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Evaluation of on-line optical sensing techniques for monitoring curd moisture content and solids in whey during syneresis

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ABSTRACT

This study focuses on the prediction ability of several optical sensing techniques, namely single wavelength (980 nm), broad spectrum and colour coordinates, for monitoring key syneresis indices during cheese manufacture. Three series of trials were undertaken in which milk gel was cut and stirred in an 11 L cheese vat. Three full factorial designs were employed with experimental variables consisting of: (i) three curd stirring speeds and three cutting programmes; (ii) three milk fat levels and three gel firmness levels at cutting; and (iii) two milk protein levels and three fat:protein ratio levels in the respective experiments. Models developed using the range of techniques investigated demonstrated that an on-line visible–NIR sensor was able to predict curd moisture content. However, the broad spectrum technique was the only one capable of predicting whey solids. The findings show that on-line sensing techniques can significantly improve the control of curd moisture content in cheese factories, across the range of experimental variables used in this study.

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1. Introduction

Several studies, involving on-line NIR sensors, were carried out for predicting essential parameters in cheese manufacture, i.e., yield of whey, fat and solids in whey and curd moisture content (Fagan, Castillo, O'Donnell, O'Callaghan, & Payne, 2008; Mateo, O'Callaghan, et al., 2009). In some cases the on-line sensor response was combined with others factors for the purpose of obtaining better on-line prediction. Various statistical approaches were used to quantify how good the calibration models were, based either on broad spectrum or single wavelength responses, i.e. coefficient of correlation (R), standard error of prediction (SEP), etc. In general, the sensing techniques used in this study offer advantages over traditional methods, such as Rose–Gottlieb, Gerber and Soxhlet methods. These include omission of sample preparation/use of reagents, and potential to give real-time, non-destructive, automated measurement of critical process parameters (Forcato, Carmine, Echeverría, Pécora, & Kivatinitz, 2005; McGann, 1978; O'Sullivan, O'Connor, Kelly, & McGrath, 1999). On-line measurement technologies with these characteristics are required because of the increasing scale of dairy product manufacture.

Chemometrics refers to the processing of chemical data, where the raw data is numerically complex, e.g., in the form of spectra, with various statistical techniques in order to extract useful information. Chemometric data analysis tools include smoothing and multi-variate analysis techniques such as partial least squares regression (PLS). Partial least squares analysis reduces the large amount of spectral data and using principal components (factors) that describe the parts of the spectrum that are sensitive to a parameter of interest e.g. production of whey, enabling the spectrum to be handled in a data reduced manner. The principal components are chosen in such a way that they are orthogonal to each other and thus multicollinearity is avoided. Using PLS, the most useful wave bands for prediction of a particular parameter can be identified. Their chemical significance can be inferred by reference to spectral peaks which are known to be associated with the location of particular molecular bonds, e.g. O–H, C–H. The maximum peak where water molecules absorb in a curd/whey mixture is located at 975–980 nm according to Brennan, Alderman, Sattler, O'Connor, and O'Mathuna (2003), who used 975 nm wavelength in milk.

2. Materials and methods

2.1. Experimental design

In this study, three experiments were undertaken using different experimental variables and designs.

Experiment 1 consisted of a full factorial experimental design with three gel cutting intensities (***CI***) and three curd stirring speeds (***SS***) and was undertaken in three replicate blocks ($N = 27$).

Experiment 2 involved a series of 27 trials, which were carried out in triplicate using recombined milk with a range of milk fat

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levels (FL_m) (0, 2.5 and 5.0 g 100 g^{-1}) with constant protein level (3.3 g 100 g^{-1}) and the gel was cut at a range of firmness (G') levels (5, 35 or 65 Pa).

Experiment 3 was carried out using a randomised factorial design with two experimental factors, namely milk protein level (***PLm***) and fat:protein ratio (***F:PLm***). The levels of ***PLm*** were 3.3 and 3.7 g 100 g^{-1}, while the levels of ***F:PLm*** were 0.3, 0.7 and 1.1, giving a total of 24 trials.

In the three experiments carried out milk was coagulated in an 11 L cheese vat (Pierre Guerin Technologies, Mauze, France) and the gel was cut at fixed firmness (G') levels. Fat level adjustment and the rheological determination of gel times were determined according to Mateo, Everard, et al. (2009) and Mateo, O'Callaghan, et al. (2009)

2.2. Milk preparation

In the three experiments, whole milk was recombined using skim milk powder, distilled water, cream (Dairygold, Cork, Ireland) and $CaCl_2 \cdot 2H_2O$ at 2.04 mM in a laboratory cheese vat.

