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Development of an optic control technology of the emulsification degree in meat emulsions

"Desarrollo de una tecnología óptica de control del grado de emulsificación en emulsiones cárnicas"

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INFORMAN

Que el trabajo de investigación titulado: “Desarrollo de una tecnología óptica de control del grado de emulsificación en emulsiones cárnicas” ha sido realizado, bajo su supervisión y tutela, por Zulay Estefanía González Martínez dentro del Máster en Calidad de Alimentos de Origen Animal de la Universitat Autònoma de Barcelona.

Bellatera, Julio de 2017

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ABSTRACT

The stability of comminuted products plays an important role in the economy of meat industries in terms of yield and quality. Proper formulation of the product and establishment of suitable conditions of chopping can significantly contribute to control cooking losses. However, the last feature has not been optimized at the industry level yet. The purpose of the present research was to study the relationship between a large number of parameters obtained by optical backscatter technology and the cooking losses, in order to develop prediction models as a way to optimize the chopping end-point. Two types of formulations, with or without starch, with their corresponding samples of pre-chopping and three different emulsion chopping speeds (low, standard and high) were processed. For each of the samples, the light backscatter spectrum was analyzed to identify possible optical predictors and to build up cooking losses prediction models by means of statistical analyses, i.e., ANOVA, Pearson's correlations and maximum R^2 procedure. Formula with starch showed lower cooking losses compared to formula without starch. Some optical predictors showed significant differences in at least a couple of chopping speeds in both formulations. Only formulations without starch showed optical predictors differentiating the three speeds. Emulsions without starch showed a higher amount of predictors correlating with cooking losses. Prediction equation models with R^2 values > 0.999 were obtained when applying 5 or 6 significant predictors for both emulsions. These results point out the potential of light backscatter technology as a control tool during chopping.

Keywords: meat emulsions, emulsion stability, emulsification, starch, cooking losses, chopping speed, optical predictors, prediction models.

RESUMEN

La estabilidad de los productos cárnicos picados juega un rol importante en la industria cárnica en términos de rendimiento y calidad. La apropiada formulación del producto y el establecimiento de unas condiciones adecuadas de picado pueden contribuir a optimizar el control de las pérdidas por cocción. Sin embargo, esta variable no ha podido ser aún optimizada a nivel industrial. La finalidad de esta investigación fue estudiar la relación entre un amplio número de parámetros obtenidos mediante dispersión de luz y las pérdidas por cocción, a fin de desarrollar modelos de predicción de las pérdidas por cocción. Se analizaron dos tipos de formulaciones, con y sin almidón, con sus correspondientes muestras pre-picadas y procesadas a tres velocidades diferentes de corte (baja, estándar y alta). En cada muestra se estudió el espectro de dispersión para identificar posibles predictores ópticos y construir modelos de predicción mediante análisis estadísticos como ANOVA, correlación de Pearson y procedimiento de máximo R^2. La emulsión con almidón presentó menores pérdidas por cocción. Algunos predictores ópticos mostraron diferencias significativas en al menos un par de velocidades en ambas formulaciones. Solo las emulsiones sin almidón mostraron predictores ópticos que diferenciaron las tres velocidades. Las muestras de alta calidad presentaron mayor cantidad de predictores correlacionados con las pérdidas por cocción. Los modelos de predicción obtenidos presentaron valores de $R^2 > 0.999$, al aplicar 5 y 6 predictores significativos en ambas emulsiones. Estos resultados indican la potencialidad de la tecnología de dispersión de luz como una herramienta de control durante el picado.

Palabras clave: emulsiones cárnicas, estabilidad de la emulsión, emulsificación, almidón, pérdidas por cocción, velocidad de picado, predictores ópticos, modelos de predicción

1 Introduction

1.1 Meat emulsions

Meat emulsions are composed of water, proteins and fat. Among these, proteins are released and activated by phosphates or salt after cutting to immobilize water and cover fat. Solubilized and activated proteins stabilize both components in a gel matrix o/w emulsion where fat is partially in the liquid form (Feiner, 2006).

Production of Frankfurters, which are an example of a meat emulsion product, involves comminution of 30–40% lean meat, 20–30% water, 15–30% fat and 1.6–1.8% salt, being the chopping process the most important industrial processing step, since it determines the emulsification degree of the products. In fact, the optimal extent of comminution gives the typical final texture to this product (Puolanne, 2010).

Water holding capacity is an important aspect in meat sausages production and depends on the emulsion stability, which is defined by the product composition and processing conditions. Focusing on it, the objective relies on the control of all these parameters to reach high cooking yields, represented by less cooking losses (Knipe, 2014).

1.2 Meat emulsions stability

Product composition affects directly the emulsion microstructure. As told before, fat, water and lean are the basic components in sausages, being the last the most important because of its protein content. Meat emulsions depend on two types of myofibrillar proteins, myosin and actin, to bind to fat and water, respectively. During chopping, myosin solubilized (activated) protein locates as a thin layer around fat particles in order to prevent fat separation through thermal treatment. The thicker the protein layer the better emulsion stability degree is obtained. Actin solubilized protein contributes to immobilize water. The interaction of these two proteins with fat and water set up the tridimensional emulsion matrix (Barbut, 1995; Feiner, 2006).

In addition, in order to make the emulsion more stable, meat industries add some extra additives according to the final product requirements. The inclusion of these is commonly done to control the stability of the product focused on the water holding capacity, sensorial quality and also microbial inhibition (Sebranek, 2003). The most popular additives in frankfurters are phosphates and salts, as both have an effect on protein solubilization from meat tissue. Phosphates are involved in emulsion pH regulations focused on enhancing water holding capacity and protein extraction. Salt triggers the ability of meat to catch water during cooking (Knipe, 2014). In terms of quality attributes, phosphates can control microbial spoilage and reduce product oxidation process by chelating prooxidative cations in the meat (antioxidant system), and salt inhibits proteolytic microorganism ability (Sebranek, 2003).

Finally, in some cases starch is also used to improve water and protein binding, generally in low-cost or secondary products, to make them more profitable. Emulsion sausages formulated with starch create a more compact and strong network where water is better retained due to starch's ability to swell and interact with meat proteins. As a result, the water expelled during heat is reduced. The contrary occurs in only meat products where starch is not added (García-García & Totosaus, 2008), yielding increased sausage weight losses. Binders and extenders in general are limited in the USA to 3.5% (Sebranek, 2003).

Another factor is associated to the adjustment of the optimal emulsification time during chopping. In this regard, it is very important to check the meat batter temperature and the cutting duration to avoid two possible defects: a) one less firm product unstable because of too much fat surface area to be covered, which enhances water and fat separation (over-chopping); and b) one type of product with incomplete solubilized proteins and visible fat particles making it less attractive to the consumer (under-chopping). Chopping temperature is controlled to avoid fat melting problems (Feiner, 2006; Knipe, 2014). During cooking, proteins change their conformational structure promoting aggregation. The characteristics of obtained gels depend on the stability of the pre-cooked emulsion, i.e., fat properly covered by proteins, and the decrease of temperature after cooking. Shrinkage provokes gel deformation and concomitant cooking losses (Tornberg, 2005).

As mentioned before, a standardized content of ingredients/additives, consistent manufacturing conditions and the application of a standardized chopping time can guarantee a high quality product in terms of nutritional value, structure, product stability, sensorial value and microbial safety (Knipe, 2014; Sebranek, 2003). Moreover, meat industries economy could benefit from the reduction in cooking losses if all parameters above mentioned get adjusted.

1.3 Economic impact

Nowadays, cooking losses are a common problem found at the last stage of meat emulsions processing. As an example frankfurter-type sausages report between 5% and 18% of losses, pointing out the great potential economic impact of minimizing losses taking into account the ever-increasing production of meat emulsions worldwide (Grigelmo-Miguel et al., 1999; Shan et al., 2014). Furthermore, Álvarez et al. (2010) reported an annual economic loss of 0.2 billion US dollars with an average cooking loss of 2.64% under optimum chopping conditions, whilst losses between 1.20–1.65 billion US dollars were calculated for over- and under-chopping processing. In Spain, estimated losses range between 5–40 million euros. These economic losses rise with reprocessing of low quality final products as more energy and extra resources are needed (Nieto et al., 2014).

