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An in-line optical technology to control the emulsification degree in a continuous industrial emulsifier for meat sausage production

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ABSTRACT

The stability of comminuted products plays an important role in the economy of meat industries. Proper formulation and the establishment of suitable emulsification conditions can significantly contribute to cooking losses control. The purpose of this research was to study the relationship between light backscatter parameters and cooking losses and develop prediction models that would allow the optimization of the emulsification process in a continuous industrial emulsifier. The optical response of meat emulsions, produced at industrial scale, depended drastically on the formulation (with and without starch) and the degree of emulsification. Furthermore, formula with starch showed significantly lower cooking losses than formula without starch, but for both formulas, several optical parameters correlated with cooking losses. Models for the prediction of cooking losses with R^2 values > 0.999 were obtained with five or six statistically significant optical predictors depending on the formula. These results point out the potential of light backscatter technology as a control tool during emulsification.

1. Introduction

Meat emulsions are the result of the comminution of water, proteins, and fat (Puolanne, 2010). During emulsification, myosin solubilized protein covers fat particles to prevent fat separation through thermal treatment, while actin solubilized protein immobilizes water. The interaction between proteins, fat, and water set up a tridimensional emulsion matrix (Barbut, 1995; Feiner, 2006, pp. 239–286). Composition and processing conditions determine emulsions stability which has a direct effect on water holding capacity or cooking losses (Sebranek, 2003). In some cases, starch is used to improve water and protein binding, hence increasing yield and profitability. Meat emulsions with starch show a compact network where water is better retained due to starch swelling ability and the interaction with meat proteins (García-García & Totosaus, 2008).

Optimizing the emulsification degree requires avoiding three possible processing-related defects: a) less firm unstable product with undue fat surface area (over-processing), which enhances water and fat separation (Hoogenkamp, 2011); b) product with fat melting problems (over-processing), as a result of excessive emulsion temperature (Feiner, 2006, pp. 239–286; Knipe, 2014); and c) product with visible fat particles (under-processing), having incomplete solubilized proteins and/or salts. The stability of pre-cooked emulsions defines gel characteristics. During cooking, proteins change their conformational structure promoting aggregation. Shrinkage provokes gel deformation and concomitant cooking losses (Tornberg, 2005) which have been reported between 5 and 18% in frankfurters (Grigelmo-Miguel, Abadías-Serós, & Martín-Belloso, 1999; Shan et al., 2014), representing 0.38–1.36 American billion US dollars calculated with the index 0.076 American billion US dollars per 1% loss of Álvarez, Castillo, Payne, Cox, and Xiong (2010).

There are few works on emulsion stability control through optical sensor technologies based on light backscatter (Álvarez, Castillo, Payne, & Xiong, 2009, 2007;Álvarez, Castillo, Payne, et al., 2010; Álvarez, Castillo, Xiong, & Payne, 2010; Nieto, Xiong, Payne, & Castillo, 2015, 2014; Torres, 2016). The implementation of this type of technology control could favor monitoring during emulsification, to determine in time, the homogenization end-point or speed and prevent cooking

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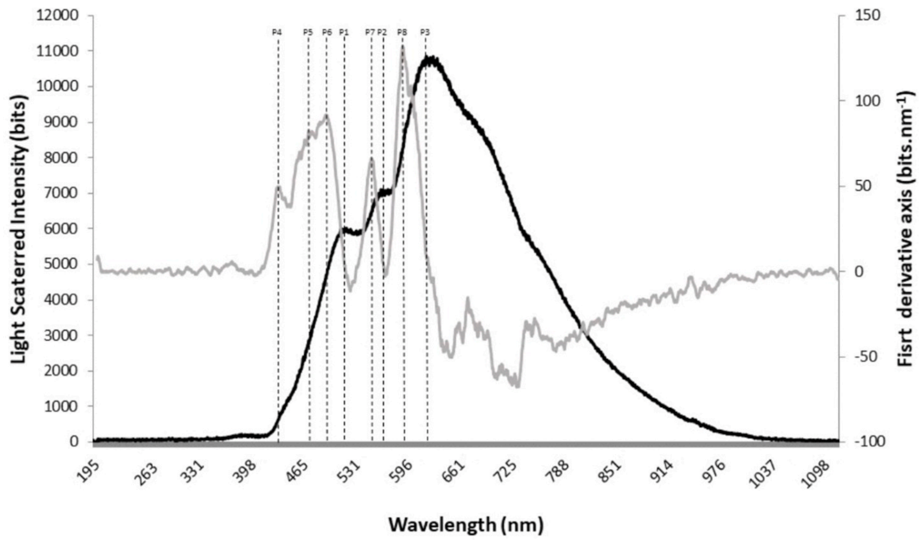

