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SCIENTIFIC PAPER

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OPTIMIZATION OF ENERGY CONSUMPTION DURING IMMERSION FRYING OF PEANUTS

Article Highlights

- Due to non-linear temperature behavior, the existence of an optimal set of parameters was assumed
- The best solution produced approximately 570 kJ/kg of specific energy consumption
- This regime allows twice less energy consumption than the previously reported data

Abstract

This study investigated the influence of different regimes of immersion batch frying of peanuts on its specific energy consumption. The investigation was conducted via simulation, where energy consumption was calculated using various heat power/peanut mass ratios. As the result of the applied optimization procedure within the examined domain and calculation data, it was estimated that a regime with 24 kW of heating power and 28.6 kg of peanuts gave the minimum specific energy consumption. Besides that, the resulting surface could serve as a basis for designing and operating the frying equipment in more favorable regimes in terms of energy efficiency.

Keywords: immersion frying, peanuts frying, energy consumption optimization.

Immersion frying (or deep-fat frying) is a process of thermal treatment of food, where food is immersed in a large volume of oil (unlike the so-called shallow or contact frying, where food is placed in the frying pan that contains a thin layer of oil), as defined by Oreopoulou *et al.* [1]. Immersion frying is a usual practice in both industrial and domestic conditions since the fried food products provide unique flavor and texture, being quite popular with customers, as reported by Rossell [2]. According to Kong *et al.* [3], peanut production in the world is 34.4 billion kg/year, and it is indicated that its consumption may have various health benefits. Deep-fried peanuts are popular in Asian countries, unlike in the USA, for instance, where peanuts are usually boiled or roasted (by roasting, contact frying is understood). Immersion frying is a complex process to describe physically, as many individual processes are involved, as described by Alvis *et al.* [4]. These processes, as mentioned by Farid and Kizilel [5], primarily refer to simultaneous heat and mass transfer, in addition to oil uptake and moisture loss. Material oil uptake and its moisture loss also appear simultaneously, as the frying oil fills the space left by the evaporated moisture, described by Ziaiifar *et al.* [6].

Frying equipment in current usage is very diverse, from various industrial fryers of different types and capacities to small-scale domestic ones, according to Sahin and Sumnu [7]. What all have in common is the immersion of material in the frying oil, which is

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previously warmed up usually at 150–200°C, as mentioned by Farkas *et al.* [8], and retention in oil for a certain time - enough to be fried, but not for too long, since the product could easily become over fried and lose its nutritional quality and flavor, which is reported by Kita and Figiel [9]. Most accessible frying systems are of smaller volume and more convenient for domestic or catering services. At the same time, large continuous fryers are typically used for industrial applications, according to Oke *et al.* [10].

In the scope of this paper is a batch frying system and, in particular, the optimization of the specific energy used for heating. Since oil is preheated to the desired temperature, the temperature drop will occur as a colder material is immersed. The observed temperature difference between the oil and the material will be highly dependent on the heating power and the amount of material that undergoes frying at a particular moment. On the other hand, the amount of material per one round of batch frying will eventually influence the overall frying time, thus will reduce the overall heat consumed. In terms of the facts mentioned above, it is reasonable to assume that such processes are suitable for optimization, which could ultimately contribute to the more efficient planning of the process. Considering the widespread presence of frying systems [7], the research on possibilities for optimal energy consumption concerning treated product mass could contribute to more energy-efficient management of existing or developing new frying systems. In such conditions, process simulation could serve as a powerful tool that should ultimately provide significant data needed for a deeper understanding of the process.

MATERIALS AND METHODS

Materials

As mentioned, peanuts without shells are used as a material for the conduction of the frying simulation. Peanuts are usually fried at temperatures between 160°C and 180°C [9], which mainly depend on the capacity of frying equipment, production rate demands, and food quality requirements, according to Shi *et al.* [11]. On the other side, as the oil commonly used for peanut frying, as reported by Erickson [12], sunflower oil is chosen for the calculation. Table 1 shows raw peanut kernel composition and the heat capacities of each component [13].

Table 1. Raw peanut composition and properties.