1.4 Backscatter optical technology

There are few works that have studied emulsion stability control by the use of a novel optical sensor technology based in light backscatter and all done by our research group (Álvarez et al., 2007, 2009, 2010a, b; Nieto et al., 2014, 2015; Torres, 2016). The optical device proposed implements some color and optic parameters correlations with water or fat losses in order to determine the exact emulsification end-point in meat emulsions. These studies have demonstrated the relation between cooking losses and the optical response. Additionally, all these studies, except for Torres (2016), manufactured samples under laboratory/pilot plant processing, so the effect of real industrial conditions on the optical technology feasibility has not been analyzed yet. In that view, the present study had the purpose of providing valuable information with the use of industrial meat samples thus going forward towards a new in-line control system.

Otherwise, the implementation of this type of technology control could favor meat emulsion monitoring during chopping, emulsification end-point or velocity adjustment, and prevention of cooking losses. In that way, all final products would not be affected by emulsion breakdown with an associated improvement of yield and quality (Nieto et al., 2014).

The aim of this work was to find out a relation between some optical parameters and the cooking losses of two different meat emulsions (with or without starch) in order to establish prediction equations for the losses in both types of samples, and, as a consequence, to evaluate the feasibility of applying the backscatter optical technology as a control technology for the emulsification degree in meat emulsions.

2 Materials and methods

2.1 Experimental design

Emulsion samples were produced at industrial scale. Two types of commercial meat emulsions, determined as formula with starch and formula without starch, were analyzed to evaluate the relation of some optical parameters with the chopping speed and the cooking losses. Both types of emulsions were processed under three different chopping speeds determined as low, standard and high. Also, the pre-chopping samples of both formula were analyzed.

All samples, including pre-chopping, were examined using a light backscatter optical technology to obtain the optical intensity spectra. Then, they were also processed to obtain the cooking losses. Statistical analyses, i.e., ANOVA, Pearson's correlations and maximum R^2 procedure, were performed in order to study the effect of speed on cooking losses and optical parameters, the correlations between these mentioned parameters and generate prediction models. The whole experiment was repeated on four and three independent occasions for formula with and without starch, respectively.

2.2 Meat emulsion manufacture and composition

Meat emulsions were produced following standard industrial procedures by Grupo Alimentario ARGAL (Miralcamp, Spain), a company with a twenty five-year trajectory in the Spanish market. Lean meat, fat, salt, spices and other minor ingredients were mixed using an industrial mixer INOTEC (Model IM-4500, Reutlingen, Germany) to obtain a pre-chopping batter. Batter was introduced into a mill homogenizer INOTEC (Model – I175CDVM-90D, Reutlingen, Germany), where the emulsification process occurred. During chopping, the screw speed of the homogenizer was modified to obtain meat emulsion samples at three different speed. Each speed was monitored through the final meat emulsion extrusion temperature: 9.36 ± 0.48 °C for low speed samples, 7.41 ± 0.70 °C for standard speed samples, and 5.09 ± 0.23 °C for high speed samples at. The three different chopping-speed samples and the pre-chopping sample were collected in order to perform different analysis.

All samples were delivered to UAB refrigerated (4 ± 2 ºC) and vacuum packaged, processed the same day of reception or stored at 4 ± 2 °C overnight until the next day. Also, Grupo Alimentario ARGAL provided a composition report of the samples, which were analyzed by a Food Scan NIR Meat Analyzer (DK-3400, FOSS, Hillerod, Denmark), previously calibrated. This equipment performed the measurements in the range of 850–1050 nm, with a precision wavelength of < 0.5 nm and wavelength accuracy of < 0.01 nm.

2.3 Meat emulsion cooking losses

After weighting empty, 50 mL corning tubes with an analytical balance (Model GR-120-EC, A&D Instruments LTD., Japan), meat samples were introduced into a syringe barrel of 100 mL and pressed in the corning tube with a plunger in order to simulate casing stuffing. Then, each corning tube was weighted and placed in a water bath OVAN (Model Cubeta Inox 27L, Suministros Grupo Esper, S.L., Barcelona, Spain) at 75 °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 obtained applying 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 in sextuplicate.

2.4 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 (Spectran Specialty Optics, Avon, CN, USA). Two fiber optic ends were attached to a small optic probe -using standard SMA connectors-, which was coupled to the sample holder, while the other two ends connected to the spectrometer and the light source, respectively. This system delivered optical data from the spectrometer to the computer across a USB cable in order to analyze optical spectra using the SpectraSuite® software (Ocean Optics, Inc.).

Figure 1. Optical device used to obtain the optical data from the meat emulsions.

At first, it was necessary to turn on the light source to allow spectrometer to warm up, then SpectraSuite® software was set into 3 seconds of integration time. At that point, meat emulsion was put into the sample holder, the light source blocked and the sensor probe placed. After that, the options “scope minus dark”, “store dark” and “store dark minus” were set, consecutively. Later, the light source was unblocked and the sample spectrum saved once it remained stable. Finally, the sample was taken out and both the sensor and the sample holder cleaned with warm water. The equipment was dried with paper.

All spectrum data was loaded into a new graph by setting the options “open processed spectra” and “show as overlay”. Data from optical spectra were collected at least in sextuplicate. Pre-chopping optical data was subtracted from each type of emulsion data to the respective statistical analyses. Then, all optical data was processed in order to define some optical spectra predictors, which were identified as peaks and slopes. In addition, the ratio of peaks, the ratio of slopes and their mathematical transformations: inverse, square root and cube root were calculated. A total of three blocks of predictors named “peaks & slopes”, “peak ratios” and “slope ratios” were grouped to report the results.

2.5 Statistical analysis

Data were processed and analyzed using the Stat Graphics program. Analysis of variance (ANOVA) was used to investigate the effect of the chopping speed, the process factor, and the emulsion production batch on the optical parameters (optical predictors) and on the 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 calculated averages of optical predictors were tested using the maximum R2 procedure of the Statistical Analysis System (SAS) to obtain the best eight models of prediction.

3 Results and discussion

3.1 Meat emulsions composition and cooking losses

Composition data of all samples provided by ARGAL are shown in Table 1. As it can be observed, percentages of each ingredient were stable for each emulsion type, which showed that the chopping speed had no effect on the composition, as expected. Bañón et al. (2008) suggest that the ratio fat/lean could be used as an indicator of emulsion stability. In the present study, even though emulsions without starch showed slightly higher percentages of protein and fat, as expected since no starch was added, fat/protein ratios were similar in both formulations (1.14 and 1.32 for formulas with and without starch, respectively) and therefore did not explain the observed differences on cooking losses (Table 2).

Table 1. Proximate composition (%) of emulsions (formulas with and without starch at three chopping speeds).

Emulsion	Speed	Moisture	Protein	Fat	Salt
Formula with starch[1]	Low	63.62 ± 1.63	11.63 ± 1.08	13.47 ± 1.56	2.14 ± 0.08
	Standard	63.95 ± 1.93	11.53 ± 1.06	13.12 ± 1.76	2.07 ± 0.21
	High	63.88 ± 1.77	11.55 ± 1.06	13.06 ± 1.60	2.15 ± 0.09
Formula without starch[2]	Low	63.85 ± 0.74	13.13 ± 0.31	17.43 ± 0.26	2.09 ± 0.13
	Standard	64.16 ± 0.67	13.13 ± 0.42	16.94 ± 0.72	2.11 ± 0.09
	High	63.75 ± 0.94	13.13 ± 0.31	17.50 ± 0.15	2.09 ± 0.14

Mean value ± s.d.; [1]n = 4; [2]n = 3; no significant differences were observed per formula (*P* > 0.05).

However, starch addition could elucidate cooking losses differences observed between emulsions with and without starch since starch was only added in the former. In fact, Chen et al. (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 catch 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 (Dexter et al., 1993; Hughes et al., 1998; Bañón et al., 2008). 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 above mentioned, the same tendency of losses was found in the present study for the case of meat emulsions with starch (Table 2).

Table 2. Cooking losses depending on chopping speed and type of meat emulsion.