In Experiments 1 and 2, medium-heat skim milk powder (5.39 mg of undenatured whey protein nitrogen g^{-1} of skim milk powder) was used, as described in Mateo, Everard, et al. (2009).

Whole milk in Experiment 1 had a total solids level of 12 g 100 g^{-1} and target fat and protein levels of 3.5 g 100 g^{-1} and 3.3 g 100 g^{-1} respectively. However, whole milk in Experiment 2 had a range of milk fat levels (FL_m) (0, 2.5 and 5.0 g 100 g^{-1}), and constant protein level (3.3 g 100 g^{-1}).

In Experiment 3 low-heat skim milk powder (6.25 mg of undenatured whey protein nitrogen g^{-1} of skim milk powder) (Teagasc, Co., Cork, Ireland) was used. In this experiment, calcium chloride was added to the milk at 2.04 mM on the day of analysis.

In the three experiments mentioned above, the milk was cooled to 8 °C after the recombination of the milk and held it overnight under gentle agitation conditions (10 rpm). The ingredient mix in all experiments was formulated using least squares optimisation using the Solver tool in Microsoft Excel (v. 10 Microsoft® Excel 2002).

2.3. Clotting of milk

In each of the three experiments, the milk was heated to 32 ± 0.1 °C while being stirred at 22 rpm and pH was adjusted using HCl (1 M). In Experiments 1 and 2, milk pH was then adjusted to 6.5 at 32 ± 0.1 °C on the day following milk preparation. However in Experiment 3, pH was adjusted to 6.7 at 20 ± 0.1 °C on the day of preparation.

In each experiment milk from the cheese vat was analysed by MilkoScan (MilkoScan 605, A/S N. Foss Electric, Denmark) to determine fat, protein and lactose content. Rennet (CHY-MAX extra, EC 3.4.23.4, isozyme B, 600 IMCU mL^{-1}, Chr Hansen Ireland Ltd., Cork, Ireland) was added to the milk (0.18 g of chymosin kg^{-1} of milk) in the cheese vat while being stirred constantly at 31 rpm.

2.4. Determination of cutting time and gel cutting procedure

In the three experiments, after stirring the rennet homogeneously into the milk, a sample of milk was removed immediately from the vat and placed in a small amplitude oscillatory rheometer, which was pre-warmed to 32 ± 0.1 °C, to determine cutting time (t_{cut}). The rheometer geometry consisted of a cylindrical bob and cup used in oscillation mode at a shear strain of 0.01 and a frequency of 1 Hz, within the linear viscoelastic region (strain <0.03) reported for rennet milk gels. The milk coagulum was cut when the elastic modulus (G') reached the designed level. Cutting was carried out using a twin set of cutting blades. The moment of initiating gel cutting, i.e. t_{cut}, was taken as the reference time ($t = 0$) for all subsequent syneresis-related measurements.

In Experiment 1, the gel was cut at 35 Pa, as described in Mateo, O'Callaghan, et al. (2009). In Experiment 2, the milk coagulum was cut according to the experimental design as described in Mateo, Everard, et al. (2009). The cutting programme in Experiment 3 was described in Everard et al. (2008).

In each experiment stirring was stopped after 3 min and the cutting blades were replaced by the stirrers and stirring (at 16 rpm) commenced at $t = 4$ min and continued over the course of syneresis.

2.5. Sampling procedure for the curd/whey mixture and measurements of syneresis indices in Experiments 1, 2 and 3

Curd and whey samples were removed at 10 min intervals, from $t = 5$ min thereafter up to $t = 75$ min (i.e. 8 samples) without pausing the stirring of the vat contents using a specially designed on-line sampler as described in Mateo, O'Callaghan, et al. (2009). Each sample of curd/whey mixture was immediately separated using a stainless steel sieve and pan (Endecotts Ltd., London, England) with a 75 μm absolute pore size. Curd was analysed for curd moisture content and whey was analysed for solids in whey. Curd moisture content (M_c) and solids in whey (S_w) were determined by drying in a convection oven at 102 °C overnight, in triplicate.

