. Cooking equipment

A prototypical industrial electric steam oven manufactured by MBM (Brescello, Italy) was used for the cooking treatments (Fig. 2).

The oven is completely built of AISI 304 stainless steel, with a separate boiler for steam production. The total heating power installed is 18 kW; up to 10 food trays can be stored in the cooking chamber. On the rear wall, the inner chamber (640 × 720 × 535 mm) of the oven is equipped with a fan and a related circular heater for optimal convection heat exchange by means of air or steam. The fan rotation involves a radial air flow, which does not directly affect the meat sample. The fan is equipped with straight radial leading edges, and can reach 1400 RPM speed by means of an electric motor, which inverts its direction every 3 min.

3.3. Measurement equipment

Seven temperature sensor type K thermocouples (chromel–alumel), whose welded junction can resist up to 1200 °C, were adopted to measure the temperature of samples during cooking.

Thermocouples were connected to a Yokogawa HR2400 Hybrid Recorder (Yokogawa Europe B.V., The Netherlands) data logger, which can monitor and plot up to 30 input channels. The data logger can also be connected via serial port to a standard PC for data recording operations. The maximum allowed error of measurements performed by such equipment is within ±0.5 °C range, which is considered useful for the precision level required by the experimental tests.

A Mettler PC4400 (Mettler Toledo Italia Inc., Novate Milanese, Italy) balance, with 2000 g maximum capacity and 0.1 g readability, was used to measure the weight of the samples tested. All measurements were rounded to the nearest 1 g.

3.4. Sample preparation and cooking method

In order to make the experimental tests repeatable and significant, the following standard sample preparation and cooking procedure was adopted. The meat samples to be tested were given a cylindrical shape by means of elastic wires, and weighed by means of the balance described above. The samples' diameter D and length L were measured. The thermocouples, namely 2 core sensors and 4 surface sensors, were then placed on the samples tested, in order to monitor both core and surface temperatures of the samples. A further thermocouple was placed inside the oven chamber.

The oven was then switched on, set to 180 °C and preheated for at least 30 min to ensure that the chamber reached the set temperature. Afterwards, steam was flushed into the chamber for the remainder of the cooking treatment. Each sample was positioned on a grill, which was inserted into the oven chamber; the samples were cooked separately. The temperature data logging started when a sample was placed inside the oven chamber, and ended when the core temperature of the sample reaches 80 °C, which is above the minimum core temperature of 72 °C recommended for meat products' safety (McDonald et al., 2001). Hence, the cooking process was considered complete and the sample was removed from the oven. Weight and size of the cooked sample were measured again. The weight loss of samples ranged from 15% to 18%, corresponding to a 4.1% average reduction of length and 10.17% average reduction of diameter.

4. Theoretical model for cooking meat and validation

The theoretical model for cooking meat is based on the following hypotheses (Huang and Mittal, 1995; Ou and Mittal, 2006):

(i) Meat is a homogeneous and isotropic means, where heat is transferred mainly by conduction.
(ii) The initial distribution of temperature in the sample is homogeneous.
(iii) Energy absorption due to chemical reactions, such as protein denaturation or Maillard reactions, is neglected in the energy balance.

