Usefulness of a large field of view sensor for physicochemical, textural, and yield predictions under industrial goat cheese (Murcia al Vino) manufacturing conditions

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ABSTRACT

The applicability of a light backscatter sensor with a large field of view was tested for on-line monitoring of coagulation and syneresis in a goat cheese (Murcia al Vino) manufactured under industrial conditions. Cheesemaking was carried out concurrently in a 12-L pilot vat and a 10,000-L industrial vat following the normal cheesemaking protocol. Cheese moisture, whey fat content, hardness, springiness, and adhesiveness were measured during syneresis. The results obtained show that cutting time is best predicted by considering the coagulation ratio at the inflection point and the percentage increase in the ratio during coagulation, with no need for the first derivative. The large field of view reflectance ratio provided good results for the prediction of moisture content, yield, hardness, springiness, and adhesiveness of the final cheese.

Key words: moisture, yield, cutting time, sensor

INTRODUCTION

Predictions of cutting time, moisture, and cheese yield are useful for adjusting technological procedures during cheesemaking and are therefore considered an appropriate tool for ensuring high-quality products and profitability. Formaggioni et al. (2008) reviewed the different predictive formulas proposed in the literature for calculating cheese yield, and Emmons et al. (1990) described the various predictive formulas of cheese moisture in the literature and developed new formulas, using an approach based on theoretical considerations concerning the distribution of solids and moisture in the different phases but under experimental conditions (Formaggioni et al., 2008).

Cutting time, moisture content, and cheese yield have been predicted by means of optical sensors, such as the CoAguLite fiber optic sensor (Reflectronics Inc., Lexington, KY) developed by Payne et al. (1997). The CoAguLite sensor is not only able to predict cheesemaking indices, such as cutting time and cheese yield, but it can also be used to develop algorithms of curd moisture and fat loss during milk coagulation. The sensor has been used to study (1) the effects of temperature, inocula, and CaCl_2 concentrations in experimental conditions without applying all the manufacturing processing steps (Castillo et al., 2000, 2002, 2003); (2) a possible application during cheesemaking until cutting time; and (3) the ability to predict cheese yield, moisture, and fat contents in cow milk and under experimental conditions without applying all the processing steps involved in cheese production (Fagan et al., 2007d, 2008). Nevertheless, this sensor showed low applicability for predicting the above parameters after curd cutting. To improve the results observed, a light backscatter sensor with a large field of view (LFV) was developed as a prototype model and tested in experimental conditions using different milk protein and fat contents, firmness and protein ratio levels, and stirring speeds (Fagan et al., 2007b,c,d; Mateo et al., 2010). Its ability to predict whey production and fat content in whey at syneresis was confirmed, with the results being better than those obtained with the CoAguLite sensor. The same authors highlighted the importance of testing the LFV sensor under industrial conditions, following the processing steps involved in cheese manufacturing.

The LFV sensor has been used in different experimental designs. Until now, the factorial experimental designs carried out include 3 gel-cutting intensities, 3 curd-stirring speeds, 2 protein levels and fat:protein ratios, 4 milk fat levels, and, finally, 3 firmness levels, all using recombined milk (skim milk powder and distilled water) but not pasteurized cow or goat milk, as is used in industrial cheese manufacture. In each of those

Received March 23, 2012.

Accepted July 12, 2012.

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LFV sensor application experiments, stirring continued during syneresis, without taking into account the contribution of individual steps in the overall process, such as the pitching, washing, and cooking processes, which take place in many industrial manufacturing processes and that have a great effect on final cheese properties and yield (Mateo et al., 2010). In addition, different cutting programs have been tested for the application of this sensor in recombined milk (12% TS; Mateo et al., 2009) without considering the variations involved in day-to-day production.

Only one study was found regarding the application of the LFV sensor that took into account the manufacturing processes involved in a common goat cheese variety. Rovira et al. (2011) applied the prototype LFV sensor for the on-line monitoring of fresh goat cheese during its manufacture on an experimental scale. These authors used the CoAguLite sensor as a reference to select suitable configuration details for the LFV sensor for this type of cheese and manufacturing design, finding the appropriate wavelengths to be 990, 1,000, and 1,010 nm.

Unavoidable day-to-day variations are of great importance for the application of any prediction algorithm derived from the sensor and should be taken into account if the obtained results are to be directly transferred to industrial conditions. All preliminary prediction algorithms so far developed with the LFV sensor include sensor parameters that are difficult to measure in industrial conditions and by cheese makers in general.

The aim of this work was to apply the LFV prototype sensor under industrial processing conditions to a washed pressed goat cheese (Murcia al Vino), developing new algorithms for the prediction of cutting time, moisture, and cheese yield. Such a study is a necessary step if the LFV sensor is to be useful on an industrial scale.