Emulsion	**Speed**		
	Low	**Standard**	**High**
Formula with starch[1]	4.078 ± 1.793^{a}	3.472 ± 1.568^{b}	3.996 ± 1.580^{a}
Formula without starch[2]	4.774 ± 1.151^{a}	5.471 ± 2.363^{a}	4.884 ± 1.711^{a}

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

A study in meat emulsions and frankfurters pointed out increases in the losses when the chopping time passed from 3 to 7 minutes at 2000 and 3000 rpm, respectively in a 30L Stephan pilot equipment (Allais et al., 2004). Similarly, other studies have borne out that an increment in the chopping time increased cooking losses in comminuted pork meats (Álvarez et al., 2007; Bañón et al., 2008). This finding 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 chopping speeds on cooking losses. For example, in samples with starch, the ANOVA revealed a significant difference between the standard speed from the other two speeds, which is also where the lowest cooking loss occurred (3.47%). This difference can be associated with the precise production conditions that have been implemented in ARGAL premises, being the standard speed the optimum speed condition to produce cost-effective starch-sausages. On the contrary, there were no significant differences between chopping speeds for cooking losses in emulsions without starch, may be due to erratic standard deviations observed in this type of emulsion, which could interfere in the visualization of the differences (Table 2).

Finally, it should be pointed out that the mill homogenizer used in the present study, which was industrial, may not have been versatile enough for differentiating non-optimized speeds from the standard one. In other words, since the difference between chopping speed rates was too close, almost no significant differences on cooking losses were observed.

3.2 Optical predictors, correlations, and cooking loss prediction equations

All data was synthesized in blocks in order to show all the information. There were three blocks of predictors named “peaks & slopes”, “peak ratios” and “slope ratios” for each emulsion type. Some transformations as the inverse, square root and cubic root were calculated. A total of 193 predictors were studied in the whole three blocks.

Additionally, before generating the predictors, pre-chopping data of all samples was subtracted from the optical data of each type of emulsified samples to exclude the composition influence in the cooking losses as observed in other works (Allais et al., 2004; Bañón et al., 2008). (Allais et al., 2004; Bañón et al., 2008).

3.2.1 Emulsions with starch

The ANOVA analysis performed with the whole set of optical data showed that chopping speed could be statistically differentiated by some specific predictors, which could identify and set apart one type of speed as different from the other two speeds. Almost all of these predictors were found in the “peaks & slopes” block, a fact of interest since, also, the majority of predictors that correlated with cooking losses were found in this block (Table 3).

As a result, predictors identified by black rectangles in Table 3 are part of the cooking losses prediction equations. It can be seen that Pearson correlation values of some of them did not correlate significantly ($P > 0.05$) with the losses, though. 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 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 4). 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 included color parameters, which are less convenient for the point of view of building a sensor technology.

Otherwise, all predictors delimited by black rectangles in the tables for blocks "peak ratios" and "slope ratios" (Tables 5 and 7), were included in their respective cooking losses prediction models. On one hand, for the case of "peak ratios", predictors 108 and 126 were the only ones that correlated significantly with cooking losses ($P \leq 0.05$), but these showed up only in Models III*** ($R^2 = 0.900$), IV*** ($R^2 = 0.913$) and VIII ($R^2 > 0.999$) (Table 6). On the other hand, for the case of "slope ratios", there were no predictors that correlated with losses (Table 7), however, the models showed high determination coefficients starting from Model II*** with R^2 of 0.936 (Table 8). This pointed out 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 estimation potential of predictors from the three blocks together was analyzed and shown in Table 9. The cooking losses prediction models showed R^2 values of 0.997 for Model IV***, 0.999 for Model V*** and > 0.999 for Models VI*** VII*** and VIII***.

These results suggest that only the optical information of "peaks and slopes" and its transformations were valuable when establishing prediction equations for cooking loss in meat emulsions with starch. Furthermore, the best model to reach a determination coefficient > 0.999 with less number of variables was Model VI*** in Table 4. The representation of predicted *vs.* experimental cooking losses using Model VI*** is shown in Figure 2.

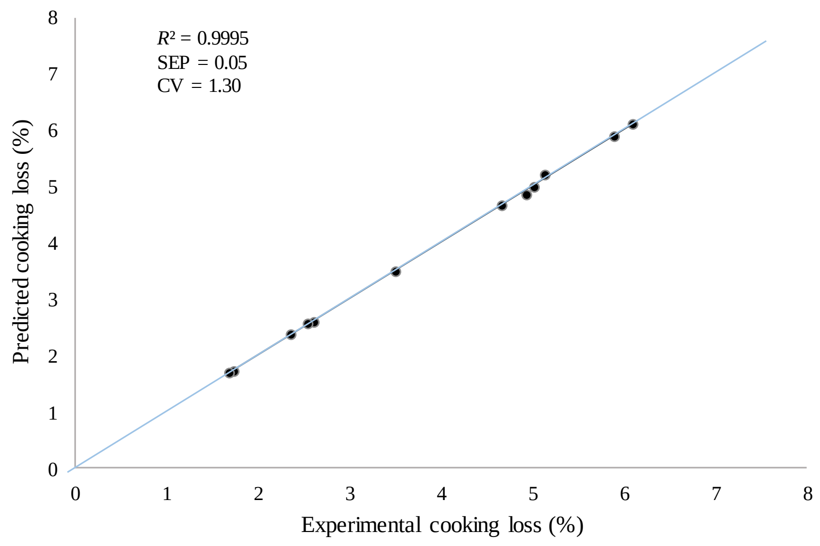

Figure 2. Predicted cooking loss obtained by Model VI*** from the "Peaks & slopes" block for emulsions with starch. n = 12; R^2: determination coefficient corrected for the means; SEP: standard error of prediction (%); CV: coefficient of variation (%).

Table 3. Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "Peaks & slopes"† of emulsions with starch.

Pred.	**Speed**			***r***	**Pred.**	**Speed**			***r***
	Low	**Std.**	**High**			**Low**	**Std.**	**High**	
Pred. 1	b	a	b	-0.661	**Pred. 9**	a	a	a	ns
Pred. 59	a	b	a	-0.662	**Pred. 67**	b	a	a	-0.414
Pred. 75	b	a	b	-0.661	**Pred. 83**	a	a	a	ns
Pred. 91	b	a	b	-0.660	**Pred. 99**	a	a	a	ns
Pred. 2	b	a	b	-0.544^{***}	**Pred. 10**	a	a	a	-0.372
Pred. 60	a	b	a	-0.486	**Pred. 68**	a	a	a	0.552^{***}
Pred. 76	a	a	a	-0.545	**Pred. 84**	a	a	a	-0.289^{*}
Pred. 92	b	a	b	0.543	**Pred. 100**	a	a	a	ns
Pred. 3	a	b	a	ns	**Pred. 11**	a	b	a	ns
Pred. 61	b	a	b	ns	**Pred. 69**	b	a	b	ns
Pred. 77	a	b	a	ns	**Pred. 85**	a	b	a	ns
Pred. 93	a	b	a	ns	**Pred. 101**	a	b	b	ns
Pred. 4	a,b	b	a	ns	**Pred. 12**	a	a	a	ns
Pred. 62	a	a	a	ns	**Pred. 70**	a	a	a	0.432
Pred. 78	a,b	b	a	ns	**Pred. 86**	a	a	a	ns
Pred. 94	a,b	b	a	ns	**Pred. 102**	a	a	a	ns
Pred. 5	a	b	a	-0.271	**Pred. 13**	a	b	b	ns
Pred. 63	b	a	b	0.277	**Pred. 71**	b	a	a	0.575
Pred. 79	a	b	a	-0.270	**Pred. 87**	a	b	b	ns
Pred. 95	a	b	a	-0.268	**Pred. 103**	a	b	a,b	ns
Pred. 6	b	b	a	0.558^{***}	**Pred. 14**	a	b	a,b	ns
Pred. 64	a	a	b	-0.558	**Pred. 72**	b	a	a,b	ns
Pred. 80	b	b	a	0.559^{***}	**Pred. 88**	a	b	a,b	ns
Pred. 96	b	b	a	0.560	**Pred. 104**	a	a	a	0.284
Pred. 7	a	a	a	0.487^{***}	**Pred. 15**	a	a	a	-0.283
Pred. 65	a	a	a	-0.505	**Pred. 73**	b	a,b	a	0.489
Pred. 81	a	a	a	0.487^{***}	**Pred. 89**	a	a	a	ns
Pred. 97	a	a	a	0.488	**Pred. 105**	a	a	a	ns
Pred. 8	a	a	a	-0.292^{*}	**Pred. 16**	a	a	a	-0.365
Pred. 66	a	a	a	0.300	**Pred. 74**	a	a	a	0.533
Pred. 82	a	a	a	-0.292^{*}	**Pred. 90**	a	a	a	-0.277
Pred. 98	a	a	a	-0.292	**Pred. 106**	a	a	a	ns

† "Peaks & slopes" refers to optical data obtained for peaks and slopes predictors and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 12; values without common characters were significantly different ($P < 0.05$); *r*: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models.