Initial properties	Moisture content ω_{Mi} [%]	Fat content ω_{Fi} [%]	Other components content ω_{Oi} [%]	Specific heat C_p [kJ/(kg·K)]	Volume V_p [m^3]	Density ρ_p [kg/m^3]
Value	6.50	49.24	44.26	2.23	$2.143\cdot10^{-6}$	617

Modeling procedure

Since several different phenomena occur during the process (heat transfer and the oil uptake in one direction, moisture removal in the other direction, crust region formation, etc.), and the internal distribution of any property must be clarified, the process is usually modeled via simultaneous heat and mass transfer relations, as reported by Tangduangdee *et al.* [14]. However, in this study, only the average temperature of a kernel needs to be estimated to compare the different frying regimes in terms of specific energy consumption. Hence, there is no need to model the internal temperature distribution and the lumped capacitance method could be applied for the kernel temperature estimation. According to Miyagi [15], peanuts should be fried for up to 15 minutes at high temperatures to achieve optimal flavor, texture, and nutritional quality. Besides that, some time will be needed to achieve the wanted frying temperature since colder kernels of peanuts are expected to cool down the oil. This occurrence will delay the start of the frying process itself, so the time of kernels warming up should also be taken into account. For all the mentioned reasons, the frying time was chosen to be 10 minutes, with additional 10 minutes allowed for the material to achieve the oil temperature.

Process modeling is based on the following assumptions:

- Change of material temperature does occur, as well as the change of temperature of the oil, due to the relatively large amount of material immersed at the beginning of the process;

- Every single kernel of peanuts is fully exposed to the surrounding oil;

- Due to the small dimensions, the internal temperature of peanut kernels changes uniformly; hence the lumped capacitance model of temperature change is adopted. Another reason is that the internal temperature distribution of kernels doesn't affect the main calculation results, but only its average temperature, as mentioned;

- Safari *et al.* [16] showed that moisture removal has a small effect on heat transfer. Still, water evaporation from peanuts' surface strongly influences the heat convection coefficient (it is called the "bubbling effect"), so the heat transfer coefficient must be assessed based on experimental results from the previous work;

- Heat carried by the oil mass transfer (during the oil uptake) is neglected since this amount of heat is considerably smaller in comparison to the convection heat transfer [14];

- Physical properties of kernels change during the process, but properties of oil don't;

- The heater works in an intermittent regime and is turned on until the temperature of the oil achieves the value of 165 °C. After that, the heater is turned off;

- The external heat loss to the surroundings occurs constantly during the process.

Considering all the mentioned assumptions, the process is modeled via a system of two ordinary differential equations, one for the oil temperature change and the other for peanuts temperature change, as follows:

$$\frac{dT_o}{dt} = \frac{-h \cdot A_p \cdot (T_o - T_p) + Q_h}{m_o \cdot c_o} \tag{1}$$

$$\frac{dT_p}{dt} = \frac{h \cdot A_p \cdot (T_o - T_p)}{m_p \cdot c_p} \tag{2}$$

The mass of oil is calculated as oil density is multiplied by its volume, which is obtained as a difference between the volumes of the vessel and immersed peanuts:

$$m_o = \rho_o \cdot (V_v - V_p) \tag{3}$$

Since peanuts mass is a function of time, where it changes in dependence on current moisture content (wet basis) and current fat content, it can be expressed as:

$$m_p(t) = m_{pi} \cdot (1 + \omega_F(t) - \omega_M(t)) \tag{4}$$

where $\omega_M(t)$ and $\omega_F(t)$ are obtained by linear regression based on the moisture loss and oil intake results taken from [9]. The calculated coefficients are included as fraction numerators in the previous equations:

$$\omega_M(t) = \omega_{Mi} - \frac{0.0026}{60} \cdot t \tag{5}$$

$$\omega_F(t) = \omega_{Fi} + \frac{0.0019}{60} \cdot t \tag{6}$$

The initial specific heat of 2230 J/kgK is adopted [13]. However, the specific heat slightly changes during the process. Based on a previous investigation [9], moisture loss and fat uptake take place. Therefore, the change of the initial specific heat of peanuts is calculated according to Eq. (7) [13]. Specific heat of oil is only a function of oil temperature, based on the relation reported by Rahman [17] (Eq. (8)):