MATERIALS AND METHODS

Milk Source and Compositional Analysis

The goat milk for cheese making was pasteurized in the Central Quesera Montesinos S.L (Murcia, Spain) dairy at 74.5°C for 15 to 20 s and was used immediately. The average values of milk composition (as analyzed by the suppliers) are shown in Table 1.

Cheesemaking Procedure

On 13 randomly chosen days, Murcia al Vino (a washed-curd, semihard, pressed cheese, with a cylindrical shape and a smooth rind; washed in red wine and

ripened for 45 d) goat cheeses weighing 500 g and 2 kg were manufactured in parallel at 2 different levels: in a 10,000-L vat in the Central Quesera Montesinos S.L. dairy following existing standards concerning the manufacture of Protected Designation of Origin Murcia al Vino cheese, and in a 12-L pilot scale vat (Pierre Guerin Ibérica S.A., Burgos, Spain), respectively, following the same processing steps and using the same raw materials. The average values of cheese composition are shown in Table 1.

All steps carried out were those followed for Murcia al Vino cheese manufacture. Calcium chloride (Betelgeux, S. L., Gandía, Valencia, Spain) and starter were added to the milk. When the milk reached 33.3°C, rennet (50L NG Reniplus, Caglio Star España S.A., Murcia, Spain) was added at 0.026 mg/L.

The curd was cut (for 6 s) and pitched (for 5 min) 40 min after adding the rennet. A second cut lasting 10 min was carried out, followed by 2 series of pitchings (5 min) and stirrings (10 min). The next step corresponded to draining (15% of the initial amount of milk), before washing and heating the curd at 38°C in a simultaneous process that lasted 25 to 30 min (with an approximate temperature increase of 1°C every 5 min). After heating, a series of stirring (10 min) and pitching (5 min) steps was carried out for 1 h until the pH decreased to 6.3. The curd was then molded, pressed for 2 h, and introduced into a brine bath for 1 d and left to mature under controlled temperature and humidity conditions for 45 d. Cheeses were immersed in red wine after 30 d of ripening and left to ripen for another 15 d.

On-Line Light Backscatter Monitoring Instrumentation

Two sensors were coupled to the 12-L air-conditioned vat: the CoAguLite sensor (model 5, Reflectronics Inc.;

Table 1. Physicochemical composition of milk and cheese

Parameter	Mean $\pm$ SD
Milk	
Protein (g/100 mL)	3.46 $\pm$ 0.05
Fat (g/100 mL)	4.76 $\pm$ 0.22
DM (g/100 g)	13.30 $\pm$ 0.02
pH	6.77 $\pm$ 0.01
Acidity ($^{\circ}$ Dornic)	13.96 $\pm$ 0.33
Cheese	
Protein (g/100 g)	23.52 $\pm$ 0.97
DM (g/100 g)	65.74 $\pm$ 1.30
Fat (g/100 g)	39.12 $\pm$ 1.70
pH	5.25 $\pm$ 0.10
Hardness (N)	26.34 $\pm$ 4.66
Springiness (mm)	7.31 $\pm$ 1.12
Adhesiveness (N.s)	1.84 $\pm$ 0.81
Cheese yield (L/kg)	7.50 $\pm$ 0.17

Table 2. Definition of parameters during coagulation and syneresis

Parameter ¹	Unit	Definition
t_{cut}	min	Time of the first cutting
t_{max1}	min	Time of the first maximum of the first derivative
t_{max2}	min	Time of the second maximum of the first derivative
t_{max3}	min	Time of the third maximum of the first derivative
Coagulation R_{max}	—	Ratio at the maximum point during coagulation
Coagulation decrease	%	Ratio decrease from t_{max} and the t_{cut}
Second cutting decrease	%	Ratio decrease during the second cutting
Coagulation increase	%	Ratio increase from the beginning of coagulation to R_{tmax}
Final experimental moisture	%	Final product moisture content in the experimental vat
R	—	Ratio at vat emptying
R_{tmax1}	—	Peak of the first derivative
R_{tcut}	—	Ratio at the cutting time
$R_{\text{1st Pitching max}}$	—	Ratio of the maximum point of the first pitching
$R_{\text{2nd Pitching max}}$	—	Maximum ratio obtained during the second pitching
$R_{\text{3rd Pitching min}}$	—	Minimum ratio obtained during the third pitching
$R_{\text{heating end}}$	—	Ratio at the end of heating
$R_{\text{washing step}}$	—	Ratio after draining
Cheese yield	L/kg	Liters of milk necessary to produce 1 kg of cheese
Hardness	N	Maximum strength of the first compression
Springiness	mm	Height that the cheese recovers between the end of the first compression and the start of the second compression
Adhesiveness	N·s	Value of the negative curve area that appears after the first compression

¹ R = light backscatter (sensor) ratio.