Fig. 1. Typical optical spectrum and the identification of eight basal predictors.

losses. In that way, products would not be affected by emulsion breakdown improving yield and quality (Nieto, Xiong, Payne, & Castillo, 2014). The optical device proposed implements correlations of some color and optic parameters with water or fat losses to determine the exact emulsification end-point in meat emulsions. These studies have demonstrated the relation between cooking losses and the optical response. All these studies, except for Torres (2016), were manufactured under laboratory/pilot plant processing, so the effect of real industrial conditions on the optical technology feasibility has not been analyzed yet.

In order to achieve faster comminution and processing, conventional cutters are being replaced by continuous emulsifiers with a coarse chopping step followed by the emulsification step executed with a combination of blades and perforated plates (Morin, Reeve, Tomey, Wilke, & Lucke, 2005; Powers, Schack, & Anderson, 1987; Rudibaugh, 1995). None of the previous studies have used continuous emulsifiers. In that view, the present study had the purpose to provide valuable information with the use of industrial meat samples thus going forward towards a new in-line control system. The present work aimed to find out a relation between some optical parameters (excluding color coordinates for practical purposes), and the cooking losses of two different meat emulsions (with and without starch) produced through continuous emulsification, to establish prediction equations for the losses in both types of samples, and, as a consequence, to evaluate the feasibility of applying the optical backscatter technology as a control technology for the emulsification degree in meat emulsions.

2. Materials and methods

2.1. Meat emulsion manufacture and composition

Two types of meat emulsions (with and without 10% potato starch) were produced at industrial scale following standard procedures by a large pioneer company in the meat industry. Lean trimmings (pork, chicken, and turkey), fat (pork fat trimmings and rind), salt, spices, potato starch, and functional additives were purchased from suppliers approved by the European Union. Appropriate proportions, not specified by the meat company due to confidentiality on industrial formulations, were calculated to obtain a base theoretic formula of 70, 17, and 13% of moisture, fat, and proteins. All required ingredients were mixed using an industrial mixer (Model IM-4500, INOTEC, Reutlingen, Germany) to obtain pre-emulsified batters which were introduced into a continuous industrial emulsifier (Model I175CDVM-90D, INOTEC, Reutlingen, Germany), where the emulsification process occurred. Different degrees of emulsification were obtained by means of volumetric flow adjustment, and monitored through the temperature of the product during extrusion: under-processed samples (5.09 ± 0.23 °C), samples with medium-degree of processing (hereafter referred as to medium-processed samples; 7.41 ± 0.70 °C), and over-processed samples (9.36 ± 0.48 °C). One pre-emulsified sample and the three samples with different emulsification degrees constituted one replicate. Proximate composition of emulsions with and without starch, characterized with a Food Scan NIR Meat Analyzer (DK-3400, FOSS, Hillerod, Denmark), was approximate: 62.82 and 65.92% of moisture, 13.21 and 17.29% of fat, 11.57 and 13.13% of proteins and 2.12 and 2.10% of salt, respectively. All samples were vacuum packaged and delivered refrigerated. Analyses were performed on the same day of reception at UAB or the next day (storage at 4 ± 2 °C overnight).

2.2. Meat emulsion cooking losses

Cooking losses were measured using a modified method of Bañón, Díaz, Nieto, Castillo, and Álvarez (2008) and Nieto et al. (2009), where meat emulsions were introduced into a syringe barrel of 100 mL and pressed inside a weighted 50 mL corning tube with a plunger, to simulate casing stuffing. Then, each corning tube was weighted again and placed in a water bath (Ovan Inox 27 L Model, Suministros Grupo Esper S.L., Barcelona, Spain) at 75 ± 1 °C for 45 min. After cooking, all tubes were placed inverted on a metal mesh during 1 min to drain the expelled liquid and finally weighted.

Cooking losses were calculated with the formula $CL = \left(\frac{W_0 - Wf}{W_0}\right)\cdot 100$, where W_0 was initial emulsion weight and Wf final cooked emulsion weight. Each trial was performed sixfold.

2.3. Light backscatter measurement of meat emulsions

The experiment was carried out on a High-Resolution Fiber Optic Spectrometer (Model HR4000, Ocean Optics, Inc., Dunedin, FL, USA) fed by a tungsten halogen bulb (300–1100 nm) as light source (LS-1, Ocean Optics, Inc.) and communicated with a double-jacketed sample holder through two fiber optic cables of ~600 μm diameter each (Ocean Optics, Inc.). Both optic fiber ends were attached to a light backscatter probe and coupled to the sample holder; the other two ends were connected to the spectrometer and the light source, respectively. This system delivered optical data from the spectrometer to the SpectraSuite® software (Ocean Optics, Inc.) to obtain light backscatter spectra.