$$c_p(t) = c_{pi} + c_F \cdot (\omega_F(t) - \omega_{Fi}) + c_M \cdot (\omega_M(t) - \omega_{Mi}) \tag{7}$$

$$c_o(T) = 1.5951 \cdot (T_o + 273.15) + 0.0097 \cdot (T_o + 273.15)^2 \tag{8}$$

Calculation and optimization procedure

Figures 1a and 1b show the temperatures change as the result of preliminary simulation made for two different cases on an 1800 s basis, 6000 peanut kernels (7.8 kg) and 36000 peanut kernels (46.8 kg), respectively, both made for the maximum heating power of 28 kW. As seen, no significant temperature changes occur above 1200 s (which is, as mentioned, taken as the total time for the simulation). The observed difference in the initial oil temperature drop suggests some optimal solutions in terms of peanuts mass fried per "round" of frying and the used heat capacity - in other words, the bigger the mass of peanuts immersed, the larger the initial oil temperature drop will occur. Hence, greater heat power will be needed to warm the peanuts to the desired temperature in some reasonable time interval. On the other hand, a bigger mass of peanuts per "round" of frying means that fewer "rounds" will be needed to fry a similar amount of peanuts. Thus, the overall energy consumption will be reduced in that sense.

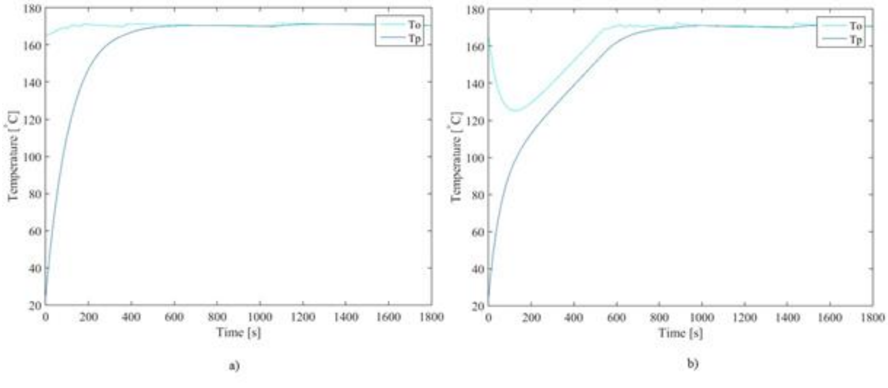

Figure 1. Preliminary model running results on an 1800 s basis with 28 kW heating power: a) 7.8 kg of peanuts (minimal mass) and b) 46.8 kg of peanuts (maximal mass).

However, not all the domain on this surface is feasible. The feasibility criterion was made under the conditions that provide high-quality products, i.e., the only feasible regimes are those in which the frying temperature is achieved at least in 10 minutes. After that, it is assumed that the frying process at around 170 °C lasts another 10 minutes. Thus, in 1 hour, three frying rounds could be obtained. In Figure 2, the simplified testing results of feasibility are shown. Only the most representative curves are displayed, i.e., the ones that express the class of feasible values or the ones that show the cases that break the feasibility criterion. Only the cases that drop in the right upper quadrant are considered feasible for usage. For instance, regimes with dark-blue, green, and red lines are feasible, and all the other cases between them are also feasible. Yellow and cyan lines represent the cases that are not suitable for such regimes and were not taken into account as they pass through the right lower quadrant.