Payne, et al., 1993), which measures at 880 nm, and the LFV sensor (prototype, University of Kentucky, Lexington; Fagan et al., 2007c, 2008), which measures at wavelengths from 200 to 1,100 nm. The light backscatter response from the 2 sensors was continuously monitored throughout the processing steps described (the same as those carried out in the industrial vat), from the time of rennet addition (t_0) to the end of syneresis, considered as the time when the vat began to be emptied. Response data were collected every 10 s. The initial voltage (V_0) was calculated by averaging the first 4 data points obtained before rennet addition. The light backscatter ratio (R), the first derivative (R') of the light backscatter ratio profile, and time at the maximum ratio of the first derivative (t_{max}) were calculated as described by Fagan et al. (2007d). The second derivative (R'') was calculated in a similar manner by using 60 data points to smooth the R'' profile (Fagan et al., 2007b).

The LFV prototype sensor is related to curd particle size. The light emerging from the fiber optic cable is processed in the spectrometer, allowing identification of differences in intensity throughout cheesemaking as described by Fagan et al. (2007a). The optical configuration details and the optical parameters derived (t_{max} , t_{cut} , R_{max} , and R_{cut} , defined in Table 2) were as described by Fagan et al. (2007a, 2008). The sensor response at 990 nm was used in this study (as determined in previous studies by Rovira et al., 2011). The sensor provided measurements every 100 ms and each spectrum was derived from 100 sensor scans. The spectrum was automatically processed every 10 s. The voltage values

for the first 14 s of data were averaged within each wavelength $V(w)$ to calculate initial voltage [$V_0(w)$]. The light backscatter ratio for the LFV sensor (R_{LFV}) and t_{max} was obtained as described by Fagan et al. (2008).

Several light backscatter parameters were derived from the response of both the LFV and CoAguiLite sensors during coagulation and syneresis (see Table 2).

Chemical and Texture Analyses

Seven samples were collected from both the pilot and industrial vats at the following time points: at the first (t_1) and second (t_2) cuts, before washing (t_3), after washing (t_4), at the end of heating (t_5), at the second pitching (t_6), and before molding (t_7).

Curd and whey samples were separated using a dairy cloth. For moisture content, grated cheese samples were dried to constant weight according to ISO (1997).

A texture profile analysis was carried out using a QTS-25 texture analyzer (Brookfield CNS Farnell, Borehamwood, UK) equipped with a load cell of 25 kg and Texture Pro V. 2.1 software (Brookfield CNS Farnell). For texture profile analysis, 4 cube-shaped samples (1 cm³) were cut from a rindless cheese, wrapped in aluminum foil, and equilibrated at 20°C $\pm$ 0.5°C for 3 h before testing. The testing conditions were as follows: 20°C (room temperature); 2 consecutive cycles of 50% compression; cross-head constant speed of 30 mm/min; and a trigger point of 0.05 N. Texture variables, hardness (N), springiness (mm), and adhesiveness (N·s), were calculated as described by Bourne (1978). Five measurements per sample were made.

Testing a Suitable Algorithm for Moisture Content Prediction

To test whether moisture content could be predicted in an appropriate way by algorithm IX, 10 additional cheesemaking trials were carried out in the pilot-scale vat in the same way as described in the Cheesemaking Procedure section.

Control of Moisture by a Selected Prediction Algorithm

To test whether the moisture content at vat emptying could be controlled by the algorithm selected, another 4 cheesemaking trials were carried out in the same way as described above, but selecting 2 desired final moisture percentages (54% and 57%). This was made possible by solving the parameter ratio from the equation for each selected moisture content:

$$M = 85.22 R_{\text{heating end}} + 35.66 R,$$

$$[R = M - (85.22 R_{\text{heating end}})/35.66],$$

where M = moisture content, $R_{\text{heating end}}$ = ratio at the end of heating, and R = ratio at vat emptying. Once solved, vat emptying was carried out when the ratio reached the value determined for each moisture content (54% or 57%).

Statistical Analysis

Statistical treatment of the data was performed by SPSS v15.0 (2006, SPSS Ibérica S.L.U., Madrid, Spain). One-way ANOVA was used to determine significant differences between the pilot and the industrial vat. Multivariate linear regression analysis fitted to several regression models was performed to develop the prediction algorithms.