The acquisition time was set to 3 s (i.e., integration time). Each meat emulsion was stuffed into the sample holder, the light source blocked and the sensor probe placed until the head of the sensor reached the emulsion. After that, the options "scope minus dark", "store dark" and "store dark minus" were set, consecutively, in order to subtract the background noise. Then, the light source was unblocked and the sample spectrum saved when stable. Data from optical spectra were collected at least sixfold per sample. In the range of 420–635 nm, eight predictors were identified as peaks (maxima on the light backscatter intensity spectra) and inflection points (maximum rate of light backscatter intensity increase identified as maxima on the first derivative *vs.* wavelength curve) (Fig. 1). Data was analyzed as intensity and wavelength for peaks and inflection points. A non-variable zone in the spectra was detected at 450 nm and was used as a normalization factor. To exclude the composition influence in the cooking losses observed in other works (Allais, Viaud, Pierre, & Dufour, 2004; Bañón et al., 2008) average values of pre-emulsified samples, per production, were subtracted from the respective data of each type of emulsion (under-, medium- and over-processed). From the normalized basal predictors, the ratio of peaks, the ratio of inflection points, and their mathematical transformations (inverse, square, and cube) were calculated only with intensity data. The ratio between the intensity at 450 nm and peaks or inflection points were also studied. With this described procedure, a total of 190 predictors were obtained and distributed in three blocks named "Peaks & inflection points" (wavelength and intensity values of peaks and inflection points and their mathematical transformations), "Ratios of peaks" (ratios of the intensities of peaks and/or the intensity at 450 nm, and their mathematical transformations) and "Ratios of inflection points" (ratios of the intensities at the inflection points and/or the intensity at 450 nm, and their mathematical transformations). Data was analyzed in blocks in order to evaluate the accuracy of prediction obtained with regard to the readiness of predictors calculation.

Table 1
Cooking losses (%) depending on emulsification degree and formula.

Emulsion	Emulsification degree		
	Under-processed	Medium-processed	Over-processed
Formula with starch[1]	3.996 ± 1.580^a	3.472 ± 1.568^b	4.078 ± 1.793^a
Formula without starch[2]	4.884 ± 1.711^a	5.471 ± 2.363^a	4.774 ± 1.151^a

Mean value ± s.d.; [1]n = 72; [2]n = 54; a, b: values by rows with different superscript letter were significantly different ($P < 0.05$).

2.4. Statistical analysis

The whole experiment was repeated on four and three independent occasions for formula with and without starch, respectively. Analysis of variance (ANOVA) was performed with the Statistical Analysis System (SAS) in order to investigate the effect of emulsification degree, the process factor, and the emulsion production batch on optical predictors and cooking losses, including into the statistical model both factors and their interaction. LSD test was used for comparison of sample data, and evaluations were based on a significance level of ($P < 0.05$). Furthermore, Pearson's correlation coefficients between optical predictors and cooking losses were determined. Different regression models for predicting cooking losses with the optical predictors were tested using the maximum R^2 procedure of SAS to obtain the best eight models of cooking losses prediction for each of the three different blocks of data as well as for all data together.

Table 2
Models for the prediction of cooking losses in meat emulsions with starch (^{ns}, not significant $P \geq 0.05$).