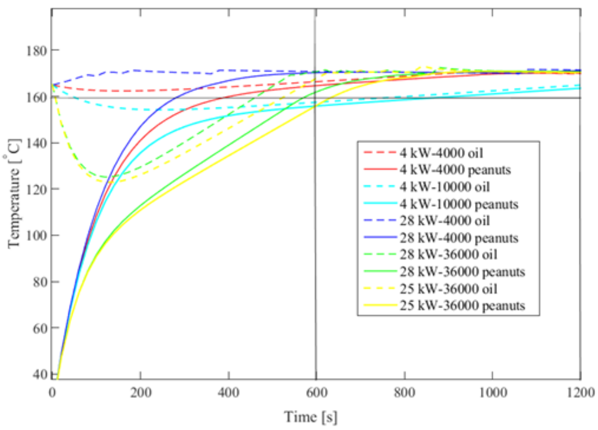

Figure 2. Representation of the feasibility assessment procedure.

Calculation procedure

The calculation was conducted by solving the system of differential Eqs. (1) and (2) via Matlab built-in solver "ode45", which utilizes the Runge-Kutta numerical method. Simultaneously, the algebraic Eqs. (3–8) were also solved for every numerical iteration step. The calculations were made for the 4–28 kW heat power range and the 6000–36000 kernel samples range (7.8 kg and 46.8 kg, respectively). The expected results are the energy consumption values per one kg of fried peanuts. Heat transfer coefficients mainly used rely on those reported by Sahin *et al.* [18]

Since the upper temperature is limited to 170°C (according to [9]), it means that the heater is turned off then the temperature exceeds the limit (the Matlab algorithm is set to make heater power Q_h = 0 in this case). The heater is turned on again when the temperature drops below the limit (the Matlab algorithm returns the current heater power Q_h value). Hence, during the observed period of 20 minutes, energy is consumed only when the heater is turned on. Following the total 60 time steps, Boolean matrix **B** is created, where zeroes are assigned to the elements that correspond to time steps where the heater was turned off, so those time steps do not contribute to the total time duration of the process. All other elements have the value "1". The Boolean matrix **B** elements were then summed to provide the total number of time steps involved in the process. Finally, this sum of "active" time steps is multiplied by the selected simulation time step of 20 seconds, which equals the ultimate time duration of the process where heat is being consumed:

$$t_{ht} = \sum_{i=1}^{60} \mathbf{B}_{1,i} \cdot \Delta t \tag{9}$$

The specific heat consumption value is then calculated as follows:

$$E = \frac{Q_h \cdot t_{ht}}{m_p} \tag{10}$$

In Table 2, the constant calculation values are summarized.

Table 2. Process parameters used for calculation.

Process parameter	Value	Unit	Source
Peanuts kernel effective diameter, d	8	mm	-
Heat transfer coefficient, h	90	W/(m^{2}K)	[17]
Oil density, ρ_o	900	kg/m^3	[7]
Peanuts density, ρ_p	617	kg/m^3	[13]
Maximum heat loss to the environment, Q_{lmax}	500	W	assumed
Total time, t	1200	s	[9]
Time step used for calculation, Δt	20	s	-
Initial oil temperature, T_{oi}	165	°C	[1], [2]
Initial peanuts temperature, T_{pi}	25	°C	assumed

Data fitting procedure

As the calculation resulted in discrete energy consumption values per one kg of fried peanuts, the calculated results were fitted by polynomial using Matlab Fitting Toolbox to obtain a functional dependence instead of discrete data.

Optimization algorithm

After the polynomial function is obtained, one can conduct an optimization procedure. For this particular problem, the particle swarm optimization algorithm was chosen primarily because of its ability to point out an optimal domain rather than just the optimum point itself. It is achieved by selecting the large "population" number, followed by a relatively small number of iterations, so not every "individual" can achieve the optimum – but still, all the "individuals" are being closely gathered around the optimum point after the final iteration. Optimization was also run in Matlab, and the algorithm was suited following procedures described by Arora [19] and Lazzus *et al.* [20]:

1. In the first place, the initial values of i_{max}, w, φ_1, φ_2, n, x_{imin}, and x_{imax} are set;

2. Starting position of k[th] individual and velocities are calculated as:

$$x_{i,k} = x_{i,\min} + \left(x_{i,\max} - x_{i,\min}\right)u_i \quad ,k = 1 \cdots n \tag{9}$$

where u_i is the random number generated between 0 and 1 (uniform distribution).