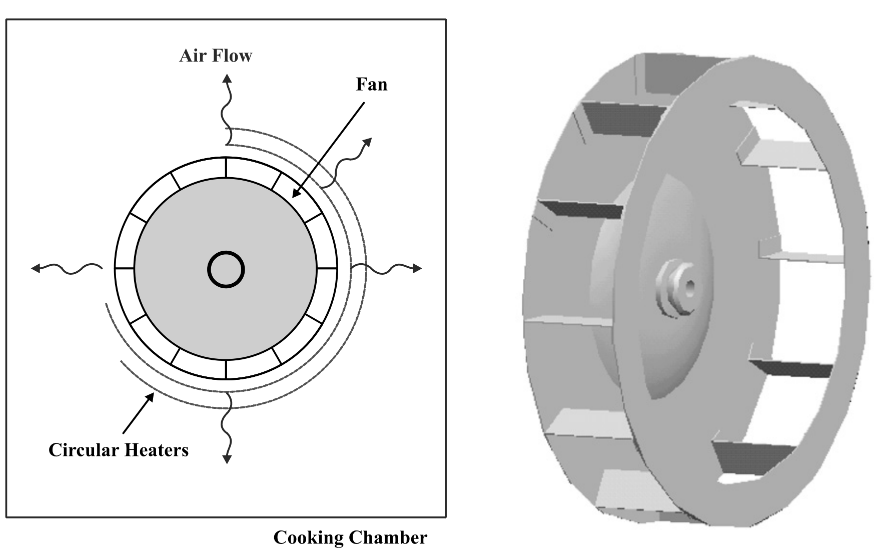

Fig. 2. Qualitative scheme of the electric steam oven.

(iv) As cooking is performed in a steam oven, the effect of latent heat from water vaporization during meat cooking is neglected in the energy balance. For the same reason, the effects of crust formation on thermal and physical properties of the samples are neglected.
(v) Fat transport is neglected.
(vi) Size reduction, as a result of cooking, is neglected. As a consequence, the model developed always refers to the original size of the samples.

On the basis of the assumptions above, under unsteady thermal conditions the three-dimensional heat transfer equation can be described, according to Fourier's equations of heat conduction (Incropera and De Witt, 2002), as

$$\frac{\partial}{\partial x}\left(\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(\frac{\partial T}{\partial y}\right)+\frac{\partial}{\partial z}\left(\frac{\partial T}{\partial z}\right)=\frac{1}{\alpha}\frac{\partial T}{\partial t} \tag{1}$$

subject to the following boundary condition:

$$\begin{cases} -k\frac{\partial T}{\partial n}=h(T_S-T_\infty) & \text{when } t\leqslant t|_{T_S=100} \\ T_S=100 & \text{when } t>t|_{T_S=100} \end{cases} \tag{2}$$

From Eq. (2), it can be appreciated that the effects of heat transfer by conduction and convection are fully balanced as long as T_S is lower than 100 °C; conversely, once T_S has reached 100 °C, the boundary condition imposes temperature to be constant in time. The initial temperature of the sample was set at a uniform value T_0 resulting from experimental measurements. Eqs. (1) and (2) were numerically solved under Comsol Multiphysics release 3.2 (COMSOL S.r.l., Brescia, Italy) commercial package. As a consequence of the approximately cylindrical shape of samples, rotational and axial symmetries of the system were assumed. This allows to numerically solve the model for a portion of the entire domain, resulting from the intersection of the cylinder and a plane containing the rotational axis, as shown in Fig. 3. α in Eq. (1) was estimated comparing the numerical outcomes with time–temperature experimental data related to the cooking treatments of three meat samples. Specifically, α was set at the numerical value that minimizes the mean square error between numerical solution and experimental results (Huang and Mittal, 1995). Results indicate that α can range from 1.72×10^{-7} to 1.80×10^{-7} m^2/s for the samples examined; this is in line with previous studies by Sheridan and Shilton (2002), who report $\alpha = 1.84\times10^{-7}$ m^2/s for lean meat, and Huang and Mittal (1995), who suggest $\alpha = 1.80\times10^{-7}$ m^2/s, providing validation of the estimated values. Fig. 4a–c shows the comparison between temperature trends resulting from the numerical model and experimental measurements.

Once α was determined, k was derived on the basis of typical ρ and c_p values of meat available in literature. Specifically, we set ρ at 1040 kg/m^3 (Sanz et al., 1987), and c_p at 3500 ÷ 3625 J/kg °C (Rahman, 1995).

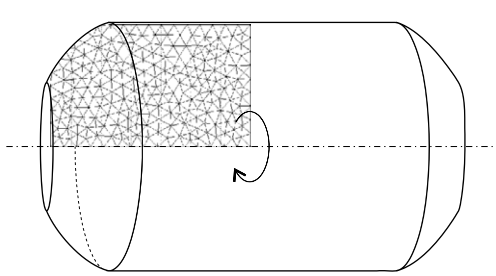

Fig. 3. Domain section and mesh used for cooking model solution.