Data	Model	Equation	R^2
Peaks & inflection points	I**	$C_{loss} = 3.60 + 1.62P_7$	0.623
	II***	$C_{loss} = 4.38 + 1.36P_7 - 2.44P_{82}$	0.902
	III***	$C_{loss} = 4.98 + 1.11P_7 - 1.81P_{82} - 0.462P_2$	0.964
	IV***	$C_{loss} = 5.82 + 0.888P_7 - 0.879P_2 - 2.18{\cdot}10^{-6}P_{83} - 1.02P_8$	0.989
	V***	$C_{loss} = 5.66 + 0.665P_7 - 0.870P_2 - 0.754P_8 - 9.10{\cdot}10^{-9}P_{103} + 0.157P_6$	0.996
	VI***	$C_{loss} = 7.28–1.84P_2 - 6{\cdot}10^{-8}P_{103} - 0.00179P_{13} - 0.0880P_{80} - 0.109P_{81} + 4.38{\cdot}10^{-6}P_{84}$	>0.999
	VII***	$C_{loss} = 6.90–1.75P_2 - 6.07{\cdot}10^{-8}P_{103} + 0.0859P_6 - 0.0684P_{80} - 0.121P_{81} + 3.98{\cdot}10^{-6}P_{84} - 3.47P_{68}$	>0.999
	VIII***	$C_{loss} = 6.85–1.74P_2 - 6.03{\cdot}10^{-8}P_{103} + 0.0890P_6 - 0.0678P_{80} - 0.121P_{81} + 3.96{\cdot}10^{-6}P_{84} - 3.57P_{68} + 0.0226P_{61}^{ns}$	>0.999
Ratios of peaks	I**	$C_{loss} = 5.08–25.3P_{18}$	0.556
	II***	$C_{loss} = 6.25–55.2P_{18} + 4460.7P_{123}$	0.820
	III***	$C_{loss} = 5.51–185.6P_{18} - 153.8P_{17} + 254.7P_{108}$	0.900
	IV***	$C_{loss} = 5.39–207.7P_{18} - 178.8P_{17} + 265.2P_{108} + 2.01P_{126}^{ns}$	0.913
	V***	$C_{loss} = 6.84–170.8P_{18} - 90.6P_{17}^{ns} - 16.9P_{22} + 138.2P_{122} + 288.1P_{107}$	0.968
	VI***	$C_{loss} = 7.87–100.8P_{18} + 486.7P_{122} + 718.8P_{107} - 2.30P_{115} - 718{,}849P_{129} + 80P_{19}$	0.993
	VII***	$C_{loss} = 7.78–100P_{18} + 564.8P_{122} + 672.5P_{107} - 2.34P_{115} - 904{,}374P_{129} + 79.2P_{19} - 0.184P_{127}^{ns}$	0.996
	VIII***	$C_{loss} = 7.49–70.9P_{18} + 15.4P_{126} + 530.7P_{122} - 0.113P_{115} - 716{,}421P_{129} + 74P_{19} - 0.256P_{127} + 44.5P_{112}$	>0.999
Ratios of inflection points	I**	$C_{loss} = 5.80 + 56.9P_{45}$	0.755
	II***	$C_{loss} = 6.50 + 62.2P_{45} - 40.6P_{142}$	0.936
	III***	$C_{loss} = 6.35 + 63.9P_{45} - 32.8P_{142} + 467.2P_{180}$	0.964
	IV***	$C_{loss} = 6.37 + 80.7P_{45} - 30.1P_{142} + 892.1P_{180} + 100.3P_{145}^{ns}$	0.977
	V***	$C_{loss} = 6.62 + 95.6P_{45} - 46.1P_{142} + 167P_{145} + 8983.3P_{171} + 9.88P_{184}$	0.989
	VI***	$C_{loss} = 6.55 + 104.7P_{45} - 46.8P_{142} + 336.3P_{145} + 11{,}116P_{171} + 11.5P_{184} - 167.2P_{176}^{ns}$	0.993
	VII***	$C_{loss} = 6.46 + 98.9P_{45} - 42.7P_{142} + 352.8P_{145} + 13{,}758P_{171} + 7.20P_{184} - 248P_{176} + 2.64P_{42}$	0.998
	VIII***	$C_{loss} = 6.69 + 96.6P_{45} - 46.2P_{142} + 477P_{145} + 13{,}334P_{171} + 13.5P_{184} - 325.5P_{176} - 11.0P_{37} + 38.5P_{57}$	>0.999
All data	I**	$C_{loss} = 5.80 + 56.9P_{45}$	0.755
	II***	$C_{loss} = 6.50 + 62.2P_{45} - 40.6P_{142}$	0.936
	III***	$C_{loss} = 5.59–31.6P_{142} - 8.54P_{46} + 0.673P_7$	0.983
	IV***	$C_{loss} = 5.84–32.9P_{142} - 8.33P_{46} + 0.589P_7 - 5.39{\cdot}10^{-4}P_{10}$	0.997
	V***	$C_{loss} = 5.86–34.9P_{142} - 8.21P_{46} + 0.613P_7 - 5.47{\cdot}10^{-4}P_{10} - 12.1P_{174}$	0.999
	VI***	$C_{loss} = 6.33–43.2P_{142} - 8.71P_{46} + 0.671P_7 - 5.58{\cdot}10^{-4}P_{10} - 21.9P_{174} - 0.270P_{61}$	>0.999
	VII***	$C_{loss} = 6.26–43.3P_{142} - 7.57P_{46} + 0.677P_7 - 5.53{\cdot}10^{-4}P_{10} - 22.4P_{174} - 0.260P_{61} - 79.3P_{147}$	>0.999
	VIII***	$C_{loss} = 6.21–42.4P_{142} - 6.64P_{46} + 0.656P_7 - 5.55{\cdot}10^{-4}P_{10} - 19.8P_{174} - 0.233P_{61} - 237.9P_{147} - 1257.4P_{177}$	>0.999