Table 4. Models for the prediction of cooking losses in meat emulsions with starch using parameters from the block "Peaks & slopes"†.

Model		$\boldsymbol{R^2}$
I**	$C_{loss} = \beta_0 + \beta_1 P_7$	0.623
II***	$C_{loss} = \beta_0 + \beta_1 P_7 + \beta_2 P_{82}$	0.902
III***	$C_{loss} = \beta_0 + \beta_1 P_7 + \beta_2 P_{82} + \beta_3 P_2$	0.964
IV***	$C_{loss} = \beta_0 + \beta_1 P_7 + \beta_3 P_2 + \beta_4 P_{83} + \beta_5 P_8$	0.989
V***	$C_{loss} = \beta_0 + \beta_1 P_7 + \beta_3 P_2 + \beta_5 P_8 + \beta_6 P_{103} + \beta_7 P_6$	0.996
VI***	$C_{loss} = \beta_0 + \beta_3 P_2 + \beta_6 P_{103} + \beta_8 P_{13} + \beta_9 P_{80} + \beta_{10} P_{81} + \beta_{11} P_{84}$	>0.999
VII***	$C_{loss} = \beta_0 + \beta_3 P_2 + \beta_6 P_{103} + \beta_7 P_6 + \beta_9 P_{80} + \beta_{10} P_{81} + \beta_{11} P_{84} + \beta_{12} P_{68}$	>0.999
VIII***	$C_{loss} = \beta_0 + \beta_3 P_2 + \beta_6 P_{103} + \beta_7 P_6 + \beta_9 P_{80} + \beta_{10} P_{81} + \beta_{11} P_{84} + \beta_{12} P_{68} + \beta_{13} P_{61}$	>0.999

† "Peaks & slopes" refers to obtained optical data for peaks and slopes and their mathematical transformations.

n = 12; C_{loss}: cooking losses; $\beta_{0\text{-}13}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 4. Continuation.

Model	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$	$\boldsymbol{\beta_5}$	$\boldsymbol{\beta_6}$	$\boldsymbol{\beta_7}$	$\boldsymbol{\beta_8}$	$\boldsymbol{\beta_9}$	$\boldsymbol{\beta_{10}}$	$\boldsymbol{\beta_{11}}$	$\boldsymbol{\beta_{12}}$	$\boldsymbol{\beta_{13}}$
I**	3.60***	1.62**	-	-	-	-	-	-	-	-	-	-	-	-
II***	4.38***	1.36***	-2.44***	-	-	-	-	-	-	-	-	-	-	-
III***	4.98***	1.11***	-1.81***	-0.462**	-	-	-	-	-	-	-	-	-	-
IV***	5.82***	0.888***	-	-0.879***	$-2.18\cdot10^{-6***}$	-1.02***	-	-	-	-	-	-	-	-
V***	5.66***	0.665***	-	-0.870***	-	-0.754***	$-9.10\cdot10^{-9**}$	0.157**	-	-	-	-	-	-
VI***	7.28***	-	-	-1.84***	-	-	$-6.00\cdot10^{-8***}$	-	-0.00179***	-0.0880***	-0.109**	$4.38\cdot10^{-6***}$	-	-
VII***	6.90***	-	-	-1.75***	-	-	$-6.07\cdot10^{-8***}$	0.0859***	-	-0.0684***	-0.121***	$3.98\cdot10^{-6***}$	-3.47***	-
VIII***	6.85***	-	-	-1.74***	-	-	$-6.03\cdot10^{-8***}$	0.0890***	-	-0.0678***	-0.121***	$3.96\cdot10^{-6***}$	-3.57***	0.0226^{ns}

n = 12; $\beta_{0\text{-}13}$: regression coefficients; Significance: ^{ns} $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 5. Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "peak ratios"† of emulsions with starch.

Pred.	**Speed**			***r***	**Pred.**	**Speed**			***r***
	Low	**Std.**	**High**			**Low**	**Std.**	**High**	
Pred. 17	a	a	a	ns	**Pred. 24**	b	a,b	a	ns
Pred. 107	a	a	a	ns	**Pred. 114**	a	a	a	ns
Pred. 119	a	a	a	ns	**Pred. 126**	a	a	a	-0.237*
Pred. 19	a	a	a	ns	**Pred. 27**	a	a	a	ns
Pred. 109	b	a	b	ns	**Pred. 117**	a	a	a	ns
Pred. 121	a	a	a	ns	**Pred. 129**	a	a	a	ns
Pred. 23	a	a	a	ns	**Pred. 20**	a	a	a	ns
Pred. 113	a	a	a	ns	**Pred. 110**	b	b	a	ns
Pred. 125	a	a	a	ns	**Pred. 122**	a	a	a	ns
Pred. 26	a	a	a	ns	**Pred. 22**	a	a	a	ns
Pred. 116	a	a	a	ns	**Pred. 112**	a	a	a	ns
Pred. 128	a	a	a	ns	**Pred. 124**	a	a	a	ns
Pred. 18	a	a	a	ns	**Pred. 25**	b	a,b	a	ns
Pred. 108	a	a	a	-0.238*	**Pred. 115**	a	a	a	ns
Pred. 120	a	a	a	ns	**Pred. 127**	a	a	a	ns
Pred. 21	a	a	a	ns	**Pred. 28**	a	a	a	ns
Pred. 111	a	a	a	ns	**Pred. 118**	b	a	b	ns
Pred. 123	a	a	a	ns	**Pred. 130**	a	a	a	ns

† "peak ratios" refers to optical data obtained for peaks and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 12; values without common characters were significantly different ($P < 0.05$); r: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models.

Table 6. Models for the prediction of cooking losses in meat emulsions with starch using parameters from the block “peak ratios”†.

Model		$\boldsymbol{R^2}$
I**	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18}$	0.556
II***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_2 P_{123}$	0.820
III***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_3 P_{17} + \beta_4 P_{108}$	0.900
IV***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_3 P_{17} + \beta_4 P_{108} + \beta_5 P_{126}$	0.913
V***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_3 P_{17} + \beta_6 P_{22} + \beta_7 P_{122} + \beta_8 P_{107}$	0.968
VI***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_7 P_{122} + \beta_8 P_{107} + \beta_9 P_{115} + \beta_{10} P_{129} + \beta_{11} P_{19}$	0.993
VII***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_7 P_{122} + \beta_8 P_{107} + \beta_9 P_{115} + \beta_{10} P_{129} + \beta_{11} P_{19} + \beta_{12} P_{127}$	0.996
VIII***	$C_{\text{loss}} = \beta_0 + \beta_1 P_{18} + \beta_5 P_{126} + \beta_7 P_{122} + \beta_9 P_{115} + \beta_{10} P_{129} + \beta_{11} P_{19} + \beta_{12} P_{127} + \beta_{13} P_{112}$	>0.999

† “peak ratios” refers to obtained optical data for peaks and their mathematical transformations.

n = 12; C_{loss}: cooking losses; $\beta_{0\text{-}13}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 6. Continuation.

Model	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$	$\boldsymbol{\beta_5}$	$\boldsymbol{\beta_6}$	$\boldsymbol{\beta_7}$	$\boldsymbol{\beta_8}$	$\boldsymbol{\beta_9}$	$\boldsymbol{\beta_{10}}$	$\boldsymbol{\beta_{11}}$	$\boldsymbol{\beta_{12}}$	$\boldsymbol{\beta_{13}}$
I**	5.08***	-25.3**	-	-	-	-	-	-	-	-	-	-	-	-
II***	6.25***	-55.2***	4,460.7**	-	-	-	-	-	-	-	-	-	-	-
III***	5.51***	-185.6**	-	-153.8*	254.7**	-	-	-	-	-	-	-	-	-
IV***	5.39***	-207.7**	-	-178.8*	265.2**	2.01^{ns}	-	-	-	-	-	-	-	-
V***	6.84***	-170.8**	-	-90.6^{ns}	-	-	-16.9*	138.2*	288.1**	-	-	-	-	-
VI***	7.87***	-100.8***	-	-	-	-	-	486.7***	718.8***	-2.30***	-718,849***	80.0***	-	-
VII***	7.78***	-100.0***	-	-	-	-	-	564.8**	672.5***	-2.34**	-904,374**	79.2**	-0.184^{ns}	-
VIII***	7.49***	-70.9***	-	-	-	15.4***	-	530.7***	-	-0.113***	-716,421***	74.0***	-0.256**	44.5***

n = 12; $\beta_{0\text{-}13}$: regression coefficients; Significance: ^{ns} $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 7. Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "slope ratios"† of emulsions with starch.