The global heat transfer coefficient, required in Eq. (2) to describe the first phase of the cooking treatment, was estimated on the basis of the energy balance of the meat sample. The computation was discretized as per the following equation:

$$\rho\cdot c_p\cdot V\cdot(\overline{T}_{t+\Delta t}-\overline{T}_t)=\bar{h}\cdot S\cdot\int_t^{t+\Delta t}(T_\infty-\overline{T}_s)\mathrm{d}t \tag{3}$$

where T_S was set at the surface temperature recorded during experimental measurements and α was set at the values previously derived. From Eq. (3) the average global heat transfer coefficient $\bar{h}$ for each Δt was derived. Outcomes of the computation of $\bar{h}$ showed no substantial differences between the samples; hence, the average value of $\bar{h}$ from the three samples resulting within 0 ÷ 300 s time interval ($\bar{h}\cong 55$ W/m^2 °C) was considered in subsequent analyses. This is also in line with suggested values of surface heat transfer coefficient (Toledo, 2007).

5. Numerical simulations

The numerical model was exploited to investigate the unsteady thermal conditions of meat products characterized by several different sizes (L and D). The aim of such an investigation is to assess whether, and to what extent, sample size and diameter may affect the core temperature trend during cooking as a function of t. During simulation runs, the model parameters were set at the following numerical values:

- T_0 = 10 °C
- ρ = 1040 kg/m^3
- c_p = 3625 J/kg °C
- h = 55 W/m^2 °C
- L = 0.05 ÷ 0.30 m (step 0.01 m)
- D = 0.05 ÷ 0.15 m (step 0.01 m)

By combining the values of D and L within the above ranges, 286 numerical simulations were performed in total, covering a wide amount of real products. The results of the simulation runs provide the core temperature trend as a function of the logarithmic time τ for each combination of D and L examined. From the simulation outcomes, proposed in Fig. 5, it can be appreciated that, adopting adimensional temperature $\theta'(0\leqslant\theta'\leqslant1)$ defined according to the following equation

$$\theta'=1-\theta=1-\frac{T-T_\infty}{T_0-T_\infty}=\frac{T_0-T}{T_0-T_\infty} \tag{4}$$

time–temperature curves exhibit a very similar trend, no matter the sample geometry.

In particular, for all the combinations of D and L examined, numerical simulations reveal that $\theta'(\tau)$ curves exhibit a rather linear trend, with positive slope, and that the cooking process is complete when $\theta'\approx0.40$, corresponding to a final core temperature of about 80 °C.

The curve trends can be analytically justified as follows. The cylindrical geometry of the sample can be interpreted as the intersection of an infinite cylinder and a plane wall; Fourier's equations of heat conduction under unsteady thermal conditions, previously proposed in Eq. (1), can be analytically solved for both geometries, providing, as output, the adimensional temperature distributions. Combining those results, the trend of the adimensional temperature θ' at the core of the meat sample can be described by the following equation (Incropera and De Witt, 2002):