3. Results and discussion

3.1. Meat emulsions composition and cooking losses

Starch addition could elucidate cooking losses differences observed between emulsions with and without starch (Table 1). In fact, Chen, Lee, and Crapo (1993) showed that starch embedded in a protein gel matrix swelled during cooking and enhanced the formation of strong structures, which is represented by a more stable matrix with greater water-binding capacity. Other studies have also evidenced the ability of starch to entrap water and the consequent reduction in cooking losses when it is incorporated like in low-fat bologna sausages, low-fat frankfurters, and other pork batters (Bañón et al., 2008; Dexter, Sofos, & Schmidt, 1993; Hughes, Mullen, & Troy, 1998). It should be considered that in the previous studies, meat emulsions were processed by bowl choppers, which differs from the equipment used in this study. Independently of the process, the same tendency of losses was found in the present study for the case of meat emulsions with starch (Table 1).

A study in meat emulsions and frankfurters pointed out increases in the losses when the chopping time passed from 3 to 7 min at 2000 and 3000 rpm in a 30 L-Stephan pilot equipment, respectively (Allais et al., 2004). Similarly, other studies have borne out that an increment in the chopping time increased cooking losses in comminuted pork meats (Bañón et al., 2008; Álvarez et al., 2007). These findings showed the importance of chopping as a factor in the control of meat emulsions stability. However, in the present study, no clear tendency was observed when analyzing the effect of the emulsification degree on cooking losses. For example, in samples with starch, a significant difference was observed between the medium-degree of processing and the other two degrees, which is also where the lowest cooking loss occurred (3.47%). This difference can be attributed to the know-how of the industry, which has established medium-processed conditions in starch sausages as the optima in quality and cost-effective results. On the contrary, there were no significant differences between emulsification degrees for cooking losses in emulsions without starch, maybe due to erratic standard deviations observed in this type of emulsion, which could interfere in the visualization of the differences (Table 1).

3.2. Optical predictors, correlations, and cooking loss prediction equations

3.2.1. Emulsions with starch

The ANOVA analysis performed with the whole set of optical data showed that the emulsification degree could be statistically differentiated by some specific predictors. Although none of the predictors could differentiate the three emulsification degrees, a large number could identify and set apart one emulsification degree as different from the other two (data not shown). Almost all of these predictors were found in the "Peaks & inflection points" block, a fact of interest as the majority of predictors that correlated with cooking losses were found in this block (predictors 2, 6, 80). As a result, the above-mentioned predictors were part of the cooking losses prediction equations.

It was observed that the Pearson correlation values of some of the predictors did not correlate significantly ($P \geq 0.05$) with the losses (data not shown). This fact could be explained by their low contribution, i.e. little information, but when included in the model they potentiated the results since the R^2 values increased significantly. In this way, for the "Peaks & inflection points" block, the predictors 7, 82, 2, 83, and 8 explained the first four models, with R^2 of 0.623, 0.902, 0.964, and 0.989, respectively (Table 2). It can also be noticed that the inclusion of just two variables (Model II***) improved notably the determination coefficient ($R^2 = 0.902$) when compared to Model I** ($R^2 = 0.623$), which suggested that only two predictors could be enough to have a representative cooking loss prediction. Similar results were reported in a study made on fresh pork meat emulsions formulated with hydrolyzed potato protein and different fat levels (15% and 30%) with coefficients of determination of 0.77, 0.95, and 0.96 in the first three models when color parameters (L^* and b^*) and the optic parameter peak2 wavelength were incorporated in the models (Nieto et al., 2009, 2014). It should be noted, though, this model did include color parameters, which are less convenient for the point of view of sensor technology as compared to static light scatter readings.

All predictors for blocks "Ratios of peaks" and "Ratios of inflection points" were included in their respective cooking losses prediction models. On one hand, for the case of "Ratios of peaks", predictors 108 and 126 were the only ones that correlated significantly with cooking losses ($P < 0.05$) (Table 2 Supplementary data), but these showed up only in Models III*** ($R^2 = 0.900$), IV*** ($R^2 = 0.913$) and VIII*** ($R^2 > 0.999$) (Table 2). On the other hand, for the case of "Ratios of inflection points", there were no predictors that correlated with losses, however, the models showed high determination coefficients starting from Model II*** with R^2 of 0.936 (Table 2). This suggests that some predictors by themselves contribute with little information but when included in the models cause a notable improvement in the R^2 value.