Pred.	Speed			r	Pred.	Speed			r
	Low	Std.	High			Low	Std.	High	
Pred. 29	a	a	a	ns	**Pred. 45**	a	a	a	ns
Pred. 131	a,b	b	a	ns	**Pred. 147**	a	a	a	ns
Pred. 161	a	a	a	ns	**Pred. 177**	a	a	a	ns
Pred. 31	a	a	a	ns	**Pred. 51**	a	a	a	ns
Pred. 133	a	a	a	ns	**Pred. 153**	a	a	a	ns
Pred. 163	a	a	a	ns	**Pred. 183**	a	a	a	ns
Pred. 33	a	a	a	ns	**Pred. 56**	a	a	a	ns
Pred. 135	a	a	a	0.262	**Pred. 158**	a	a	a	ns
Pred. 165	a	a	a	ns	**Pred. 188**	a	a	a	ns
Pred. 35	a	a	a	ns	**Pred. 34**	a	a	a	ns
Pred. 137	a	a	a	ns	**Pred. 136**	a	a	a	ns
Pred. 167	a	a	a	ns	**Pred. 166**	a	a	a	ns
Pred. 49	a	a	a	ns	**Pred. 40**	b	a	a	ns
Pred. 151	a	a	a	ns	**Pred. 142**	a	a	a	ns
Pred. 181	a	a	a	ns	**Pred. 172**	a	a	a	ns
Pred. 54	a	a	a	ns	**Pred. 44**	a	a	a	ns
Pred. 156	a	a	a	ns	**Pred. 146**	a	a	a	ns
Pred. 186	a	a	a	ns	**Pred. 176**	a	a	a	ns
Pred. 30	a	a	a	ns	**Pred. 47**	a	a	a	ns
Pred. 132	a	a	a	ns	**Pred. 149**	a	a	a	ns
Pred. 162	a	a	a	ns	**Pred. 179**	a	a	a	ns
Pred. 37	a	a	a	ns	**Pred. 52**	b	a,b	a	ns
Pred. 139	a	a	a	ns	**Pred. 154**	a	a	a	ns
Pred. 169	a	a	a	ns	**Pred. 184**	b	a,b	a	ns
Pred. 39	b	a,b	a	ns	**Pred. 57**	a	a	a	ns
Pred. 141	a	a	a	ns	**Pred. 159**	a	a	a	ns
Pred. 171	a	a	a	ns	**Pred. 189**	a	a	a	ns
Pred. 41	a	a	a	ns	**Pred. 36**	a	a	a	ns
Pred. 143	a	a	a	ns	**Pred. 138**	a	a	a	ns
Pred. 173	a	a	a	ns	**Pred. 168**	a	a	a	ns
Pred. 50	a	a	a	ns	**Pred. 42**	b	a,b	a	ns
Pred. 152	a	a	a	ns	**Pred. 144**	a	a	a	ns
Pred. 182	a	a	a	ns	**Pred. 174**	a	a	a	ns
Pred. 55	a	a	a	ns	**Pred. 46**	a	a	a	ns
Pred. 157	a	a	a	ns	**Pred. 148**	a	a	a	ns
Pred. 187	a	a	a	ns	**Pred. 178**	a	a	a	ns
Pred. 32	a	a	a	ns	**Pred. 48**	a	a	a	ns
Pred. 134	a	a	a	ns	**Pred. 150**	a	a	a	ns
Pred. 164	a	a	a	ns	**Pred. 180**	a	a	a	ns
Pred. 38	a	a	a	ns	**Pred. 53**	b	a,b	a	-0.256
Pred. 140	a	a	a	ns	**Pred. 155**	a	a	a	0.232
Pred. 170	a	a	a	ns	**Pred. 185**	a	a	a	-0.268
Pred. 43	a	a	a	0.256	**Pred.58**	a	a,b	b	ns
Pred. 145	a	a	a	ns	**Pred. 160**	a	a	a	ns
Pred. 175	a	a	a	ns	**Pred. 190**	a	a	a	ns

† "slope ratios" refers to optical data obtained for peaks and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 12; values without common characters were significantly different ($P < 0.05$); r: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models

Table 8. Models for the prediction of cooking losses in meat emulsions with starch using parameters from the block "slope ratios"†.

Model		R^2
I**	$C_{loss} = \beta_0 + \beta_1 P_{45}$	0.755
II***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142}$	0.936
III***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_3 P_{180}$	0.964
IV***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_3 P_{180} + \beta_4 P_{145}$	0.977
V***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_4 P_{145} + \beta_5 P_{171} + \beta_6 P_{184}$	0.989
VI***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_4 P_{145} + \beta_5 P_{171} + \beta_6 P_{184} + \beta_7 P_{176}$	0.993
VII***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_4 P_{145} + \beta_5 P_{171} + \beta_6 P_{184} + \beta_7 P_{176} + \beta_8 P_{42}$	0.998
VIII***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142} + \beta_4 P_{145} + \beta_5 P_{171} + \beta_6 P_{184} + \beta_7 P_{176} + \beta_9 P_{37} + \beta_{10} P_{57}$	>0.999

† "slope ratios" refers to obtained optical data for slopes and their mathematical transformations.

n = 12; C_{loss}: cooking losses; $\beta_{0\text{-}10}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 8. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}
I**	5.80***	56.9***	-	-	-	-	-	-	-	-	-
II***	6.50***	62.2***	-40.6***	-	-	-	-	-	-	-	-
III***	6.35***	63.9***	-32.8**	467.2*	-	-	-	-	-	-	-
IV***	6.37***	80.7***	-30.1**	892.1*	100.3ns	-	-	-	-	-	-
V***	6.62***	95.6***	-46.1***	-	167.0*	8,983.3**	9.88**	-	-	-	-
VI***	6.55***	104.7***	-46.8***	-	336.3*	11,116**	11.5**	-167.2ns	-	-	-
VII***	6.46***	98.9***	-42.7***	-	352.8**	13,758**	7.20*	-248.0*	2.64*	-	-
VIII***	6.69***	96.6***	-46.2***	-	477.0***	13,334***	13.5***	-325.5***	-	-11.0**	38.5**

n = 12; $\beta_{0\text{-}10}$: regression coefficients; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 9. Models for the prediction of cooking losses in meat emulsions with starch for "all data"†.

Model		R^2
I**	$C_{loss} = \beta_0 + \beta_1 P_{45}$	0.755
II***	$C_{loss} = \beta_0 + \beta_1 P_{45} + \beta_2 P_{142}$	0.936
III***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7$	0.983
IV***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7 + \beta_5 P_{10}$	0.997
V***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7 + \beta_5 P_{10} + \beta_6 P_{174}$	0.999
VI***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7 + \beta_5 P_{10} + \beta_6 P_{174} + \beta_7 P_{61}$	>0.999
VII***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7 + \beta_5 P_{10} + \beta_6 P_{174} + \beta_7 P_{61} + \beta_8 P_{147}$	>0.999
VIII***	$C_{loss} = \beta_0 + \beta_2 P_{142} + \beta_3 P_{46} + \beta_4 P_7 + \beta_5 P_{10} + \beta_6 P_{174} + \beta_7 P_{61} + \beta_8 P_{147} + \beta_9 P_{177}$	>0.999

† "all data" refers to obtained optical data for peaks, slopes, peak ratios, slope ratios and their mathematical transformations.

