SENSOR FUSION AS A TOOL TO MONITOR DYNAMIC DAIRY PROCESSES

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Abstract

A system for monitoring milk and fat concentration in a dynamic milk/water system by fusing information from several sensors was investigated. Standard instrumentation for food production was used, the sensors were a conductivity meter, a density meter and an optical instrument used to measure backscattered light. The system was applied to a dynamic mixing situation. Prediction error did not exceed 2% in the milk concentration and 0.1% fat in the total fat concentration. The applicability of the sensor fusion approach in field conditions was

demonstrated by mounting the sensors in a dairy plant and monitoring the start-up of a pasteurizer.

Keywords: Sensor fusion, multivariate calibration, conductivity, density, turbidity, milk, dairy process

1. Introduction

Interest in advanced, model-based, process control systems is increasing in the food industry. Traditionally, good product quality has been ensured by monitoring parameters such as temperature, pressure and density, with emphasis on maintaining the correct process conditions during steady-state operation. For the dairy industry the trend towards wider product ranges and shorter turnover times has led to a demand for short product runs and flexible processes. Shorter product runs mean that it will become more important to control dynamic conditions at start-up, product change-over and rinsing in order to maintain a good process economy and to minimize the environmental load (Trystam & Courtois, 1994). In a dairy, large amounts of both milk and rinsing water are wasted during process start-up, intermediate rinsing and product change-over. This leads to economic losses in the form of product wastage and the cost of treating liquid waste.

In Scandinavia, losses of milk with waste water are estimated to range from 1% for liquid milk to 7% in cultured milk (Hogaas Eide, 2002). Balannec, Gésan-Guiziou, Chaufer, Rabiller-Baudry & Daufin (2002) claim that 1–3% of processed milk is wasted.

While the measurement of temperature, flow rate, density and pressure poses no problems, the real-time monitoring of composition on-line has only rarely been implemented in the dairy industry, apart from the area of fat standardisation. The principal commercial candidate is

NIR (Near Infra Red) (Hoyer, 1997) but the instruments are rather expensive for routine use, and not fast enough for control on timescales shorter than minutes. Other multivariate techniques tried are based on the electronic nose or electronic tongue concept (Cimander, Carlsson & Mandenius, 2002; Ampuero & Bosset, 2003; Deisingh, Stone & Thompson, 2004).

The dynamic conditions during start-up and rinsing are traditionally not very well controlled. The starting point for production i.e. the time at which the milk is considered to be of the right quality, is traditionally defined by a fixed time interval or in advanced situations, by conductivity or turbidity measurements (van Boxtel & de Vries, 1985; Payne, Crofcheck, Nokes & Kang, 1999; Danao & Payne, 2003). However, the information provided by separate conductivity or turbidity measurements is rather limited and may not be easy to interpret since both milk and fat contents influence the measurements.

1.1. Sensor fusion

If the quantitative relationships between simple sensor measurements and physical or chemical characteristics of a sample are known, or can be empirically established (calibration), these relationships can be used to determine the characteristics of a new sample from sensor measurements on that sample. Simple sensors are easily calibrated using standards, and occasionally, calibrations made by the sensor manufacturer can be used. When two or more sensors are used jointly, the calibration is called multivariate calibration (Sundberg, 1999). Two or more characteristics (e.g. milk and fat concentrations) can be determined simultaneously if at least the same number of sensors is used. There are, however, advantages in using more sensors than the minimum number. Not only will the precision in

the determination of a characteristic be increased, but also error control is possible, for example, to detect a malfunctioning sensor or a process failure.

In the present study we used three different types of sensors, a conductivity meter, a density meter and an optical instrument measuring turbidity, in order to make simultaneous determinations of milk and fat concentrations. The potential of sensor fusion based on standard instrumentation and multivariate calibration for the on-line monitoring of the composition of milk-water mixtures was investigated by monitoring the milk and fat concentrations of the mixture during the start-up of a dairy pasteurizer.