2.6. Syneresis optical measurements

The on-line visible–NIR sensor used to carry out this study is described in Mateo, O'Callaghan, et al. (2009). The sensor employed a 6 W tungsten halogen light source (model LS1B, Ocean Optics, Inc., Dunedin, FL, USA), which transmitted light to the mix of curd and whey through a fixed large diameter optical fibre (Ø = 5 mm) (Fiberoptics Technology, Inc., Pomfret, CT, USA), a vertical polarizer (Edmund Optics, Inc., Barrington, NJ, USA) and a glass window (Ø = 20 mm). Backscattered light was collected over a large area through the glass window. This reflected light was then transmitted through a second fibre (Ø = 5 mm) and a collimating lens (Edmund Optics Inc.) that focussed the scattered light onto a ~800 μm diameter fibre optic cable (Spectran Specialty Optics, Avon, CN, USA) leading to the master unit of a miniature fibre optic spectrometer (HR2000CG-UV-NIR, Ocean Optics B.V., Duiven, Netherlands), which was used as a light detector.

2.7. Statistical analysis

Cross-validation is a method for fitting a regression model leaving out one trial (or a combination of trials) while making predictions concerning the omitted trial(s) using the other trials (Stone, 1974). It can be used in conjunction with Jack-knifing, which is a technique for eliminating useless wavelengths. In this case, the variance on each regression coefficient due to the omission of trials is calculated. Wavelengths having regression coefficients with high uncertainty (Student's t) are considered useless and are eliminated using a t-test (Martens & Martens, 2000).

Partial least squares (PLS) with cross-validation with or without Jack-knifing was carried out for developing prediction models for curd moisture content in all experiments using The Unscrambler software (v 9.2, Camo Process AS, Oslo, Norway). The type of cross-validation applied in this study was leave-one-out, which consists in removing one trial (consisting of eight samples, i.e. eight times points) and estimating its predicted value based on the model developed with all the other trials. Models were compared for prediction ability using the standard error of prediction (SEP). Significance of difference in model fit was tested using an F-test for equal variance (Minitab® 15, Minitab Ltd., Coventry,

UK). Range error ratio (RER) was calculated by dividing the range of the response variable by the SEP of the prediction model and used as an indication of practical utility of the models (Fagan, Castillo, O'Callaghan, Payne, & O'Donnell, 2009).

3. Results and discussion

3.1. Spectra of visible–NIR on-line sensor response during syneresis

Analysis of spectra obtained from the visible–NIR on-line sensor during syneresis at two fixed times after gel cutting in Experiment 3, shows an effect of fat:protein ratio (***F:PLm***) on the light intensity (Fig. 1). This suggests that the visible–NIR sensor is susceptible to changes in syneresis kinetics with ***F:PLm***. A comparable observation was found with respect to temperature (Fagan et al., 2007). It was also observed that the signal from the visible–NIR sensor was affected by the time after gel cutting. At t = 5 min the signal response form the sensor was higher than the signal at the end of syneresis (t = 75 min) (Fig. 1).

3.2. Prediction models for curd moisture content

Linear models for predicting M_c using the three techniques investigated i.e. single wavelength (980 nm) alone or in combination with other compositional and technology parameters and using broad spectrum, are shown (Fig. 2). Model 1.1 developed using a single wavelength explained 65% of the variation in curd moisture content, involving only one factor, namely light backscatter reflection ratio (R_t) (Fig. 2a). Model 2.3 was developed using a single wavelength in conjunction with other compositional and technology parameters, involving four significant factors, namely time after gel cutting, light backscatter reflection ratio (R'), milk fat level (FL_m) and cutting time (t_{cut}), in order of standardised coefficient (Fig. 2b). This model gave a R^2 = 0.95. Model 3.2 based on the broad spectrum and developed using Jack-knifing (JK) involved five loadings and gave a good prediction in terms of R^2 = 0.87, i.e. proportion of variation explained (Fig. 2c). It appears that where there is no composition variation, as in Experiment 1, a simple single wavelength model is adequate, whereas a more complex model is required in Experiments 2 and 3.

For the purpose of comparing models within this study and with other studies, using different techniques, prediction models for M_c were arranged according to descending SEP within each experiment (Table 1).