n = 12; C_{loss}: cooking losses; $\beta_{0\text{-}9}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 9. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
I**	5.80***	56.9***	-	-	-	-	-	-	-	-
II***	6.50***	62.2***	-40.6***	-	-	-	-	-	-	-
III***	5.59***	-	-31.6***	-8.54***	0.673***	-	-	-	-	-
IV***	5.84***	-	-32.9***	-8.33***	0.589***	$-5.39\cdot10^{-4}$***	-	-	-	-
V***	5.86***	-	-34.9***	-8.21***	0.613***	$-5.47\cdot10^{-4}$***	-12.1*	-	-	-
VI***	6.33***	-	-43.2***	-8.71***	0.671***	$-5.58\cdot10^{-4}$***	-21.9***	-0.270**	-	-
VII***	6.26***	-	-43.3***	-7.57***	0.677***	$-5.53\cdot10^{-4}$***	-22.4***	-0.260***	-79.3**	-
VIII***	6.21***	-	-42.4***	-6.64***	0.656***	$-5.55\cdot10^{-4}$***	-19.8***	-0.233***	-237.9*	-1,257.4*

n = 12; $\beta_{0\text{-}9}$: regression coefficients; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

3.2.2 Emulsions without starch

Concerning emulsions without starch, it was found that at least one type of chopping speed could be differentiated from the rest of the speeds by some of the predictors (shown as different letters by rows in Tables 10, 12 and 14). This trend was widely found in the three blocks; however, predictors 11, 69, 85 and 101, which corresponded values/transformations of the same optical parameter and were part of the "peaks & slopes" block, could differentiate individually the three chopping speeds (Table 10). 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 (Tables 10, 12 and 14).

The following cooking losses prediction models and the corresponding regression coefficients for "peaks & slopes" (Table 11), "peak ratios" (Table 13) and "slope ratios" (Table 15) showed that for a three variable model the regression coefficients were 0.917 with the predictors 105, 100, 4 for the "peaks & slopes", 0.900 with the predictors 19, 110, 119 for "peak ratios" and 0.918 with the predictors 156, 161, 47 for "slope ratios", respectively.

The highest determination coefficients were shown in the "peaks & slopes" and "slope ratios" blocks. Nevertheless, the fact that Pearson's coefficient of some of the "slope ratios" predictors mentioned above were not significant suggests that "peaks & slopes" prediction models had more valuable information. Indeed, predictors 94, 105 and 100 of "peaks & slopes" block (Table 11) were included within the Models I**, II** and III** when all the blocks were analyzed together (Table 16).

All predictors introduced in the cooking losses prediction models were marked in each block with a black rectangle. Particularly some of them did not show a significant correlation value with 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 the whole set of data (Table 16) 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 Figure 3.

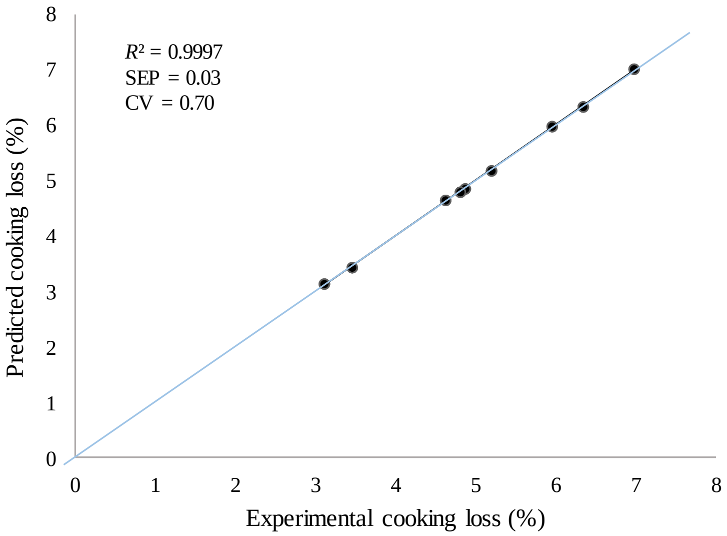

Figure 3. Predicted cooking loss obtained by Model V*** from "all data" for emulsions without starch. n = 9; R^2: determination coefficient corrected for the means; SEP: standard error of prediction (%); CV: coefficient of variation (%).

Table 10. Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "Peaks & slopes"[†] of emulsions without starch.

Pred.	**Speed**			***r***	**Pred.**	**Speed**			***r***
	Low	**Std.**	**High**			**Low**	**Std.**	**High**	
Pred. 1	a	a	a	ns	**Pred. 9**	a	a	b	ns
Pred. 59	a	a	a	ns	**Pred. 67**	b	b	a	-0.320
Pred. 75	a	a	a	ns	**Pred. 83**	a	a	b	ns
Pred. 91	a	a	a	ns	**Pred. 99**	a	a	b	ns
Pred. 2	a	a	a	ns	**Pred. 10**	a	a	b	0.418
Pred. 60	a	a	a	ns	**Pred. 68**	b	b	a	-0.452
Pred. 76	b	a	a,b	ns	**Pred. 84**	a	a	b	0.373
Pred. 92	a	a	a	ns	**Pred. 100**	a	a	b	0.314^{*}
Pred. 3	a	a	a	-0.376	**Pred. 11**	a	b	c	ns
Pred. 61	a	a	a	0.380	**Pred. 69**	c	b	a	ns
Pred. 77	a	a	a	-0.374	**Pred. 85**	a	b	c	ns
Pred. 93	a	a	a	-0.373	**Pred. 101**	a	b	c	ns
Pred. 4	a	a	a	-0.465^{***}	**Pred. 12**	a	a	a	0.426^{**}
Pred. 62	a	a	a	ns	**Pred. 70**	b	b	a	-0.424
Pred. 78	a	a	a	-0.465	**Pred. 86**	a	a	a	0.426
Pred. 94	a	a	a	-0.465^{***}	**Pred. 102**	a	a	a	0.430
Pred. 5	a	a,b	b	-0.452	**Pred. 13**	a	a	b	ns
Pred. 63	b	a,b	a	0.451	**Pred. 71**	b	b	a	ns
Pred. 79	a	a,b	b	-0.453	**Pred. 87**	a	a	b	-0.292
Pred. 95	a	a,b	b	-0.454	**Pred. 103**	a	a,b	b	-0.333
Pred. 6	a	a	a	-0.343	**Pred. 14**	a	a	b	ns
Pred. 64	a	a	a	-0.343^{*}	**Pred. 72**	b	b	a	-0.303
Pred. 80	a	a	a	-0.343	**Pred. 88**	a	a	b	ns
Pred. 96	a	a	a	-0.343	**Pred. 104**	a	a	b	ns
Pred. 7	a	b	a,b	ns	**Pred. 15**	a	a	b	0.413
Pred. 65	b	a	a,b	ns	**Pred. 73**	b	b	a	-0.448
Pred. 81	a	b	a,b	ns	**Pred. 89**	a	a	b	0.373
Pred. 97	a	b	a,b	ns	**Pred. 105**	a	a	b	0.320^{**}
Pred. 8	a	a	a	-0.347	**Pred. 16**	a	a	b	0.315
Pred. 66	a	a	a	0.347	**Pred. 74**	b	b	a	-0.389
Pred. 82	a	a	a	-0.347	**Pred. 90**	a	a	b	ns
Pred. 98	a	a	a	-0.347	**Pred. 106**	a	a	b	ns

[†] "Peaks & slopes" refers to optical data obtained for peaks and slopes predictors and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 9; values without common characters were significantly different ($P < 0.05$); *r*: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models.

Table 11. Models for the prediction of cooking losses in meat emulsions without starch using parameters from the block “Peaks & slopes”†.