3. The fitness of the k^{th} individual is computed as:

$$p_{i,k} = f\left(x_{i,k}\right) \quad ,k = 1 \cdots n \tag{10}$$

4. Since this is the initialization step, the best fitness of each individual is p_k itself. That is,

$$pbest_{i,k} = p_{i,k}$$

and global fitness is

$$g\,best_i = minimum\left(p\,best_{i,k}\right)$$

The location of $p_{best\ k}$ and gbest is given by p_{xik} and g_{ix}.

5. Starting with an initial velocity of $v_{i,k}$, the velocity of the individual is updated using the equation:

$$v_{i+1,k} = w_1 v_{i,k} + \phi_1\left(p_{xik} - x_{i,k}\right)u_i + \phi_2\left(g_{ix} - x_{i,k}\right)u_i \tag{11}$$

where w_1, ϕ_1, and ϕ_2 are the tuning factors of the algorithm.

6. The position of each individual can be updated as follows:

$$x_{i+1,k} = x_{i,k} + v_{i+1,k} \tag{12}$$

7. Based on the new position, the fitness of the k^{th} individual is computed as:

$$p_{i+1,k} = f\left(x_{i+1,k}\right) \tag{13}$$

8. If $p_{i+1,k} < p\,best_{i,k}$ then $pbest_{i+1,k} = p_{i+1,k}$, so if this fitness is lower than $pbest_{i,k}$, then $p_{best\,i,k}$ should be replaced with $p_{i+1,k}$.

9. The global best fitness is computed as

$$gbest_{i+1} = minimum\left(pbest_{i+1,k}\right) \tag{14}$$

10. The steps are repeated for a certain number of iterations. If the final iteration is not reached, the algorithm returns to step 5.

Optimization parameters are presented in Table 3.

Table 3. Particle swarm optimization parameters.

Optimization parameter	Value
Number of iterations, i_{max}	20
Weight, w	1–20 (for each iteration)
Tuning parameter 1, φ_1	1.05
Tuning parameter 2, φ_2	1.1
Population size, n	50
Lower boundary, x_{imin}	4000
Upper boundary, x_{imax}	28000

RESULTS AND DISCUSSION

Figure 3 and Figure 4 show the surface representations of the simulation results. In Figure 3, the blank surface represents the unfeasible data that were not considered, while the colored surface shows the feasible results. Figure 4 presents the unfeasible data with the dark-blue field (upper-left area of the contour diagram). These data are discrete results of numerical simulation and were subject to later data fitting, as the usage of the data alone could lead to the finding of minimum values that are exclusively valid for the shown data and wouldn't have any universal meaning. Besides that, finding a minimum discrete data array is trivial. Three values with the lowest value are shown in Figure 4 with red circles and are pointed with arrows.

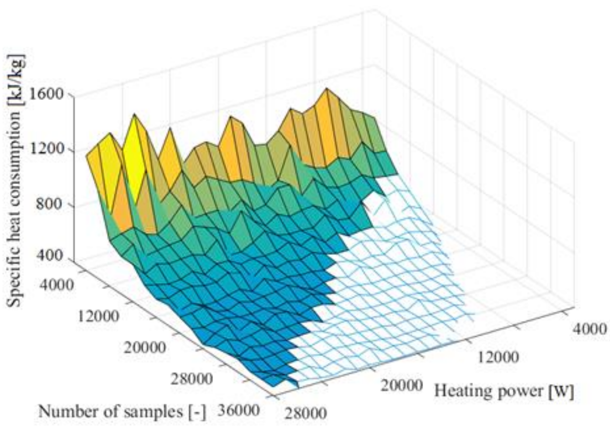

Figure 3. Main simulation results in the surface diagram with feasible (colored) and unfeasible (blank) region.