2. Materials and methods

For the calibrations and for the dynamic tests homogenized pasteurized milk of different fat contents (0.05, 0.5, 1.5, 3.0%) and pasteurized unhomogenized cream (40% fat) were obtained from Skånemejerier, Malmö, Sweden. Milk of 4.5% fat content was prepared by mixing milk with a fat content of 3.0% with the cream and homogenizing it at a pressure of 150 bars with a Tetra Pak SHL 05 homogenizer (Tetra Pak, Lund, Sweden).

A sensor set was configured using the following industrial sensors: an optical instrument measuring the backscattered light, FCO Turbidity (Holmqvist MV, Tomelilla, Sweden), an industrial conductivity meter, FCC (Holmqvist MV, Tomelilla, Sweden), a thermocouple, Pt100 (Pentronic, Gunnebo, Sweden) and a mass flow and density meter, TRIO-MASS (ABB Automation Products GmbH, Göttingen, Germany).

The FCO turbidity meter employs diffuse reflection, the reflection from the surface being monitored at 890 nm at an angle of 90°. By measuring the reflected or backscattered light it is possible to measure more concentrated solutions than with the nephelometric technique (Sadar, 1998).

2.1. Calibration of the instruments

The FCC conductivity meter was calibrated at two temperatures, 20 and 60°C. For calibration at 20°C, eight solutions of NaCl (Merck, Darmstadt, Germany), 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6 and 0.7% w/w, were prepared. For the calibration at 60°C, seven solutions of NaCl were prepared, 0, 0.00774, 0.01050, 0.014454, 0.02360, 0.05486 and 0.1000 mol kg⁻¹.

The TRIO-MASS mass flow and density meter was delivered with a specified accuracy, but this was the common specification for all TRIO-MASS instruments. To achieve better accuracy a specific calibration was performed. The TRIO-MASS density meter was calibrated from 998 kg/m³ to 1038 kg/m³ with NaCl solutions of 0, 1.40, 2.79, 4.19 and 5.61% w/w at 20°C and also with water from 7 to 70°C.

For the calibration of the optical instrument measuring turbidity, milk batches of 0.1, 1.5, 3.0 and 4.5% fat (w/w) were diluted to seven concentrations in deionised water. The milk concentrations were 0, 5, 10, 15, 25, 50, 75 and 100% (w/w). Three replicate samples were studied at each dilution. Each sample was heated from 2°C to 70°C and measured at 2, 10, 20, 30, 40, 50, 60 and 70°C.

2.2. Dynamic tests

As a proof of concept, controlled dynamic experiments were performed to evaluate the overall accuracy of the measurements, calibration and the evaluation algorithm. One 150 litre tank was filled with milk of 3% fat, and another with water. Flows from both tanks were manually mixed using a three-way valve. From the valve the solution was led to a centrifugal pump, Alfa Laval ALC-1D/130 (Alfa Laval, Lund, Sweden), and then to the sensor set as

illustrated in Figure 1. By regulating the flows from both tanks, different milk concentrations could be achieved during the test. The flow conditions were measured by the TRIO-MASS mass flow meters making it possible to compare the concentrations based on mass balance and the concentrations predicted by the signals from the sensor set.

2.3. Factory experiments

The sensor set was mounted in a commercial milk pasteurization line at the outlet of the final cooling stage of the heat exchanger. Partial homogenization was employed in the pasteurization line, which was run at 16 000 litres/hour (Figure 2). The plate heat exchanger was an Alfa Laval H10-FMC (Alfa Laval, Lund, Sweden), the separator an Alfa Laval 614 (Alfa Laval, Lund, Sweden) and the homogenizer a Rannie Blue Top 1-85-340 (APV Rannie, Lockerbie, Scotland).

In partial homogenization, cream with 40% fat is separated from the skim milk. The fat content of the commercial milk is controlled by routing excess cream into a separate cream processing line. The correct amount of cream is mixed with part of the skim milk to 10% fat content, homogenized (here at 150 bar) and mixed with the remaining skim milk before re-entering the heat exchanger. Milk entry into the system during the start-up process was monitored using the sensor set.