RESULTS AND DISCUSSION

Comparison of Pilot Plant and Industrial Cheese Vat

The prototype LFV sensor is currently not available for coupling to industrial vats; hence, it was necessary to determine whether differences exist in the physico-chemical and yield properties of cheeses made in the pilot and industrial vats following the same manufacturing process and with the same raw materials and ingredients. After applying an ANOVA test, no differences were observed in moisture content or whey fat content, although significant differences were observed for cheese yield (P -values = 0.28, 0.13, and 0.04, re-

spectively). These data confirm an adequate degree of parallelism for the pilot scale and industrial vats. Using the same raw materials, ingredients, and processes on both production scales allowed us to obtain a final product that meets the same specifications. This allows a preliminary conclusion that the algorithms developed could be useful on an industrial scale in the manufacture of this cheese. As no differences were observed between vats, any further results obtained for the pilot scale vat should be applicable to industrial-scale cheesemaking.

Development of Algorithms for Predicting Cutting Time

One of the most important applications of the LFV sensor in the manufacturing process is to predict different cheesemaking indices that affect final product quality, such as cutting time. Based on the results for the sensor response during coagulation in the 13 cheese manufacturing processes considered, 8 models were obtained for prediction of cutting time (Table 3). The first model corresponded to the reference prediction algorithm, obtained using the data derived from the Co-AguLite sensor response. This sensor has demonstrated its suitability for predicting cutting time (Castillo et al., 2000; Fagan et al., 2007c) in goat milk during coagulation and was therefore used as a reference for comparing the other algorithms developed. Model II was similar to the reference equation, with the same regression coefficient and similar equation coefficient (β_1) and standard error of prediction (SEP) values, which demonstrates the ability of the LFV sensor to predict cutting time with the same accuracy as the reference sensor.

One of the cutting time prediction models developed by Castillo et al. (2006a) using the reference sensor CoAguLite ($t_{\text{cut}} = \beta_0 + \beta_1 t_{2\text{max}2}$) included a significant intercept (β_0) and a significant time-based parameter ($t_{2\text{max}2}$). However, this model had a higher SEP (14.7 min) than the prediction models developed here, as can be seen in Table 3. The inclusion of other parameters in the prediction models described by the same research group improved the statistical results (Castillo et al., 2006b), which must still be considered less appropriate (SEP = 7.91) than the results obtained in this study (maximum SEP = 4.80). Moreover, previous models proposed by Payne et al. (1998; $t_{\text{cut}} = \beta_0 + \beta_{1\text{tmax}} + \beta_2 R'_{\text{max}}$, SEP = 15.1) and Crofcheck et al. (1999; $t_{\text{cut}} = \beta_{1\text{tmax}} + \beta_2 S$, SEP = 23.7), included t_{max} , as did this study, but in both cases this parameter was related to others, leading to a much greater error than that obtained by the LFV sensor in this study.

Although algorithm III had the same regression coefficient ($R^2 = 0.96$) but lower SEP (1.21 min) than

Table 3. Prediction of cutting time (t_{cut}) by large field of view sensor during goat cheese manufacture¹

Model ²	Equation ³	df	β_1	R^2	SEP (min)
Ref.	$t_{\text{cut}} = \beta_1 t_{\text{max}}$	12	3.42***	0.96	1.40
II	$t_{\text{cut}} = \beta_1 t_{\text{max1}}$	12	3.52***	0.96	1.44
III	$t_{\text{cut}} = \beta_1 t_{\text{max2}}$	12	2.58***	0.96	1.21
IV	$t_{\text{cut}} = \beta_1 t_{\text{max3}}$	12	1.34***	0.99	0.22
V	$t_{\text{cut}} = \beta_1$ Coagulation decrease	12	1.69***	0.86	4.80
VI	$t_{\text{cut}} = \beta_1$ 2nd cutting decrease	12	0.82***	0.99	0.40
VII	$t_{\text{cut}} = \beta_1$ Coagulation increase	12	6.61***	0.99	3.83
VIII	$t_{\text{cut}} = \beta_1$ Coagulation R_{max}	12	38.24***	0.99	0.02

¹ β_1 = equation coefficient; R^2 = regression coefficient; SEP = standard error of prediction.

²Ref. = model obtained by reference sensor, CoAguLite (Reflectronics Inc., Lexington, KY), in the same conditions.

³See Table 2 for definition of equation terms.

*** $P < 0.001$.

algorithm II ($R^2 = 0.96$, SEP = 1.44 min), the latter should be considered more suitable because this second model is closer to the reference model.

Factor t_{max3} of model IV was not observed on all cheesemaking days or in previous models. Hence, algorithm IV can be dismissed as a tool for predicting cutting time, because an algorithm must be appropriate for all cheesemaking processes.

We studied the possibility of predicting cutting time from other parameters derived from the LFV sensor response (Table 3). All algorithms demonstrated potential for use in cheesemaking as they showed high regression coefficients and a greater significance level ($P < 0.0001$) than models reported by other authors using the reference sensor CoAguLite (Payne et al., 1998; Crofcheck et al., 1999; Castillo et al., 2006a) in other types of milk.