$$\theta'=1-\theta=1-C_AC_B\mathrm{e}^{(-\zeta_A^2Fo_A-\zeta_B^2Fo_B)} \tag{5}$$

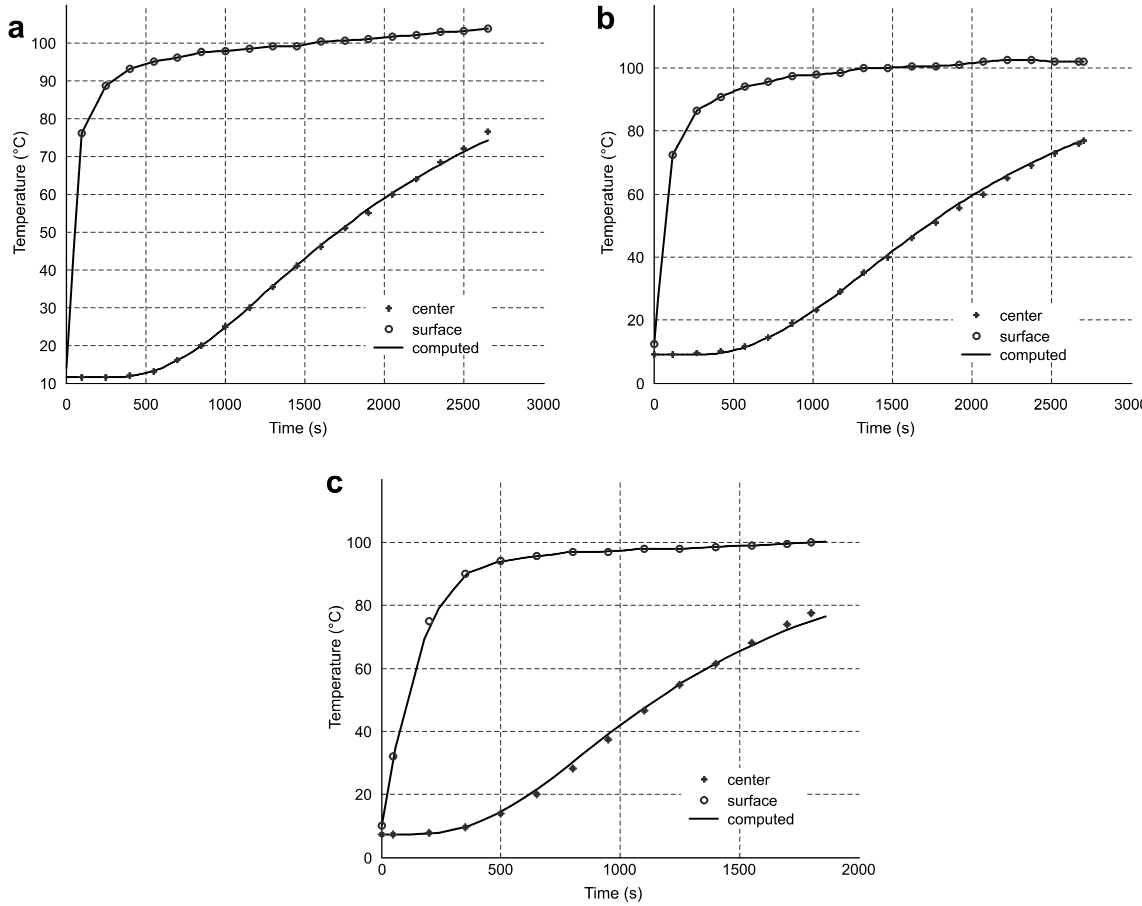

Fig. 4. (a–c): Comparison between experimental and numerical results of the core temperature trend as a function of time for samples 1(a), 2(b) and 3(c).