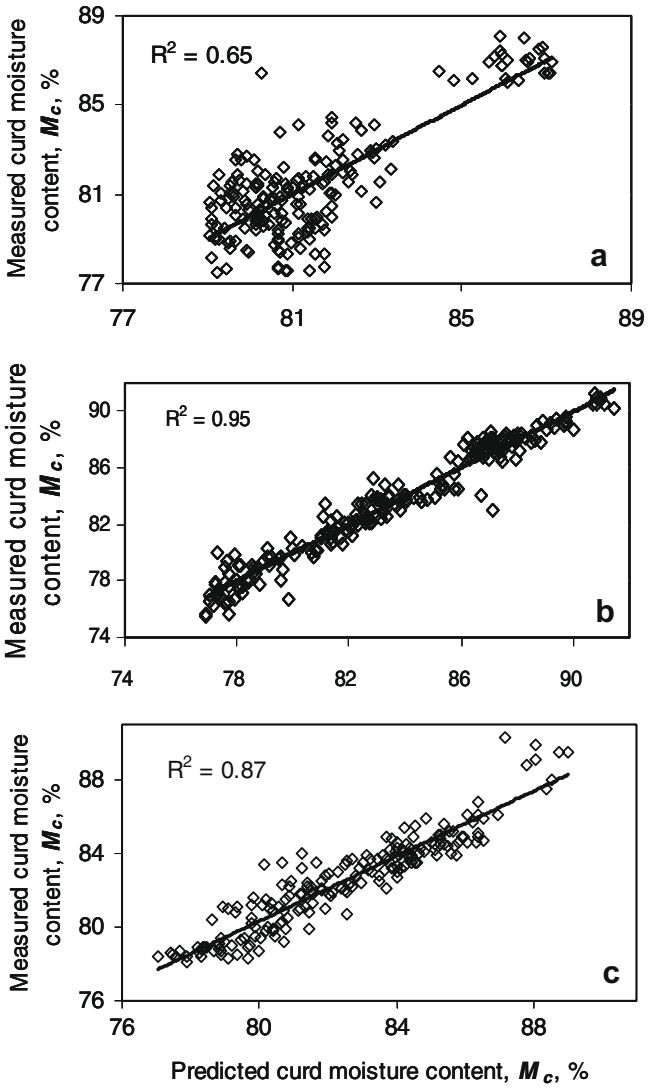

Fig. 2. Measured vs. predicted curd moisture content, M_c, at 10 min intervals from t = 5 to 75 min after gel cutting. (a) Model 1.1 for M_c using single wavelength response (980 nm) alone giving a linear model, M_c (R_t), N = 200, (b) model 2.3 for M_c using single wavelength response in conjunction with compositional and technology parameters gave a model, M_c (t, R', FL_m, t_{cut}), N = 216, (c) model 3.2 for M_c using broad spectrum response by Jack-knifing method with five loadings, N = 192 cf. Table 1.

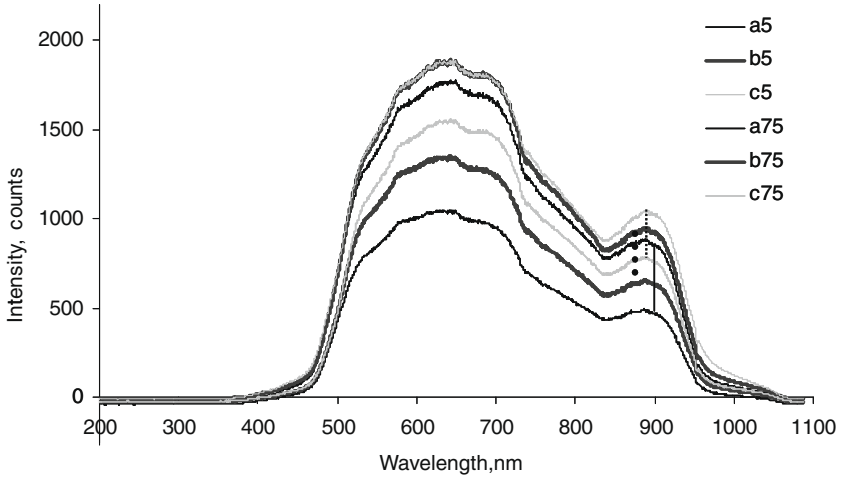

Fig. 1. Visible–NIR reflectance spectra showing the effect of fat:protein ratio (***F:PLm***) (a = 0.3, b = 0.7 and c = 1.1) on the light intensity for two times after gel cutting, i.e. 5 min and 75 min. The spectra shown is untreated and represent three trials (a, b and c) during syneresis at 5 and 75 min after gel cutting. Notation: a_5 denotes trial a at 5 min, etc.