Finally, the potential estimation of predictors from the three blocks together was analyzed. The cooking losses prediction models showed R^2 values of 0.997 for Model IV***, 0.999 for Model V*** and >0.999 for

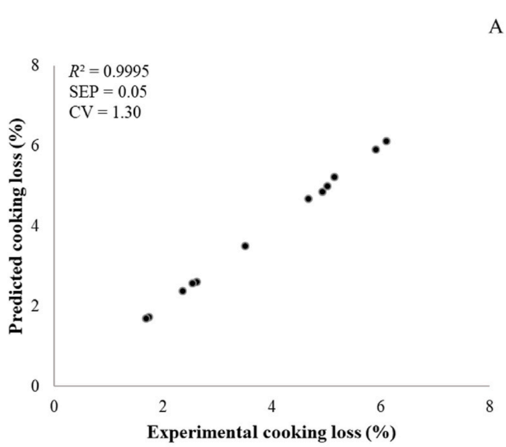

Fig. 2. A) Predicted values of cooking losses for meat emulsions with starch by Model VI ($P \leq 0.001$) with "Peaks & inflection points" block. B) Predicted values of cooking losses for meat emulsions without starch by Model V ($P \leq 0.001$) with "All data" block. R^2: determination coefficient; SEP: standard error of prediction (%); CV: coefficient of variation (%).

Models VI***, VII*** and VIII*** (Table 2).

These results suggest that, regarding meat emulsions with starch, the optical information of "Ratios of inflection points" and their transformations was valuable when establishing prediction equations with a small number of predictors (from 1 to 3; Table 2). However, using only the data from this block, 8 predictors were needed to reach a determination coefficient >0.999. In fact, the best model to reach a determination coefficient >0.999 with less number of variables was Model VI*** with 6 predictors of the "Peaks & inflection points" block, which is represented in Fig. 2A.

3.2.2. Emulsions without starch

Concerning emulsions without starch, it was found that at least one type of emulsification degree could be differentiated from the rest by some of the predictors (data not shown). This trend was widely found in the three blocks; however, at the "Peaks & inflection points" block, only four predictors (11, 69, 85, and 101) were able to differentiate individually the three emulsification degrees. These four predictors came from the same optical parameter and the corresponding transformations. Furthermore, looking at Pearson's coefficients, although these predictors did not correlate with cooking losses, many other predictors in all the three blocks showed significant correlations with cooking losses (predictors 100, 105, 19, 108, 110, 28, 40, 47, 173, 150).

The following cooking losses prediction models and the corresponding regression coefficients for "Peaks & inflection points", "Ratios of peaks" and "Ratios of inflection points" (Table 3) showed that for a three-variable model the regression coefficients were 0.917 with the predictors 105, 100, 4 for the "Peaks & inflection points", 0.900 with the predictors 19, 110, 119 for "Ratios of peaks" and 0.918 with the predictors 156, 161, 47 for "Ratios of inflection points", respectively.

The highest determination coefficients were shown in the "Peaks & inflection points" and "Ratios of inflection points" blocks. Nevertheless, the fact that Pearson's coefficient of some of the "Ratios of inflection points" predictors mentioned above were not significant suggests that "Peaks & inflection points" prediction models had more valuable information. Indeed, predictors 94, 105, and 100 of "Peaks & inflection points" block were included within the Models I**, II** and III** when all the blocks were analyzed together (Table 3).

Particularly, some of the predictors did not show a significant correlation value with cooking losses, which could be attributed to their little information by themselves; but when included in the models the coefficients of determination (R^2) improved significantly.

In addition, it can be noted that Model V*** of "All data" block (Table 3) reached the maximum determination coefficient ($R^2 > 0.999$) using 5 predictors which suggests that 5 optical predictors could be enough to represent, virtually without error, the cooking loss in meat emulsions without starch. The representation of predicted *vs.* experimental cooking losses using Model V*** is shown in Fig. 2B.