Model		R^2
I**	$C_{loss} = \beta_0 + \beta_1 P_{94}$	0.658
II**	$C_{loss} = \beta_0 + \beta_1 P_{94} + \beta_2 P_{105}$	0.806
III**	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4$	0.917
IV**	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4 + \beta_5 P_{75}$	0.970
V***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4 + \beta_5 P_{75} + \beta_6 P_{12}$	0.997
VI***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4 + \beta_5 P_{75} + \beta_6 P_{12} + \beta_7 P_{64}$	>0.999
VII***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4 + \beta_5 P_{75} + \beta_6 P_{12} + \beta_7 P_{64} + \beta_8 P_{62}$	>0.999

† “Peaks & slopes” refers to obtained optical data for peaks and slopes and their mathematical transformations.

n = 9; C_{loss}: cooking losses; β_{0-8}: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 11. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
I**	5.48***	-0.276**	-	-	-	-	-	-	-
II***	6.50***	-0.430**	$-7.12\cdot10^{-11ns}$	-	-	-	-	-	-
III***	5.73***	-	$-1.03\cdot10^{-9*}$	$7.32\cdot10^{-10*}$	-1.32**	-	-	-	-
IV***	5.91***	-	$-1.22\cdot10^{-9**}$	$8.78\cdot10^{-10**}$	-1.45***	-0.0649^{ns}	-	-	-
V***	6.32***	-	$-1.26\cdot10^{-9***}$	$9.28\cdot10^{-10***}$	-1.87***	-0.0735**	$-4.93\cdot10^{-3*}$	-	-
VI***	6.11***	-	$-1.40\cdot10^{-9***}$	$1.035\cdot10^{-9***}$	-1.83***	-0.0713***	$-5.22\cdot10^{-3**}$	0.138*	-
VII***	6.09***	-	$-1.36\cdot10^{-9**}$	$1.01\cdot10^{-9**}$	-1.83***	-0.0656**	$-6.25\cdot10^{-3**}$	0.118*	-0.0648^{ns}

n = 9; β_{0-8}: regression coefficients; Significance: ^{ns} $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 12 Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "peak ratios"[†] of emulsions without starch.

Pred.	**Speed**			***r***	**Pred.**	**Speed**			***r***
	Low	**Std.**	**High**			**Low**	**Std.**	**High**	
Pred. 17	a	a,b	b	ns	**Pred. 24**	a	a	a	ns
Pred. 107	a	a	a	ns	**Pred. 114**	a	a	a	ns
Pred. 119	a	a	a	ns	**Pred. 126**	a	a	a	ns
Pred. 19	a	a	b	0.350^{**}	**Pred. 27**	a	a	b	0.466
Pred. 109	a	a	b	0.314^{*}	**Pred. 117**	a,b	b	a	ns
Pred. 121	a	a	a	0.284	**Pred. 129**	a	a,b	b	0.271
Pred. 23	a	a	a	ns	**Pred. 20**	b	b	a	-0.396
Pred. 113	a	a	a	ns	**Pred. 110**	b	b	a	-0.379^{**}
Pred. 125	a	a	a	ns	**Pred. 122**	b	b	a	-0.348
Pred. 26	a	a,b	b	0.538	**Pred. 22**	a,b	b	a	-0.561
Pred. 116	b	b	a	ns	**Pred. 112**	a,b	b	a	-0.517
Pred. 128	a	a	a	0.329	**Pred. 124**	b	b	a	-0.468
Pred. 18	b	b	a	ns	**Pred. 25**	a	a	a	ns
Pred. 108	b	b	a	ns	**Pred. 115**	a	a	a	ns
Pred. 120	b	a,b	a	ns	**Pred. 127**	a	a	a	ns
Pred. 21	a	a	a	0.601^{***}	**Pred. 28**	a	a,b	b	0.527^{***}
Pred. 111	a	a	a	0.603	**Pred. 118**	a	a	a	0.369^{**}
Pred. 123	a	a	a	0.598^{***}	**Pred. 130**	a	a	a	0.415

[†] "peak ratios" refers to optical data obtained for peaks and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 9; values without common characters were significantly different ($P < 0.05$); r: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models.

Table 13. Models for the prediction of cooking losses in meat emulsions without starch using parameters from the block “peak ratios”†.

Model		R^2
I*	$C_{loss} = \beta_0 + \beta_1 P_{21}$	0.556
II*	$C_{loss} = \beta_0 + \beta_2 P_{19} + \beta_3 P_{110}$	0.820
III*	$C_{loss} = \beta_0 + \beta_2 P_{19} + \beta_3 P_{110} + \beta_4 P_{119}$	0.900
IV*	$C_{loss} = \beta_0 + \beta_3 P_{110} + \beta_5 P_{107} + \beta_6 P_{123} + \beta_7 P_{28}$	0.913
V*	$C_{loss} = \beta_0 + \beta_3 P_{110} + \beta_5 P_{107} + \beta_6 P_{123} + \beta_7 P_{28} + \beta_8 P_{120}$	0.968
VI*	$C_{loss} = \beta_0 + \beta_5 P_{107} + \beta_6 P_{123} + \beta_8 P_{120} + \beta_9 P_{108} + \beta_{10} P_{109} + \beta_{11} P_{118}$	0.993
VII*	$C_{loss} = \beta_0 + \beta_4 P_{119} + \beta_5 P_{107} + \beta_6 P_{123} + \beta_8 P_{108} + \beta_9 P_{108} + \beta_{10} P_{109} + \beta_{11} P_{118}$	0.996

† “peak ratios” refers to obtained optical data for peaks and their mathematical transformations.

n = 9; C_{loss}: cooking losses; $\beta_{0\text{-}11}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 13. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}
I**	6.13***	14.066*	-	-	-	-	-	-	-	-	-	-
II*	6.59***	-	50.84*	31.4ns	-	-	-	-	-	-	-	-
III*	9.49**	-	175.5ns	131.9ns	4326.1ns	-	-	-	-	-	-	-
IV*	8.45***	-	-	210.6*	-	-1,911.6*	4,568.4*	266.3*	-	-	-	-
V*	8.59**	-	-	236.7*	-	-1,902.7*	4,858.7*	313.6*	-303.0ns	-	-	-
VI*	4.06*	-	-	-	-	-3,097.0*	11,199*	-	-1,129.1ns	619.0ns	4,764.6*	-14,687*
VII*	3.83*	-	-	-	-8518.9ns	-3,657.5*	11,587*	-	-2,283.7*	734.8*	5,016.2*	-15,588*

n = 9; $\beta_{0\text{-}11}$: regression coefficients; Significance: ^{ns} $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 14. Optical predictors per chopping speed (low, standard and high) and their Pearson's correlation with cooking losses for "slope ratios"† of emulsions without starch.

Pred.	**Speed**			***r***	**Pred.**	**Speed**			***r***
	Low	**Std.**	**High**			**Low**	**Std.**	**High**	
Pred. 29	b	a,b	a	0.451	**Pred. 45**	a	a	b	ns
Pred. 131	a	a	a	ns	**Pred. 147**	a	a,b	b	ns
Pred. 161	a	a	a	ns	**Pred. 177**	a	a,b	b	ns
Pred. 31	a,b	a	b	0.459	**Pred. 51**	a	b	a,b	ns
Pred. 133	b	b	a	ns	**Pred. 153**	a	a	a	ns
Pred. 163	a	a	a	ns	**Pred. 183**	a	a	a	ns
Pred. 33	a	a	b	0.475	**Pred. 56**	a	a	b	0.499
Pred. 135	b	b	a	-0.291	**Pred. 158**	b	b	a	ns
Pred. 165	a	a	b	0.363	**Pred. 188**	a	a	b	0.280
Pred. 35	a	a	a	0.476	**Pred. 34**	a	a	a	0.303
Pred. 137	a	a	a	ns	**Pred. 136**	a	a	a	ns
Pred. 167	a	a	a	0.307	**Pred. 166**	a	a	a	ns
Pred. 49	a	a	a	ns	**Pred. 40**	b	b	a	0.454***
Pred. 151	a	a	a	ns	**Pred. 142**	b	b	a	0.3355
Pred. 181	a	a	a	ns	**Pred. 172**	b	b	a	ns
Pred. 54	a	a	a	ns	**Pred. 44**	a	a	a	0.375
Pred. 156	a	a	a	ns	**Pred. 146**	a	a	a	0.308
Pred. 186	a	a	a	ns	**Pred. 176**	a	a	a	ns
Pred. 30	a	a	a	0.292	**Pred. 47**	a	a,b	b	0.551***
Pred. 132	a	a	a	ns	**Pred. 149**	a	a	a	0.548
Pred. 162	a	a	a	ns	**Pred. 179**	a	a	a	0.537
Pred. 37	b	b	a	-0.347	**Pred. 52**	a	a	a	ns
Pred. 139	b	b	a	ns	**Pred. 154**	a	a	a	ns
Pred. 169	b	b	a	ns	**Pred. 184**	a	a	a	ns
Pred. 39	b	b	a	-0.504	**Pred. 57**	a	a	b	0.468
Pred. 141	b	b	a	-0.392	**Pred. 159**	b	b	a	-0.303
Pred. 171	b	b	a	-0.313	**Pred. 189**	a	a	b	0.302
Pred. 41	a	a	a	-0.508	**Pred. 36**	a	a	a	0.317
Pred. 143	a,b	b	a	-0.505	**Pred. 138**	a	a	a	ns
Pred. 173	a,b	b	a	-0.479***	**Pred. 168**	a	a	a	ns
Pred. 50	a	a	a	ns	**Pred. 42**	b	b	a	0.391
Pred. 152	a	a	a	ns	**Pred. 144**	b	b	a	0.304
Pred. 182	a	a	a	ns	**Pred. 174**	b	b	a	ns
Pred. 55	b	a,b	a	0.552	**Pred. 46**	b	b	a	ns
Pred. 157	b	b	a	0.477	**Pred. 148**	b	b	a	ns
Pred. 187	b	b	a	0.440	**Pred. 178**	b	b	a	ns
Pred. 32	a	a	a	0.251	**Pred. 48**	b	b	a	-0.474
Pred. 134	a	a	a	ns	**Pred. 150**	b	b	a	-0.386**
Pred. 164	a	a	a	ns	**Pred. 180**	b	a,b	a	-0.307
Pred. 38	a	a	a	0.427	**Pred. 53**	a	a	a	ns
Pred. 140	b	a,b	a	0.363	**Pred. 155**	a	a	a	ns
Pred. 170	b	b	a	0.293	**Pred. 185**	a	a	a	ns
Pred. 43	a	a	a	-0.434	**Pred.58**	a	a,b	b	0.509
Pred. 145	a	a	a	-0.400**	**Pred. 160**	a	a	a	ns
Pred. 175	a	a	a	-0.338	**Pred. 190**	a	a,b	b	0.405