Table 1
Comparison of predictive models for curd moisture content, M_c, during syneresis in various studies.[a]

Model reference[b]	Parameters in model	Range of milk fat level, %, w/w	Sensing technique	SEP[e]	Correlation coefficient, R	Range of response variable	RER[f]	Number of loadings or parameters in model	No. of data-points, N	Reference
1.1	Light backscatter reflection ratio	3.5[d]	980 nm	1.5[a]	0.81	77.5–88.1	7.1	1	208	Mateo, Everard, et al. (2009) and Mateo, O'Callaghan, et al. (2009)
1.2	Principal components of the spectrum (CV)[c]	3.5[d]	Broad spectrum (189–1100 nm)	1.3[b]	0.86	77.5–88.1	8.1	9	216	Present study
1.3	Principal components of the spectrum (JK)[c]	3.5[d]	Broad spectrum (189–1100 nm)	1.2[c,b]	0.88	77.5–88.1	8.5	7	216	Present study
1.4	Light backscatter reflection ratio, time after gel cutting, curd stirring speed, milk fat, curd cutting programme	3.5[d]	980 nm	1.1[c,d]	0.90	77.5–88.1	9.6	5	200	Mateo, Everard, et al. (2009) and Mateo, O'Callaghan, et al. (2009)
2.1	Principal components of the spectrum (JK)[c]	0–5	Broad spectrum (189–1100 nm)	1.7[a,e]	0.91	75.5–91.3	9.3	3	216	Present study
2.2	Principal components of the spectrum (CV)[c]	0–5	Broad spectrum(189–1100 nm)	1.6[a,e]	0.92	75.5–91.3	9.9	6	216	Present study
2.3	Time after gel cutting, light backscatter reflection ratio, milk fat level, cutting time	0–5	980 nm	0.9[f]	0.98	75.5–91.3	17.7	4	216	Present study
2.4	CIE coordinates (fat level in milk, a, b, Whiteness)	0–5	Visible (colour coordinates) 360–2000 nm	0.5[c,b]	0.95	75.5–91.3	31.0	4	216	Everard et al. (2009)
3.1	Principal components of the spectrum (CV)[c]	1.1–4.05	Broad spectrum (189–1100 nm)	1.2[c,b]	0.90	77.1–89.0	10.1	4	192	Present study
3.2	Principal components of the spectrum (JK)[c]	1.1–4.05	Broad spectrum (189–1100 nm)	0.97[d,f]	0.93	77.1–89.0	12.3	5	192	Present study
3.3	Light backscatter reflection ratio, time after gel cutting, fat:protein ratio, milk protein level	1.1–4.05	980 nm	0.77[g]	0.96	77.1–89.0	15.5	4	192	Present study
4.1	The time from enzyme addition to the inflexion point of the light backscatter profile (t_{max}), DSS (the decrease in the LFV signal during syneresis)	3.7[d]	980 nm	7.2[h]	0.58	56.1–77.0	2.9	2	20[g]	Fagan et al. (2007)
4.2	Principal components of the spectrum (CV)[c]	3.7[d]	broad spectrum (189–1100 nm)	4.8[i]	0.8	52.3–92.0	8.0	6	531	Fagan et al. (2009)
4.3	Principal components of the spectrum (JK)[c]	3.7[d]	broad spectrum (189–1100 nm)	4.1[j]	0.86	52.3–92.0	10.0	5	531	Fagan et al. (2009)
4.4	Temperature, t_{max}, milk fat, milk fat protein ratio	3.7[d]	980 nm	1.75[e]	0.97	52.3–92.0	22.7	4	60[g]	Fagan et al. (2008)

[a] Each model shown on this table is a regression model applied to one experiment, i.e. Experiments 1, 2, 3 or 4.
[b] Format $m \cdot n$, where m denotes the experiment number; n distinguishes between models for the same experiment.
[c] PLS models with cross-validation (CV) or Jack-knifing (JK).
[d] SD = 0.3%, w/w.
[e] The use of a common superscript indicates no difference in fit, as determined by a F-test for equal variance of the residuals.
[f] RER = range error ratio, i.e. the ratio between the range of the response variable and the SEP of the prediction model.
[g] Curd moisture content was only measured at 85 min after gel cutting during syneresis.