3.2.3. With starch vs. without starch emulsions

As already mentioned, emulsions with and without starch were characterized by different types of predictors, which notably tended to be less informative in the emulsions with starch when the effect of emulsification degree on the optical parameters and their correlations with cooking losses was studied. The contrary was found in samples without starch were a wide variety of predictors, including one group of predictors that differentiated the three emulsification degrees, provided strong information about cooking losses and the emulsification degree. The reduced number of predictors correlating with the losses in emulsions with starch could be a consequence of starch incorporation, given that it improves notably the stability of the matrix emulsion by promoting the interaction between the main components of the batter (Dexter et al., 1993). Probably, this made the emulsions more homogenous providing similar and reliable optical data during the light backscatter scanning and overshadowing some strong predictors that in the models seemed to be significant to predict the losses. The opposed situation may have occurred in emulsions without starch, where a more heterogeneous matrix may have been obtained (Lyons, Kerry, Morrissey, & Buckley, 1999). So, the effect of the emulsification degree clearly found in emulsions without starch may be suppressed when adding it.

Table 3
Models for the prediction of cooking losses in meat emulsions without starch (^{ns}, not significant $P \geq 0.05$).

Data	Model	Equation	R^2
Peaks & inflection points	I**	$C_{loss} = 5.48–0.276P_{94}$	0.658
	II**	$C_{loss} = 6.50–0.430P_{94} - 7.12 \cdot 10^{-11}P_{105}^{ns}$	0.806
	III**	$C_{loss} = 5.73–1.03 \cdot 10^{-9}P_{105} + 7.32 \cdot 10^{-10}P_{100} - 1.32P_{4}$	0.917
	IV**	$C_{loss} = 5.91–1.22 \cdot 10^{-9}P_{105} + 8.78 \cdot 10^{-10}P_{100} - 1.45P_{4} - 0.0649P_{75}^{ns}$	0.970
	V***	$C_{loss} = 6.32–1.26 \cdot 10^{-9}P_{105} + 9.28 \cdot 10^{-10}P_{100} - 1.87P_{4} - 0.0735P_{75} - 4.93 \cdot 10^{-3}P_{12}$	0.997
	VI***	$C_{loss} = 6.11–1.40 \cdot 10^{-9}P_{105} + 1.035 \cdot 10^{-9}P_{100} - 1.83P_{4} - 0.0713P_{75} - 5.22 \cdot 10^{-3}P_{12} + 0.138P_{64}$	>0.999
	VII***	$C_{loss} = 6.09–1.36 \cdot 10^{-9}P_{105} + 1.01 \cdot 10^{-9}P_{100} - 1.83P_{4} - 0.0656P_{75} - 6.25 \cdot 10^{-3}P_{12} + 0.118P_{64} - 0.0648P_{62}^{ns}$	>0.999
Ratios of peaks	I*	$C_{loss} = 6.13 + 14.066P_{21}$	0.556
	II*	$C_{loss} = 6.59 + 50.84P_{19} + 31.4P_{110}^{ns}$	0.820
	III*	$C_{loss} = 9.49 + 175.5P_{19}^{ns} + 131.9P_{110}^{ns} + 4326.1P_{119}^{ns}$	0.900
	IV*	$C_{loss} = 8.45 + 210.6P_{110} - 1911.6P_{107} + 4568.4P_{123} + 266.3P_{28}$	0.913
	V*	$C_{loss} = 8.59 + 236.7P_{110} - 1902.7P_{107} + 4858.7P_{123} + 313.6P_{28} - 303P_{120}^{ns}$	0.968
	VI*	$C_{loss} = 4.06–3{,}097P_{107} + 11{,}199P_{123} - 1129.1P_{120}^{ns} + 619P_{108}^{ns} + 4764.6P_{109} - 14{,}687P_{118}$	0.993
	VII*	$C_{loss} = 3.83–8518.9P_{119}^{ns} - 3657.5P_{107} + 11{,}587P_{123} - 2283.7P_{108} + 734.8P_{108} + 5016.2P_{109} - 15{,}588P_{118}$	0.996
Ratios of inflection points	I*	$C_{loss} = 5.91–81.5P_{150}$	0.605
	II**	$C_{loss} = 5.00 + 128.6P_{156} + 578.1P_{161}$	0.871
	III**	$C_{loss} = 4.27 + 175P_{156} + 1320.4P_{161} - 29.5P_{47}^{ns}$	0.918
	IV***	$C_{loss} = 4.70–657.5P_{145} - 1{,}558P_{147} + 129.6P_{148} + 755.1P_{151}$	0.996
	V***	$C_{loss} = 4.79–631.4P_{145} - 1491.6P_{147} + 122.5P_{148} + 772.6P_{151} - 816.8P_{173}$	0.999
	VI***	$C_{loss} = 5.06–653.1P_{145} - 1457.3P_{147} + 117.9P_{148} + 908.8P_{151} + 3428.1P_{181} + 0.395P_{40}$	>0.999
	VII***	$C_{loss} = 5.05–653.7P_{145} - 1463.9P_{147} + 118.5P_{148} + 908.5P_{151} + 3664.5P_{181} + 0.389P_{40} + 0.186P_{54}$	>0.999
All data	I**	$C_{loss} = 5.48–0.276P_{94}$	0.658
	II**	$C_{loss} = 6.50–0.430P_{94} - 7.12 \cdot 10^{-11}P_{105}^{ns}$	0.806
	III**	$C_{loss} = 2.87–1.44 \cdot 10^{-9}P_{105} + 1.16 \cdot 10^{-9}P_{100} + 237.9P_{4}$	0.924
	IV***	$C_{loss} = 4.41–3.26 \cdot 10^{-9}P_{105} + 2.49 \cdot 10^{-9}P_{100} + 2.85P_{7} + 33.1P_{31}$	0.997
	V***	$C_{loss} = 4.34–3.25 \cdot 10^{-9}P_{105} + 2.49 \cdot 10^{-9}P_{100} + 2.75P_{7} + 32.2P_{31} - 4.56 \cdot 10^{-3}P_{91}$	>0.999
	VI***	$C_{loss} = 4.29–3.19 \cdot 10^{-9}P_{105} + 2.44 \cdot 10^{-9}P_{100} + 2.74P_{7} + 36.2P_{31} - 2.62 \cdot 10^{-3}P_{91} + 0.0782P_{6}$	>0.999
	VII***	$C_{loss} = 4.29–3.18 \cdot 10^{-9}P_{105} + 2.44 \cdot 10^{-9}P_{100} + 2.73P_{7} + 36.73P_{31} - 2.52 \cdot 10^{-3}P_{91} + 0.0802P_{6} + 3.24 \cdot 10^{-3}P_{162}$	>0.999