† "slope ratios" refers to optical data obtained for peaks and their mathematical transformations.

Pred.: Predictors; Std.: Standard speed.

n = 9; values without common characters were significantly different ($P < 0.05$); *r*: Pearson's correlation coefficient; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Predictors enclosed in a rectangle are included in the prediction models

Table 15. Models for the prediction of cooking losses in meat emulsions without starch using parameters from the block “slope ratios”†.

Model		R^2
I*	$C_{\text{loss}} = \beta_0 + \beta_1 P_{150}$	0.605
II**	$C_{\text{loss}} = \beta_0 + \beta_2 P_{156} + \beta_3 P_{161}$	0.871
III**	$C_{\text{loss}} = \beta_0 + \beta_2 P_{156} + \beta_3 P_{161} + \beta_4 P_{47}$	0.918
IV***	$C_{\text{loss}} = \beta_0 + \beta_5 P_{145} + \beta_6 P_{147} + \beta_7 P_{148} + \beta_8 P_{151}$	0.996
V***	$C_{\text{loss}} = \beta_0 + \beta_5 P_{145} + \beta_6 P_{147} + \beta_7 P_{148} + \beta_8 P_{151} + \beta_9 P_{173}$	0.999
VI***	$C_{\text{loss}} = \beta_0 + \beta_5 P_{145} + \beta_6 P_{147} + \beta_7 P_{148} + \beta_8 P_{151} + \beta_{10} P_{181} + \beta_{11} P_{40}$	>0.999
VII***	$C_{\text{loss}} = \beta_0 + \beta_5 P_{145} + \beta_6 P_{147} + \beta_7 P_{148} + \beta_8 P_{151} + \beta_{10} P_{181} + \beta_{11} P_{40} + \beta_{12} P_{54}$	>0.999

† “slope ratios” refers to obtained optical data for slopes and their mathematical transformations.

n = 9; C_{loss}: cooking losses; $\beta_{0\text{-}12}$: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table15. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}
I**	5.91***	-81.5*	-	-	-	-	-	-	-	-	-	-	-
II***	5.00***	-	128.6**	578.1**	-	-	-	-	-	-	-	-	-
III***	4.27***	-	175.0**	1,320.4*	-29.5^{ns}	-	-	-	-	-	-	-	-
IV***	4.70***	-	-	-	-	-657.5***	-1,558.0***	129.6***	755.1***	-	-	-	-
V***	4.79***	-	-	-	-	-631.4***	-,1491.6***	122.5***	772.6***	-816.8*	-	-	-
VI***	5.06***	-	-	-	-	-653.1***	-1,457.3***	117.9***	908.8***	-	3,428.1***	0.395***	-
VII***	5.05***	-	-	-	-	-653.7***	-1,463.9***	118.5***	908.5***	-	3,664.5**	0.389**	0.186*

n = 9; $\beta_{0\text{-}12}$: regression coefficients; Significance: ^{ns} $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 16. Models for the prediction of cooking losses in meat emulsions without starch for “all data”†.

Model		R^2
I**	$C_{loss} = \beta_0 + \beta_1 P_{94}$	0.658
II**	$C_{loss} = \beta_0 + \beta_1 P_{94} + \beta_2 P_{105}$	0.806
III**	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_4 P_4$	0.924
IV***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_5 P_7 + \beta_6 P_{31}$	0.997
V***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_5 P_7 + \beta_6 P_{31} + \beta_7 P_{91}$	>0.999
VI***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_5 P_7 + \beta_6 P_{31} + \beta_7 P_{91} + \beta_8 P_6$	>0.999
VII***	$C_{loss} = \beta_0 + \beta_2 P_{105} + \beta_3 P_{100} + \beta_5 P_7 + \beta_6 P_{31} + \beta_7 P_{91} + \beta_8 P_6 + \beta_9 P_{162}$	>0.999

† “all data” refers to obtained optical data for peaks, slopes, peak ratios, slope ratios and their mathematical transformations.

n = 9; C_{loss}: cooking losses; β_{0-9}: regression coefficients; P: predictor; R^2: determination coefficient; Significance: * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Table 16. Continuation.

Model	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
I**	5.48***	-0.276**	-	-	-	-	-	-	-	-
II**	6.50***	-0.430**	$-7.12\cdot10^{-11}$ns	-	-	-	-	-	-	-
III**	2.87***	-	$-1.44\cdot10^{-9}$**	$1.16\cdot10^{-9}$**	237.9**	-	-	-	-	-
IV***	4.41***	-	$-3.26\cdot10^{-9}$***	$2.49\cdot10^{-9}$***	-	2.85***	33.1***	-	-	-
V***	4.34***	-	$-3.25\cdot10^{-9}$***	$2.49\cdot10^{-9}$***	-	2.75***	32.2***	$-4.56\cdot10^{-3}$*	-	-
VI***	4.29***	-	$-3.19\cdot10^{-9}$***	$2.44\cdot10^{-9}$***	-	2.74***	36.2***	$-2.62\cdot10^{-3}$**	0.0782**	-
VII***	4.29***	-	$-3.18\cdot10^{-9}$***	$2.44\cdot10^{-9}$***	-	2.73***	36.73***	$-2.52\cdot10^{-3}$***	0.0802***	$3.24\cdot10^{-3}$**

n = 9; β_{0-9}: regression coefficients; Significance: ns $P > 0.05$, * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

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 speed 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 chopping speeds, provided strong information about cooking losses and the speed. 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. Furthermore, the scarce correlation between these predictors and cooking losses could correspond to a nonlinear modelling, which would explain the insignificance of some Pearson's correlation coefficients. On the other hand, the opposed situation may have occured in emulsions without starch, where a more heterogeneous matrix may have been obtained (Lyons et al., 1999). So, the effect of the speed clearly found in emulsions without starch may be suppressed when adding it.

Similar results were found in a previous study done in meat emulsions with and without starch and light backscatter technology, reporting more predictors in the samples without starch which differentiate chopping speeds (Torres, 2016). Similar results were observed by Álvarez et al. (2007). In this study, pork emulsions were manufactured at laboratory scale with and without starch and at different lean/fat ratios. The results showed clearer response of the studied variable (lightness) with respect to the chopping time and cooking losses in emulsions without starch. These results together with those of the present study suggest a better optical response for emulsions without starch when different chopping times or speeds are applied.

Beyond all the models for each type of emulsions, the best cooking losses prediction equations were found in the "peaks & slopes" block for formula with starch (Table 4) and in "all data" for formula without starch (Table 15). 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). It should be noticed that none of the aforementioned works matched exactly with the present study conditions.

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 laboratory scale, were formulated with hydrolyzed potato protein and analyzed by light backscatter technology. Their results showed a 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 prediction equations for the cooking losses with representative 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 chopping end-point.

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