Comparing models for predicting $\boldsymbol{M_c}$ within Experiment 1, the best model in terms of SEP (1.1 g 100 g^{-1}) and coefficient of correlation ($R = 0.90$) was model 1.4, using a single wavelength (980 nm) in conjunction with compositional and technology parameters. The fact of involving more parameters in the model gave better prediction accuracy than in model 1.1 (SEP = 1.5 g 100 g^{-1}) with only one parameter, i.e. $\boldsymbol{R_t}$ (modelled light backscatter ratio during syneresis at time $\boldsymbol{t}$). Thus, 81% of variation (R^2) in curd moisture content can be accounted for model 1.4. Model 1.3 could be considered as good as model 1.4 in terms of SEP and R (1.2 g 100 g^{-1} and 0.88, respectively), according to F-test on residuals (Table 1). In general, any difference in fit between the models in Experiment 1, where milk composition did not vary, was small.

Comparison between models from Experiment 2, showed that model 2.4 (SEP = 0.5 g 100 g^{-1}, $R = 0.95$) using a colour coordinates technique was the most accurate. With regard to PLS models, the use of Jack-knifing gave a much simpler model, i.e. model 2.1 with 3 loadings, as opposed to model 2.2 with 6 loadings, having similar fit. In this experiment, the use of single wavelength technology, or the use of colour coordinates, required the inclusion of additional factors, i.e. milk fat level, to give a good fit.

When models in Experiment 3 were compared, it was concluded that the most precise model in terms of prediction accuracy was model 3.3 (SEP = 0.77 g 100 g^{-1}, $R = 0.96$) using the 980 nm wavelength in conjunction with compositional and technology parameters. The use of a single wavelength alone did not give a

useful prediction (not shown), confirming that additional parameters are required in such models when the milk composition varies.

In Experiment 4, where milk composition and renneting temperature were varied, the best model for $\boldsymbol{M_c}$ was model 4.4 (single wavelength with 4 factors) according to SEP, R and RER (1.75 g 100 g^{-1}, 0.97 and 22.7, respectively). This illustrates the fact that, provided one knows the factors which vary in industrial cheesemaking, and the ranges of variation, a suitable model can be developed, involving a single wavelength technology, which takes account of those variables. However, in industry one cannot always anticipate the sources of variation.

Comparing all the models developed in the four experiments, it was observed that the most parsimonious model overall was model 2.4 (colour + milk fat) in terms of SEP = 0.5 g 100 g^{-1} using the colour coordinates. Although, model 1.4 (single wavelength + milk fat + technology parameters, SEP = 1.1 g 100 g^{-1}) showed no significant differences between the fit of the model with model 2.4. This illustrates the importance of including milk fat as a factor in a model based on single wavelength or colour coordinate technology, where any variation occurs in fat level in milk. Model 3.1 (broad spectrum, SEP = 1.2 g 100 g^{-1}) gave a fit which was not statistically different from the two models above, showing that a broad spectrum technique can be more robust, and with reasonable accuracy, as it does not require the inclusion of compositional and technological parameters. In this study, the Jack-knifing method gave better models than cross-validation method in terms of number of loadings. The robustness of the models was improved when Jack-knifing was applied, in accordance with the conclusions of Yang and Chen (1998).

3.3. Prediction models for solids in whey

In this study prediction models for $\boldsymbol{S_w}$ were listed according to descending SEP within each experiment for comparison between one another (Table 2). The development of linear models for predicting $\boldsymbol{S_w}$ was only possible when a broad spectrum technique was used, with or without Jack-knifing.

The two models developed for $\boldsymbol{S_w}$ in Experiment 1 gave the same SEP, although model 1.6 (with Jack-knifing) was slightly better than model 1.5 in terms of coefficient of correlation (R = 0.76) and the number of loadings was reduced from 6 to 5.

Comparing the models obtained for $\boldsymbol{S_w}$ in Experiment 2, it was observed that model 2.6 (with Jack-knifing) was not significantly different in terms of SEP and R (0.23 g 100 g^{-1} and 0.83, respectively) with respect to model 2.5 (0.26 g 100 g^{-1} and 0.79, respectively). However, the use of Jack-knifing increased the number of loadings from 4 to 7.

In Experiment 3 it was observed that when Jack-knifing was used, the model developed (model 3.5) was better than model 3.4 according to SEP and R (0.23 g 100 g^{-1} and 0.83, respectively). A large number of loadings was required in both cases (14 and 13, respectively).