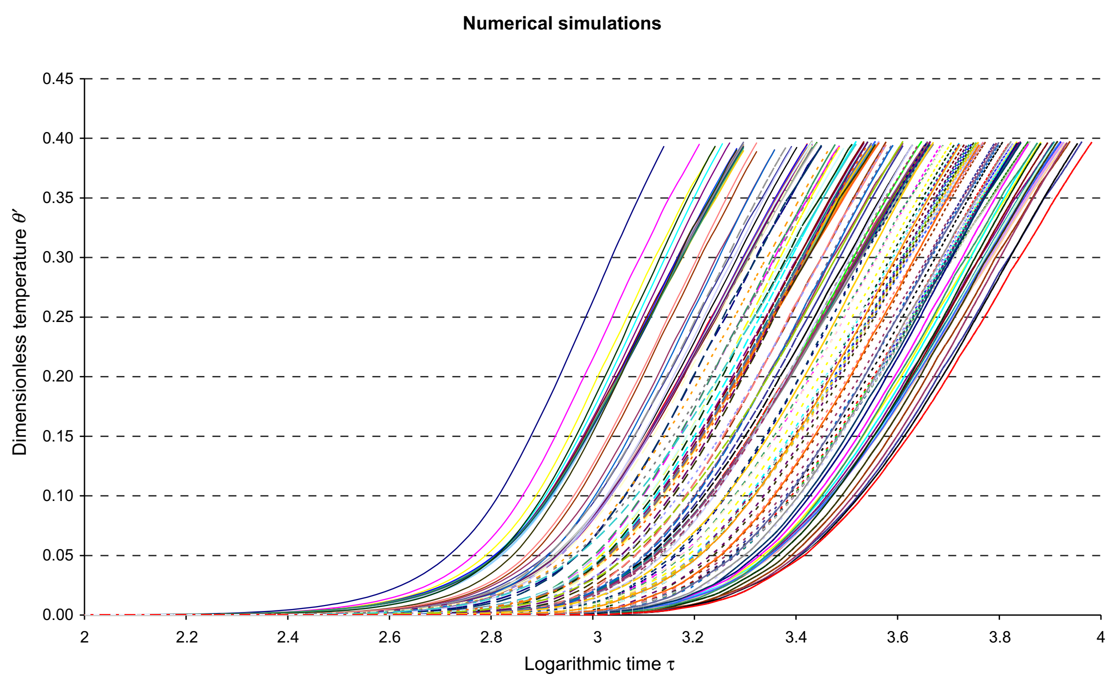

Fig. 5. Core temperature trend resulting from the numerical simulations.

The above equation is valid under the approximation of $Fo > 0.2$, and, combined with the definition of Fo (Incropera and De Witt, 2002), justifies the linear trend of the core temperature as a function of τ previously shown in Fig. 5. It should be noted that the linear trend can be appreciated for $\theta' > 0.10$, due to the approximation of Eq. (5). Moreover, from the same equations, it can be deduced that higher sample length L involves a translation of the curve along the τ-axis, which results in a slower cooking treatment.

6. Predictive model for cooking meat and validation

6.1. Model development

On the basis of the similarities between the curves, the predictive model for cooking meat was developed by deriving a parametric expression of the time–temperature curve corresponding to $L = 0.14$ m and $D = 0.14$ m, which was assumed as reference. A fourth-order polynomial trend curve was derived with Microsoft Excel© to approximate the numerical one ($R^2 \approx 1$); its equation is

$$\theta' = -1.17\tau^4 + 15.40\tau^3 - 75.35\tau^2 + 162.42\tau - 130.32 \quad (6)$$

As all temperature curves exhibit a similar trend, while differing for translation along the τ-axis, the following expression can be adopted to describe the temperature trend for a generic sample:

$$\theta' = -1.17(\tau-\delta)^4 + 15.40(\tau-\delta)^3 - 75.35(\tau-\delta)^2 + 162.42(\tau-\delta) - 130.32 \quad (7)$$

where δ is the "translation" parameter introduced to indicate the position of the curve on the τ-axis. From Fig. 5, it can be appreciated that δ is only dependent on the sample geometry (L and D); hence, it could be derived, for a sample of known L and D, by imposing that the resulting temperature curve passes through the point describing the end of the unsteady thermal conditions.

6.2. Model validation

In order to validate the analytical model for the prediction of cooking time, Eq. (7) was applied to estimate the duration of the cooking treatment of seven meat samples whose core temperature T had been experimentally monitored. Specifically, by applying Eq. (7) the trend of temperature $\theta' = \theta'(t)$ was analytically derived for each sample, starting from different couples of time–temperature values (t_i, T_i) measured during the experimental cooking treatments. From the start of cooking, couples of time–temperature values were recorded with $\Delta T = 0.5$ °C step; at each step, δ and the estimated cooking time were updated by imposing that the analytical curve $\theta'=\theta'(t)$ passed through the (t_i, T_i) point identified. The estimated cooking time was then compared with the experimental value. The comparison, in terms of (*predicted time*)/(*experimental time*), is proposed in Fig. 6 as a function of the increase reached in the core temperature; estimated δ values were updated at each core temperature value.

From Fig. 6 it can be appreciated that when the increase of core temperature is less than 4 °C (corresponding to the very beginning of the cooking process), the ratio (*predicted time*)/(*experimental time*) can range from about 0.9 to 1.3; conversely, when the increase in core temperature reaches 4 °C, the estimate allows achieving values of (*predicted time*)/(*experimental time*) very close to one, highlighting improvements in the accuracy of the predictive model.