Models V, VI, and VII used the ratio percentage decrease involved during coagulation and after the second cutting, and the increase in the ratio percentage during coagulation. The regression coefficients from models VI and VII were high (both $R^2 = 0.99$), although that of model V was slightly lower ($R^2 = 0.86$). Models V and VII had higher SEP values (4.80 and 3.83 min, respectively) than those observed for model VI (0.40 min), and so their potential value for predicting cutting time was lower.

Model VIII had a SEP very close to zero (0.02 min). The parameter introduced in this model (ratio at the highest point of coagulation) is an appropriate parameter for use in industrial manufacture as it is easier to identify than t_{max} (time to reach the maximum of the first derivative), because it is obtained directly from the sensor, rather than by applying the first derivative or other mathematical calculations.

The graphs displayed in Figure 1 plot the real values measured in this study against those predicted by the different models developed and included in Table 3. For prediction of cutting time (Figure 1), models IV, VI,

VII, and VIII showed the highest regression coefficients ($R^2 > 0.99$), but the best linear trends were observed in models III and VIII (Figure 1). Model VII should be avoided because it showed a downward trend, which is not appropriate (lower real cutting times should be associated with lower predicted cutting times, not higher).

Development of Algorithms to Predict Cheese Moisture Content

Table 4 includes all the algorithms developed to predict cheese moisture content, which, as previously stated, is very important in cheese making (Dejmek and Walstra, 2004). In the models, explanatory variables were obtained directly or derivatively from the LFV sensor response. The first 3 models (I, II, and III) were derived from coagulation parameters (t_{max1} , R_{max} , and R_{cut}), whereas the other models included variables from syneresis, which have not previously been considered ($R_{\text{1st Pitching max}}$, $R_{\text{2nd Pitching max}}$, $R_{\text{3rd Pitching min}}$, $R_{\text{heating end}}$, $R_{\text{washing step}}$; see Table 2 for definitions). These parameters were defined considering that, for moisture standardization, it is necessary to consider all processes involved in cheese manufacture because the processes may influence differences between cheese batches, leading to possible differences in the final product and thus in cheese yield. All β values obtained were highly significant ($P < 0.001$). The best regression coefficient from the first 3 algorithms corresponded to model III ($R^2 = 0.98$), which also showed the lowest SEP (0.53%). Models IV, V, and VI attempt to predict cheese moisture content based on the peak of the LFV sensor observed at curd pitching, particularly during the first 3 pitchings. The highest regression coefficient for these 3 models was obtained in model IV ($R^2 = 0.99$), which showed the lowest SEP (0.39). In addition, models V and VI showed appropriate R^2 coefficients and SEP values and should not necessarily be dis-

Figure 1. Measured versus predicted cutting time (t_{cut}); representation of the linear trend from the cutting time models detailed in Table 3. Color version available in the online PDF.

Table 4. Prediction of goat cheese moisture content and cheese yield by large field of view sensor¹

Model	Equation ²	df	β_1	β_2	R ²	SEP (%)
I	$M = \beta_1 t_{\max 1}$	12	3.45***		0.94	1.72
II	$M = \beta_1 R_{t_{\max 1}}$	12	4,111.1***		0.96	1.35
III	$M = \beta_1 R_{t_{\text{cut}}}$	12	46.81***		0.98	0.53
IV	$M = \beta_1 R_{1\text{st Pitching max}}$	12	47.81***		0.99	0.39
V	$M = \beta_1 R_{2\text{nd Pitching max}}$	12	49.42***		0.97	0.79
VI	$M = \beta_1 R_{3\text{rd Pitching min}}$	12	107.28***		0.98	0.75
VII	$M = \beta_1 R_{\text{heating end}}$	12	77.50***		0.98	0.58
VIII	$M = \beta_1 R_{\text{washing step}}$	12	80.26***		0.97	0.71
IX	$M = \beta_1 R_{\text{heating end}} + \beta_2 R$	12	35.66***	85.22***	0.98	0.39
X	$CY = \beta_1 R_{t_{\text{cut}}}$	12	9.00***		0.98	0.07
XI	$CY = \beta_1 R_{t_{\max}} + \beta_2 R_{t_{\text{cut}}}$	12	285.64***	5.88**	0.99	0.02

¹ β_1 and β_2 = equation coefficients; R² = regression coefficient; SEP = standard error of prediction.

²M = moisture content in cheese; CY = cheese yield; see Table 2 for definition of other terms.

** $P < 0.01$; *** $P < 0.001$.

carded. Finally, models VII, VIII, and IX, which used the ratio at the end of heating, the ratio at washing, and the ratio at the end of heating together with the ratio at vat emptying, respectively, showed high regression coefficients (0.98, 0.97, and 0.98, respectively) and low SEP values (0.58, 0.71, and 0.39%, respectively) and could be considered suitable for predicting cheese moisture content during the manufacture of this type of (washed-curd) cheese.