Over the three experiments listed in Table 2, the best models in terms of SEP were models 1.5 and 1.6 (0.11 and 0.11 g 100 g^{-1}, respectively), although models 2.6 and 3.5 had the best R (0.83), the latter two models differing in number of loadings. Model 2.6 had the best RER (12.6). These anomalies can be explained in terms of the different experimental designs employed.

3.4. Advantages and disadvantages of the different sensing techniques

Measurement at a single wavelength (980 nm) can be advantageous over the other two techniques investigated as it can be implemented using an energy-efficient light source, such as a laser-LED. A single wavelength system is less sensitive to interference from stray light.

The broad spectrum technique (189–1100 nm) covers a wider range of absorption bands corresponding to water and other chemical bonds. This is an advantage for predicting curd moisture content when the experimental variables include compositional parameters. The broad spectrum contains enough information to predict many parameters or indices. It can be used to determine composition of milk and hence, to provide a combination of parameters, such as fat, protein and lactose in milk which influence syneresis. Therefore, a broad spectrum sensor can provide several

Table 2
Comparison of predictive models for solids in whey, S_w, during syneresis in various studies[a].

Model reference[b]	Parameters in model	Range of milk fat level, %, w/w	Sensing technique	SEP[e]	Correlation coefficient, R	Range of response variable	RER[f]	Number of loadings or parameters in model	No. of data-points, N	Reference
1.5	Principal components of the spectrum (CV)[c]	3.5[d]	Broad spectrum (189–1100 nm)	0.11[a]	0.74	6.87–5.64	11.2	6	216	Present study
1.6	Principal components of the spectrum (JK)[c]	3.5[d]	Broad spectrum (189–1100 nm)	0.11[a]	0.76	6.87–5.64	11.2	5	216	Present study
2.5	Principal components of the spectrum (CV)[c]	0–5	Broad spectrum (189–1100 nm)	0.26[b]	0.79	7.07–4.18	11.1	4	216	Present study
2.6	Principal components of the spectrum (JK)[c]	0–5	Broad spectrum (189–1100 nm)	0.23[b]	0.83	7.07–4.18	12.6	7	216	Present study
3.4	Principal components of the spectrum (CV)[c]	1.1–4.05	Broad spectrum (189–1100 nm)	0.30[c]	0.71	7.05–5.30	5.82	13	192	Present study
3.5	Principal components of the spectrum (JK)[c]	1.1–4.05	Broad spectrum (189–1100 nm)	0.23[b]	0.83	7.05–5.30	7.6	14	192	Present study

[a] Each model shown on this table is a regression model applied to one experiment, i.e. Experiments 1, 2 or 3.
[b] Format $m \cdot n$, where m denotes the experiment number; n distinguishes between models for the same experiment.
[c] PLS models with cross-validation (CV) or Jack-knifing (JK).
[d] SD = 0.3%, w/w.
[e] The use of a common superscript indicates no difference in fit, as determined by a F-test for equal variance of the residuals.
[f] RER = range error ratio, i.e. the ratio between the range of the response variable and the SEP of the prediction model.

output parameters which can feed into a multi-variate prediction model, e.g. fat in milk combined with light reflectance. Infrared technology is capable of implementing such systems (Oulahal et al., 2009).

Colour coordinates in the visible spectrum (400–700 nm) can detect changes as seen by human eye. Colour detection technologies are well-established, readily available and may be applied to food systems such as curd syneresis, cheese, vegetables, and meat (Everard et al., 2009; Juric, Bertelsen, Mortensen, & Petersen, 2003).

4. Conclusions

Robust models were developed with an on-line visible–NIR optical sensor for predicting curd moisture content using the three sensor technologies investigated. Statistical analysis of results presented in this study suggests that optical-based sensing technologies have potential for predicting key syneresis metrics at an industrial scale. The most parsimonious models for predicting M_c were based on single wavelength (980 nm) NIR and visible spectrum (colour coordinates) in conjunction with other compositional and technology parameters. However, the broad spectrum approach opens up possibilities of wider application because of its additional information content in relation to milk composition, and can predict solids in whey, which other techniques cannot do. The findings show that on-line sensing techniques can significantly improve the control of curd moisture in cheese factories, across the range of experimental variables used in this study.

Additional studies are required before the technology investigated in this study may be employed in commercial cheese manufacture involving different cheese recipes (i.e. type of milk, cooking temperatures, pH and time to drain).

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