On the basis of the considerations above, a 4 °C increase in core temperature was considered appropriate to both analytically derive δ and estimate the cooking time of samples. To ensure immediate applicability of Eq. (7), estimation of δ values has been performed for all sample size (L and D) considered in numerical simulations. Results are shown in Table 1. As can be seen from Table 1, δ can approximately range from 0.2 to -0.9; moreover, samples with larger L and D exhibit higher δ values.

The comparison between predictions and experimental outcomes obtained by applying the model with a 4 °C increase in core temperature, as well as the corresponding percentage deviation, is proposed in Table 2. In the same table, the performance of the predictive model is also assessed by comparing the estimated cooking time with results proposed by the predictive methodology by Ball and Olson (1957). To this extent, appropriate values of heating rate index and lag factor (f_h and j_{ch}) were derived, for the samples considered, from Ball and Olson (1957).

As can be seen from Table 2, the average percentage deviation between predictions and experimental results is approximately 4.6%, highlighting good performance of the predictive model. The estimations resulting from the methodology by Ball and Olson (1957) confirm the good performance of the approach developed. In fact, for the samples considered, outcomes from approach by Ball and Olson (1957), usually underestimate the resulting cooking time, and the average error is about -7.17%.

Conversely, analytical estimates resulting from the application of our model overestimate the required cooking treatments, meaning that implementing the model in industrial applications will involve reaching a higher final core temperature than the target value of 80 °C. Sample 7, in particular, exhibits the greatest deviation (8.2%) between predicted and experimental cooking time; to assess the implications of such deviation, the trends of predicted and experimental core temperature for sample 7 have been charted in Fig. 7. The predicted temperature trend was analytically obtained by setting $\delta = -0.1665$ in Eq. (7), according to the findings in Table 1.

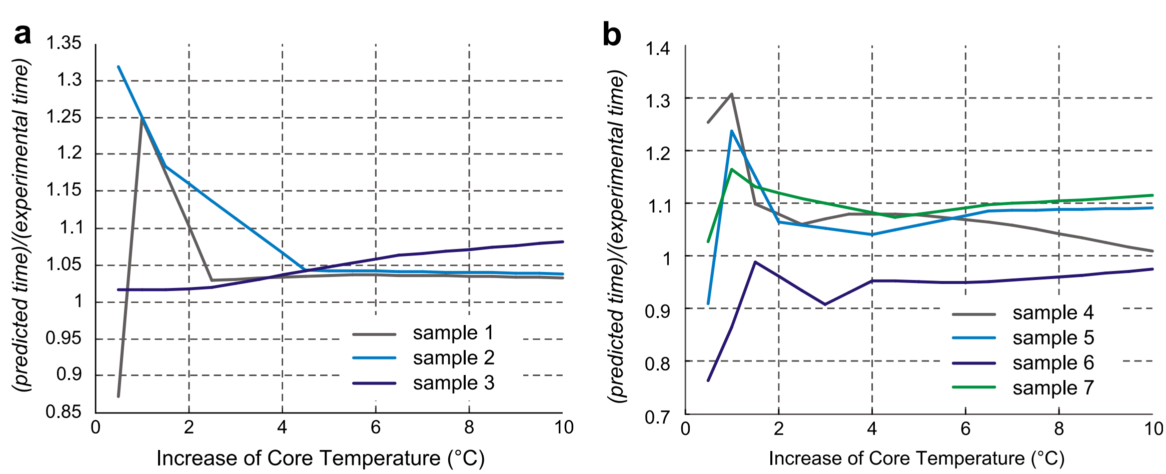

Fig. 6. (a–b): Comparison between estimated and experimental cooking time for δ values estimated at different core temperature (a: samples 1–3; b: samples 4–7).