The fitted polynomial function, obtained using Matlab Fitting Toolbox, has a coefficient of determination R^2= 0.9867 and root mean square error RMSE= 29.75. This function is shown in Figure 5, together with the particle swarm optimization procedure results. Grey circles with red edges show the results of the final iteration step. The fitted polynomial function is:

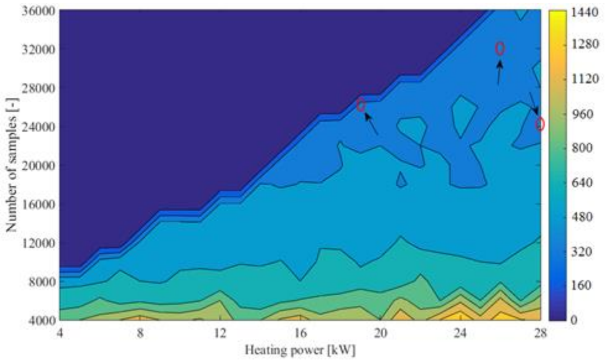

Figure 4. The main simulation results in a contour diagram with feasible (colored) and unfeasible (dark-blue) regions; red circles with arrows show the minimum values of specific energy consumption.

$$
\begin{aligned}
z &= 1310 + 0.05349x - 0.1216y - 3.075\cdot10^{-6}x^2 \\
&+ 3.183\cdot10^{-7}xy + 4.464\cdot10^{-6}y^2 \\
&+ 6.768\cdot10^{-11}x^3 - 3.242\cdot10^{-11}x^2y \\
&+ 1.91\cdot10^{-11}xy^2 - 6.08\cdot10^{-11}y^3
\end{aligned}
\tag{15}
$$

The polynomial function's dependent value "z" represents the fitted specific heat consumption.

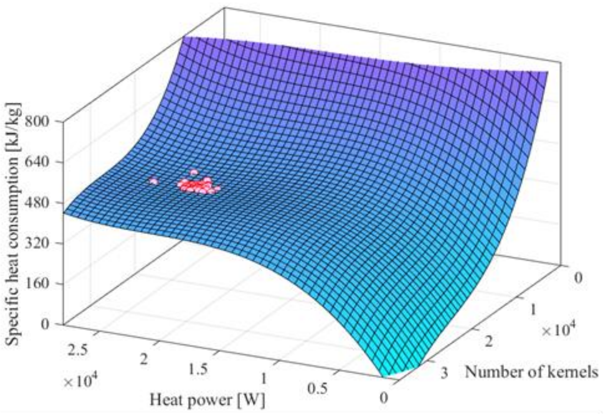

Figure 5. Optimization results on the fitted surface.

The overall analysis provided the optimal set of parameters that should be used to lower specific energy consumption as much as possible. These conclusions may provide a significant energy saving for a maximal amount of fried products per one "round" of frying. In other words, frying kinetics won't be the same, e.g., 11 kW and 10000 kernels and 22 kW and 20000 kernels. Although the energy consumption on the same time basis would be proportional (i.e., twice as bigger for the second case), one should use a 22 kW power regime rather than an 11 kW regime twice.

The optimization results suggest that the lowest specific energy consumption appears at around 24 kW of heating power and around 22000 kernel samples (i.e., 28.6 kg of peanuts without shells). Further on, the calculated minimal specific energy consumption of around 570 kJ/kg shows a significantly lower value in comparison with the reported average energy consumption for frying nuts by Gupta [21], which is 1163 kJ/kg (500 BTU/lb as it was initially reported).

An initial temperature drop is absent for a small mass of immersed peanuts. Still, this temperature drop can increase to 40 °C for certain regimes with a high mass of material. Wu *et al.* [22] reported a temperature drop of around 20 °C while frying potato slices.

The total assumed simulation time does not significantly affect the results because the heater shuts down after reaching 170 °C. This circumstance influences the temperature profile because it practically stays uniform after approximately 800 min of a simulation run.

To assess the sensitivity of the vessel volume parameter (as the volumes of vessels usually vary in dependence on the equipment manufacturer and capacity), the simulation is repeated from the very beginning, and setting the larger volume of 0.343 m^3, while keeping all the other parameters at the same values. The simulation resulted in almost the same surface shape, having a slightly bigger energy consumption than in the case where the vessel volume is 0.125 m^3, while in some spots, two surfaces are even merging. Most important, minimum values are placed at similar spots on the surface, so the similar optimal regime parameters are valid even for different volumes. The mentioned comparison is shown in Figure 6.