Fagan et al. (2007b,c,d) reported the potential of the LFV sensor for monitoring milk coagulation and syneresis, and demonstrated the potential of this prototype sensor to predict curd moisture content. However, the first prediction models developed by these authors were limited by the small data set used but were improved by Fagan et al. (2008). The last and best curd moisture prediction model developed by these authors in cow milk under experimental conditions (after curd cutting, the curd was continuously stirred for 85 min) included 4 parameters—temperature, time to reach the first maximum of the ratio ($t_{\max}$), milk fat content, and fat protein ratio of milk), which differ markedly from the parameters selected for our study. The factors included in the models (III, IV, V, VI, VII, VIII, and IX) shown in Table 4 have not previously been reported and provided better R² and SEP values than those obtained for the model developed by Fagan et al. (2008; R² = 0.94, SEP = 1.46).

The significance of the parameters included in this prediction model lies in the effect of the technical steps on the physicochemical properties of the final product. The retention of water is attributed, among other causes, to the relative rigidity and restructuring of the protein matrix derived from some of the technical steps carried out in cheesemaking, such as pitching of the curd after stirring, a step known to be significant in the prediction of cheese moisture content.

As regards the models for moisture content prediction (Figure 2), the number of values represented ($n = 13$) is lower than the number considered by Mateo et al. (2010); hence, the R² are higher (0.94–0.99) than those of Mateo et al. (2010; 0.65–0.96), who used the LFV sensor over a broad spectrum of 189 to 1,100 nm. Model IV shows the most suitable tendency and prediction coefficients, which emphasizes the importance of considering the mechanical steps in predicting final moisture content because this model takes into account the first pitching process involved during the manufacture of Murcia al Vino cheese. Other cheese moisture prediction models do not use this type of parameter (e.g., R_{pitching} , $R_{\text{heating end}}$). Model III should be avoided because lower real moisture content should be associated with lower predicted moisture content, and a downward trend is not appropriate. Moreover, model VIII should be avoided because it shows a very low slope, which reflects a lower match between the real and predicted values.

Development of Algorithms to Predict Cheese Yield

Table 4 shows the different prediction models for cheese yield, obtained by using optical parameters. The 2 models developed provided significant values for β_1 ($P < 0.001$) and β_2 ($P < 0.01$), high correlation coefficients (0.98 and 0.99 for models X and XI, respectively), and low SEP values (0.07 and 0.02%, respectively), which underlines their ability to predict cheese yield with great precision during goat cheese manufacture, although goat cheeses usually involve more intrinsic physicochemical variations than most of the cheeses derived from cow milk.

Guo et al. (2004) stated that yield is related to chemical composition, including moisture. Our results confirm that optical parameters derived from the LFV

Figure 2. Measured versus predicted final moisture (FM) content of cheese; representation of the linear trend from the final moisture content models detailed in Table 4. Color version available in the online PDF.

sensor can be considered a valid tool for predicting cheese yield (without the need to consider chemical parameters or moisture content) because the regression coefficients obtained were greater than those presented by Guo et al. (2004; $R^2 = 0.81$, no SEP reported) in fresh goat milk cheese using chemical parameters. Our results are also better than those of Fagan et al. (2008) in cow milk during 85 min of stirring; those authors predicted cheese yield in experimental conditions by taking into account milk temperature, total solids contents, and the average ratio values for the first 15 min. This provided a lower regression coefficient and a higher SEP value (0.90 and 0.95, respectively), although the experimental conditions were carefully controlled to avoid variations.

Figure 3 depicts the linear trend obtained for the prediction of cheese yield during cheese making. The predicted and real values obtained were in the same range, although the range was slightly wider in model XI. Visually, no differences were observed between the slopes of the linear trends shown in Figure 3. Nevertheless, the trend observed was better than that reported by Fagan et al. (2008) in cow milk in experimental conditions and during a single stirring; Fagan et al. (2008) reported a visibly lower slope and a lower R^2 coefficient (0.90), even though they considered chemical parameters. As can be observed, the LFV sensor allows prediction of moisture content during syneresis although different mechanical steps are involved. This is extremely important for the cheese maker as knowledge of moisture content allows profitability to be calculated at any time.