Table 1
Estimated 458 δ values as a function of L and D

Length L (cm)	Diameter D (cm)										
	5	6	7	8	9	10	11	12	13	14	15
5	−0.8198	−0.7195	−0.6424	−0.5789	−0.5301	−0.4914	−0.4753	−0.4445	−0.4346	−0.4119	−0.4100
6	−0.7531	−0.6719	−0.5973	−0.5112	−0.4635	−0.4214	−0.3858	−0.3561	−0.3304	−0.3180	−0.3030
7	−0.7187	−0.6309	−0.5669	−0.4854	−0.4245	−0.3737	−0.3217	−0.2951	−0.2577	−0.2382	−0.2152
8	−0.7082	−0.5975	−0.5098	−0.4521	−0.3847	−0.3200	−0.2708	−0.2396	−0.1974	−0.1753	−0.1507
9	−0.6950	−0.5689	−0.4750	−0.4063	−0.3705	−0.3005	−0.2359	−0.2016	−0.1435	−0.1133	−0.0972
10	−0.6724	−0.5571	−0.4733	−0.3886	−0.3324	−0.2722	−0.2253	−0.1660	−0.1242	−0.0824	−0.0406
11	−0.6731	−0.5548	−0.4483	−0.3536	−0.3075	−0.2510	−0.1972	−0.1434	−0.0923	−0.0556	−0.0233
12	−0.6737	−0.5416	−0.4305	−0.3503	−0.2765	−0.2153	−0.1635	−0.1228	−0.0694	−0.0276	0.0137
13	−0.6721	−0.5336	−0.4325	−0.3325	−0.2593	−0.1931	−0.1363	−0.0894	−0.0696	−0.0092	0.0274
14	−0.6683	−0.5407	−0.4248	−0.3209	−0.2433	−0.1700	−0.1293	−0.0819	−0.0375	−0.0027	0.0438
15	−0.6682	−0.5373	−0.4106	−0.3083	−0.2426	−0.1735	−0.1059	−0.0519	−0.0078	0.0266	0.0570
16	−0.6616	−0.5330	−0.4089	−0.3195	−0.2313	−0.1591	−0.0836	−0.0273	0.0152	0.0398	0.0849
17	−0.6666	−0.5268	−0.4046	−0.3073	−0.2218	−0.1337	−0.0896	−0.0315	0.0168	0.0616	0.0967
18	−0.6693	−0.5235	−0.4034	−0.3064	−0.2177	−0.1446	−0.0598	−0.0034	0.0410	0.0752	0.1166
19	−0.6677	−0.5245	−0.4088	−0.2984	−0.2041	−0.1221	−0.0697	−0.0098	0.0415	0.0909	0.1345
20	−0.6678	−0.5354	−0.4032	−0.2968	−0.2000	−0.1367	−0.0579	0.0055	0.0593	0.1054	0.1448
21	−0.6636	−0.5351	−0.4010	−0.3083	−0.2144	−0.1316	−0.0451	0.0164	0.0701	0.1159	0.1573
22	−0.6621	−0.5307	−0.4030	−0.3063	−0.2108	−0.1269	−0.0411	0.0228	0.0788	0.1168	0.1659
23	−0.6576	−0.5266	−0.4118	−0.3015	−0.2027	−0.1290	−0.0545	0.0289	0.0733	0.1267	0.1799
24	−0.6573	−0.5230	−0.4103	−0.3021	−0.2056	−0.1263	−0.0518	0.0192	0.0759	0.1340	0.1873
25	−0.6647	−0.5255	−0.4068	−0.3016	−0.1973	−0.1093	−0.0385	0.0318	0.0842	0.1380	0.1861
26	−0.6628	−0.5365	−0.4123	−0.2971	−0.1981	−0.1246	−0.0468	0.0261	0.0908	0.1420	0.1924
27	−0.6688	−0.5361	−0.4120	−0.2947	−0.1961	−0.1068	−0.0411	0.0292	0.0930	0.1487	0.1977
28	−0.6659	−0.5349	−0.4050	−0.2926	−0.2104	−0.1240	−0.0384	0.0333	0.0977	0.1522	0.2023
29	−0.6627	−0.5334	−0.4014	−0.3073	−0.2096	−0.1223	−0.0337	0.0374	0.1003	0.1554	0.2073
30	−0.6609	−0.5293	−0.4153	−0.3070	−0.2064	−0.1059	−0.0460	0.0418	0.0921	0.1518	0.2081