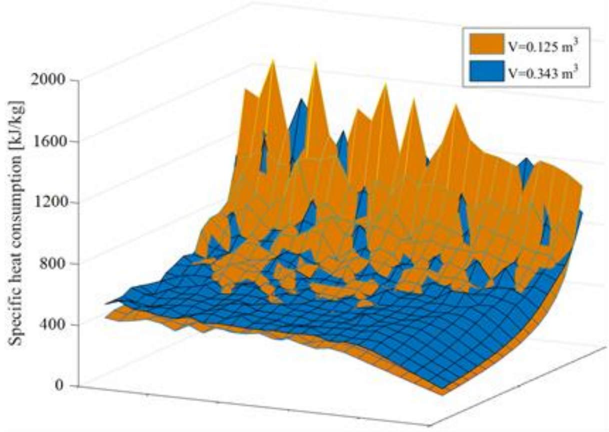

Figure 6. Comparison of resulting surfaces for two vessel volumes: blue is the basic case, while orange represents the increased volume.

CONCLUSION

Since there is a non-linear behavior of temperature functions during immersion frying, the assumption of an optimal set of process parameters for fryer power and capacity (i.e., amount of fried kernels) was valid. The presented procedure could, in a similar way, be used for other products which are subject to immersion frying treatment. The best solution was found at around 24 kW of heating power and 28.6 kg of peanuts, resulting in approximately 570 kJ/kg of specific energy consumption. Compared with previously reported data, this regime allows twice less energy consumption. Moreover, these are only the minimum values obtained as the optimization results. Besides that, the entire resulting surface (especially the close environment of the optimal area) gives better insight into the process energy demands. It can potentially help with the improvement of the process energy consumption. Thus, the wide usage of the obtained results tends to improve overall process efficiency, which could result in certain energy savings. The variation of frying vessel dimensions resulted in no significant deviations from the first solution, while the surface curvature tendency remained practically the same.

NOMENCLATURE

A	Surface area [m^2]
c	Specific heat capacity [$kJkg^{-1}K^{-1}$]
t	Time [*min*]
T	Temperature [$°C$]
a,b,c,n	Constants [-]
Q	Heat flux [*W*]
E	Specific heat consumption [kJ/kg]
d	Diameter [*m*]
w	weight (refers to optimization algorithm)
n	population size (refers to optimization algorithm)
x	particle position (refers to optimization algorithm)
p	individual particle fitness (refers to optimization algorithm)
g	global fitness (refers to optimization algorithm)
Greek letters	
ω	Mass fraction [%]
ρ	Density [kgm^{-3}]
h	Convection coefficient [$Wm^{-2}K^{-1}$)]
φ	tuning parameter (refers to optimization algorithm)
Δ	Increment, step [-]
Subscripts	
i	initial, iteration number, matrix element
p	peanuts
o	oil
M	moisture
F	fat
ht	refers to the heating periods
v	vessel

Abbreviations

RMSE	root mean square error (statistical parameter)

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NAUČNI RAD

OPTIMIZACIJA POTROŠNJE ENERGIJE PRI POTAPAJUĆEM PRŽENJU KIKIRIKIJA

Cilj ovog istraživanja bio je da se ispita uticaj različitih režima potapajućeg šaržnog prženja kikirikija na specifičnu potrošnju energije u procesu. Istraživanje je sprovedeno putem simulacije, gde je potrošnja energije izračunata korišćenjem različitih odnosa toplotne snage i mase kikirikija. Kao rezultat primenjenog postupka optimizacije u okviru ispitivanog domena i proračunskih podataka, procenjeno je da režim sa 24 kW grejne snage i 28,6 kg kikirikija daje minimalnu specifičnu potrošnju energije. Osim toga, dobijena površina bi mogla da posluži kao osnova, kako za projektovanje, tako i za rad uređaja za prženje u povoljnijim režimima u pogledu energetske efikasnosti.

Ključne reči: prženje potapanjem, prženje kikirikija, optimizacija potrošnje energije.