Development of Algorithms for Predicting the Textural Parameters of Cheese

Table 5 shows the models developed to predict textural parameters such as hardness, springiness, and adhesiveness in the final product. All models had highly significant β values ($P < 0.001$). The first 3 models (I, II, and III) predicted cheese hardness, with high R^2 values of 0.96, 0.89, and 0.94, respectively. Model I can be considered the most appropriate for predicting this parameter as it had the lowest SEP (0.02 N) and the highest R^2 value. The following 3 models (IV, V, and VI) were developed to predict springiness. The regression coefficients for these models were also high (0.95, 0.96, and 0.89, respectively). For prediction of springiness, model IV was the most appropriate as it showed the lowest SEP (0.13 mm). This model, together with model I, which best predicted cheese hardness, included the parameter ratio at cutting time (R_{tcut}) in the algorithm. This highlights the relation between the corresponding R_{tcut} and accurate prediction of the results.

The last 3 models (VII, VIII, and IX) shown in Table 5 were used to calculate final cheese adhesiveness. The regression coefficients were lower than those seen in the algorithms for predicting the other 2 texture parameters. The lowest R^2 was observed in model IX (0.76) and the highest in model VII (0.82). The lowest SEP value was that of model VII (0.02 N·s), so this model was considered the most appropriate for predicting cheese adhesiveness. The R_{tcut} derived from the LFV sensor showed great potential for predicting all 3 texture parameters. This variable, with its low SEP and high regression coefficients, was best suited to this task.

Fagan et al. (2007c) studied the application of mid-infrared spectroscopy for predicting sensory properties, comparing this technique with other recently proposed techniques: descriptive sensory analysis by a trained panel, texture profile analysis, near-infrared spectroscopy, and compression/texture profile analysis. The textural parameters most closely related to those from this study were firmness, chewiness, and fragmentability. These sensory attributes were analyzed both by sensory and mid-infrared spectroscopy to establish a relation between both sets of results. The best R^2 values obtained for the prediction of these textural param-

Figure 3. Measured versus predicted cheese yield (CY); representation of the linear trend from the cheese yield models detailed in Table 4. Color version available in the online PDF.

Table 5. Prediction of textural parameters by large field of view sensor¹

Model	Equation ²	df	β_1	R ²	SEP
I	$H = \beta_1 R_{tcut}$	12	32.14***	0.96	0.02 N
II	$H = \beta_1 R_{tmax}$	12	2,750.68***	0.89	1.45 N
III	$H = \beta_1 t_{max}$	12	2.39***	0.94	0.73 N
IV	$S = \beta_1 R_{tcut}$	12	8.71***	0.95	0.13 mm
V	$S = \beta_1 R_{tmax}$	12	777.23***	0.96	0.44 mm
VI	$S = \beta_1 t_{max}$	12	0.63***	0.89	0.41 mm
VII	$A = \beta_1 R_{tcut}$	12	2.20***	0.82	0.02 N·s
VIII	$A = \beta_1 R_{tmax}$	12	189.04***	0.80	0.10 N·s
IX	$A = \beta_1 t_{max}$	12	0.16***	0.76	0.07 N·s

¹ β_1 = equation coefficient; R² = regression coefficient; SEP = standard error of prediction.

²H = hardness; S = springiness; A = adhesiveness; see Table 2 for definition of other model terms.

*** $P < 0.001$.

eters were 0.94, 0.93, and 0.96 for firmness, chewiness, and fragmentability, respectively, which are higher than those obtained in the current study. However, they correspond to different textural parameters and different analytical tools, which cannot be compared with those addressed in this study.

As regards the models used for textural parameter prediction (Figure 4), the parameter hardness provided the best prediction results, with the most appropriate trend, although the slopes obtained for this parameter were lower than those observed for springiness, which showed better R² coefficients. Both could be adequately predicted by the LFV sensor. In this case, models III (hardness) and I and III (springiness) should be avoided because they showed a downward trend, which is not appropriate for prediction purposes.

Testing the Suitable Algorithm for Moisture Content Prediction

As can be observed in Table 4, the model showing the lowest SEP value for curd moisture prediction was model IX. This equation was developed using the mean of the ratio during the last 5 min of heating and the ratio at vat emptying. Model IV presented a SEP value of 0.39 and a higher R² than model IX, but did not take account for the manufacturing steps after the first pitching. Therefore, taking into account the lowest SEP, the adequate R², and the fact that the equation parameters included all the manufacturing processes from coagulation to vat emptying, model IX was selected.

Ten cheese productions were carried out to test the suitability of this selected equation. As can be observed in Table 6, the corresponding ratio at the end of heating barely differentiated between cheese batches, whereas the ratio at vat emptying varied, as did curd moisture. This fact highlights the usefulness of this sensor for predicting (with the selected algorithm) day-to-day production differences in moisture at vat emptying, with a mean SEP of 5.38%, which is lower than the er-

ror range (7–15%) usually obtained in the industry for the moisture content of different batches of the same cheese variety.