Table 2
Estimated cooking time for samples examined with 4 °C increase in core temperature and performance assessment

	Size (L × D) (cm)	δ	Experimental cooking time (s)	Estimated cooking time (s)	Percentage deviation (%)	Estimated cooking time with Ball and Olson (1957) approach (s)	Percentage deviation (%)
Sample 1	10.2 × 8.5	−0.3427	2700	2909	7.74	2535	−6.09
Sample 2	13.8 × 8.0	−0.3203	2650	2790	5.28	2726	2.86
Sample 3	13.6 × 6.1	−0.5312	1800	1865	3.61	1585	−11.96
Sample 4	29.0 × 11.2	−0.0259	5400	5828	7.93	5071	−6.09
Sample 5	19.5 × 8.0	−0.3016	3000	3122	4.07	2745	−8.51
Sample 6	29.5 × 10.4	−0.0938	5400	5146	−4.70	4754	−11.96
Sample 7	24 × 9.5	−0.1665	4500	4872	8.27	4120	−8.44
Mean error					4.60		−7.17

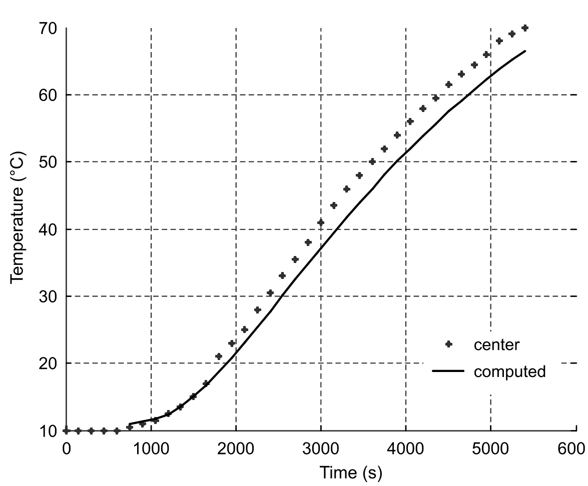

Fig. 7. Comparison between predicted and experimental core temperature trends for sample 7 ($\delta = -0.1665$).

Outcomes of Fig. 7 shows that the predictive model slightly underestimates the core temperature of the samples, in line with previous estimates of the cooking time. Consequently, a final core temperature of about 86 °C will be reached by applying the predictive model. Although this value exceeds the suggested cooking temperature for meat, it should be remarked that this is the worst case, since the model was developed considering a final core temperature of 80 °C. As studies on meat products suggest the cooking temperature could range from 63 °C for beef steaks up to 80 °C, the model could be implemented in real industrial processes by setting a lower target core temperature of meat (e.g. 72 °C), thus overcoming this issue.

7. Conclusions

The main finding of this study is the development of an analytical model that can be implemented in industrial steam ovens to predict the cooking time of meat.

The model developed has several major strong points. Firstly, the validation has shown good performance of the model, since the average percentage deviation between estimates and experimental results is about 4.6%. It is also found that the mean error of the estimate is lower than that resulting from the application of other simplified models (e.g. Ball and Olson, 1957).

Moreover, the analytical approach is substantially simpler and easier to implement than a numerical one. Numerical models may provide accurate and detailed results and can easily be reconfigurated to analyse different operating conditions, but they require punctual definition of the thermodynamic parameters of the sample examined, which can change during the cooking process and are usually difficult to determine. Moreover, such model usually suffers because of greater computational complexity. Conversely, the analytical model was developed by setting average values of thermodynamic parameters of meat, which considerably reduce the computational complexity without jeopardizing the reliability of the results. The model requires, as input, the "translation" parameter, whose value depends on the sample size and diameter and is provided as a result of this study. Finally, since the resulting estimate of the cooking time is available almost in real-time, the model appears as particularly appropriate for direct implementation in industrial ovens.

Starting from this work, future research will be aimed at defining a more general model that can be adapted to the analysis of other sample geometries and different cooking systems.

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