Similar results were found in a previous investigation done in meat emulsions with and without starch and light backscatter technology, reporting more predictors in the samples without starch which differentiate emulsification degree (Torres, 2016). Related findings were suggested in Álvarez et al. (2007) with pork emulsions manufactured at a laboratory scale with and without starch and at different lean/fat ratios. The results showed a clearer response of the studied variable (lightness) concerning the chopping time and cooking losses in emulsions without starch. These outcomes together with those of the present study, suggest a better optical response for emulsions without starch when different emulsification degrees are applied. However, it is clear from the results, that cooking losses can be optically predicted with a similar accuracy irrespectively of the presence/absence of starch in the formula.

Among all the models for each type of emulsions, the best cooking losses prediction equations were found in the "Peaks & inflection points" block for formula with starch and in "All data" for formula without starch (Tables 2–3). These models reached the maximum determination coefficient ($R^2 > 0.999$) with 5 and 6 predictors for the formula without and with starch, respectively. The results showed a noticeable improvement in the determination coefficients models proposed by Álvarez et al. (2007) ($R^2 = 0.69$, four predictors model) and Nieto et al. (2014) ($R^2 = 0.97$, five predictors model). Although none of the aforementioned works matched exactly with the present study conditions, it should be noted that, in the present study, samples were generated using a continuous industrial emulsifier and no color parameters were used as predictors.

For the case of the models proposed by Álvarez et al. (2007), the determination coefficients ranged from 0.42 to 0.69 when two different types of meat emulsions (starch and no starch) produced at laboratory scale were analyzed. The low R^2 found gave sight that the predictors proposed in their models (chopping time, temperature, and color coordinates) were not sensible enough to predict the cooking losses.

Later on, Nieto et al. (2014) incorporated for the first time optical spectra parameters in cooking losses prediction models to describe the optimum end-point of emulsification. Meat samples, manufactured at a laboratory scale, were formulated with hydrolyzed potato protein and analyzed by light backscatter technology. Their results showed an R^2 of 0.97, much lower than the maximum coefficients of determination ($R^2 > 0.999$) found in the present study. The authors suggested that the dark color of the hydrolyzed potato protein may have interfered in the optical response of the emulsion. In the present work, such difficulties were not found.

4. Conclusions

The study of the cooking losses and the optical response of two different industrial meat emulsions allowed the identification of some optical parameters as potential predictors of the cooking losses. This led to the development of statistically significant prediction equations for the cooking losses with coefficients of determination, $R^2 > 0.999$, in both types of emulsions. These results point out the potential of light backscatter technology as a tool to predict cooking losses and suggest the implementation of an in-line/on-line optical emulsification control technology that would significantly contribute to the selection of an optimum emulsification degree.

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Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lwt.2020.110562.

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