Control of Moisture by a Prediction Algorithm

Cheese characteristics result from a variety of physicochemical changes that occur during ripening, principally through glycolysis, proteolysis, and lipolysis. Therefore, proper monitoring and control during ripening is of great importance. Approaches to control these changes during ripening should include critical compositional factors during manufacture. Standardizing curd moisture at vat emptying, before ripening, could reduce costs and improve efficiency. Variations in curd moisture during manufacturing are related to differences in the final product's moisture and yield, which explains efforts by cheese makers to improve and systematize curd moisture before ripening. Delaying or bringing forward curd vat emptying was related to differences in curd moisture and so can be considered a good tool for standardization of curd moisture.

As seen in Table 7, 2 curd moisture percentages were selected by the cheese maker (54 and 57% are known to be the most appropriate moisture percentages to obtain the desired cheese features and an appropriate cheese yield) to determine whether the sensor was useful for controlling curd moisture. Taking into account equation IX from Table 4, and solving the ratio from this equation, we obtained $R = M - (85.22 R_{heating\ end})/35.66$. During manufacture, once $R_{heating\ end}$ is known, the appropriate ratio (R) to obtain the desired moisture content (M) can be obtained. Vat emptying is carried out when the ratio reaches the corresponding value for each moisture content (54 and 57%). This pilot-plant design and procedure for controlling moisture content has not been applied previously and thus we cannot compare our results. Table 7 shows the curd moisture values obtained at vat emptying and their standard deviation from the curd moisture values fixed before

Table 6. Testing suitable algorithm for curd moisture content ($\pm$ SD) prediction¹

Production	R _{heating end}	R	Curd moisture	Predicted moisture content	SEP ²
A	0.48	0.42	56.79 $\pm$ 0.22	56.04	0.75
B	0.51	0.37	60.39 $\pm$ 1.48	56.51	3.87
C	0.52	0.46	56.63 $\pm$ 2.06	60.66	4.03
D	0.52	0.52	70.34 $\pm$ 2.06	63.13	7.21
E	0.52	0.51	67.32 $\pm$ 0.73	62.96	4.36
F	0.52	0.51	68.04 $\pm$ 0.18	62.65	5.39
G	0.52	0.34	66.34 $\pm$ 0.29	56.61	9.73
H	0.52	0.41	68.53 $\pm$ 0.44	59.12	9.41
I	0.52	0.40	64.52 $\pm$ 0.80	58.76	5.76
J	0.52	0.40	49.83 $\pm$ 1.64	53.21	3.38

¹R_{heating end} = ratio at the end of heating; R = sensor ratio; predicted moisture content (M) at vat emptying is as follows: M = 85.22 R_{heating end} + 35.66 R.

²SEP = standard error of prediction (% of moisture content).

cheese manufacture. As can be observed, the mean curd moisture content obtained in the 4 manufacturing processes at 54% moisture differed by 4.75 points, whereas for the 57% moisture cheese, the difference was only 0.43 points. Higher fixed values for moisture content at vat emptying present better sensor prediction results.

This study confirmed the sensor’s suitability for controlling curd moisture under industrial conditions. We conclude that this prototype sensor will enable cheese makers to set the desired curd moisture content before cheesemaking, guaranteeing that the selected moisture content is attained in curd before ripening, with lower

Figure 4. Measured versus predicted cheese texture parameters: hardness (H), springiness (S), and adhesiveness (A); representation of the linear trend from the texture parameter models detailed in Table 5. Color version available in the online PDF.

Table 7. Controlling moisture by means of a selected prediction algorithm

Selected moisture content	Productions ¹ (n)	Curd moisture content ²	SEP ³
54%	4	52.61 ± 2.31	4.75
57%	4	57.50 ± 0.32	0.43

¹Number of productions carried out.

²Mean value (± SD) of the determined moisture content ($M = 85.22 R_{\text{heating end}} + 35.66 R$), where M = moisture content, $R_{\text{heating end}}$ = ratio at the end of heating, and R = sensor ratio.

³Mean value of the standard error of prediction (% of moisture content).

errors than the current error range (7–15%) of the same cheese variety under industrial manufacture.

CONCLUSIONS

The LFV sensor is potentially suitable for the continuous monitoring of both coagulation and syneresis under industrial conditions during goat cheese making. The prediction models developed for moisture content, cheese yield, and textural properties showed promise for applications in cheese making. The prototype LFV sensor enables cheese makers to set a given curd moisture content before cheese manufacture, guaranteeing that the selected moisture level in curd is reached before ripening. These models need to be validated directly by coupling the sensor to industrial vats.

ACKNOWLEDGMENTS

This work was financially supported by Fundación Séneca project 05721/PI/07. Research grants awarded under the University Staff Training and Research programme of the Spanish Ministry of Education (Spanish Government, Madrid, Spain) and Central Quesera Montesinos S.L. (Murcia, Spain) are also acknowledged.

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