3. Results and discussion

3.1. Calibration

3.1.1. Conductivity

Figure 3 shows the calibration of the conductivity instrument used. The measured values are plotted on log-log-scale against the theoretical conductivity values for the NaCl solutions, for both temperatures. A simple, single linear regression fitted both sets of data, so the calibration can be regarded as temperature independent. The measurement error, (residual) standard deviation, was 0.03 mS cm⁻¹. The estimated slope was 0.94 (s.e.=0.01), slightly but significantly less than 1, i.e. on the original, non-logarithmic scale the relationship showed a significant curvature.

The conductivity of milk is lower than that of its fat- and casein-free phase due to the obstruction of the charge-carrying ions by the fat and casein micelles (Dejmek, 1989). For milk, the relation between the fat content and conductivity is well understood theoretically (Bruggeman, 1935) and has been studied experimentally (Prentice, 1962). It is given by:

$$K = K_0 \cdot v^{1.5} \quad (\text{Eq. 1})$$

where K_0 is the conductivity of the fat-free milk and v is the volume fraction of the conducting medium i.e. the non-fat phase.

The conductivity of milk also changes with the age of the milk, stage of lactation of the cow, season, and dairy cow breed. Therefore, a reference value for bulk milk conductivity must be determined experimentally. Recognizing this, the effect of temperature, dilution and fat content was studied by Henningsson, Östergren & Dejmek (2004). They obtained the following general set of equations describing the conductivity of milk-water mixtures in the temperature interval 2–70°C:

$$K = K_1 \cdot c^{0.844} \cdot (1 - F)^{1.5} \quad (\text{Eq. 2})$$

$$K_1 = K_1(T) = K_{1, 25^\circ\text{C}} \cdot 10^{-781 \left(\frac{1}{T} - \frac{1}{298} \right) - 312033 \left(\frac{1}{T} - \frac{1}{298} \right)^2} \quad (\text{Eq. 3})$$

where F is the fat fraction of the milk-water mixture, c is the milk fraction, T is the absolute temperature and $K_{1, 25^\circ\text{C}}$ is the conductivity of undiluted, fat-free milk at 25°C , which varies from batch to batch. The above relationship was obtained when diluting with water of close to zero conductivity. Here we must also take account of the conductivity of the diluting process water, K_w . By assuming a similar contribution to the mix conductivity from the ions of the diluting water as from the ions of the milk, we get:

$$K = K_1 \cdot \left(c + (1-c) \cdot \left(\frac{K_w}{K_1} \right)^{\frac{1}{0.844}} \right)^{0.844} \cdot (1-F)^{1.5} \quad (\text{Eq. 4})$$

There is some potential for reducing the errors by using even more sophisticated models for the relationships, as the power law relationship in Eq. (2) has some bias. However, the model above was found good enough, and instead of trying to model the bias even further, the bias was regarded as a random model error. The overall variance was calculated according to:

$$\text{overall variance} = \text{variance sensor} + \text{variance model} \quad (\text{Eq. 5})$$

The standard deviation of the sensor was found to be proportional to the conductivity itself. A lower bound for the standard deviation was applied when the conductivity was very low.

3.1.2. Density

The results of the absolute calibration of the density meter are given in Figure 4. The deviation from the nominal density was interpreted as a density-dependent bias and a temperature-dependent bias as shown in Figure 4a and b respectively and fitted to polynomial in density, b_{rho} , respectively in temperature, b_{temp} . The temperature-dependency was due to temperature effects on the material of the density meter. The apparent minimum in b_{temp} is an artefact of the chosen polynomial fit. A corrected (off-set compensated) density, ρ_{corr} , was calculated from the instrument density ρ_{ins} using the relation:

$$\rho_{corr} = \rho_{ins} + b_{rho}(\rho_{ins}) + b_{temp}(t) \quad (\text{Eq. 6})$$

The standard deviation of the difference between the literature values and the offset-compensated measured density, $\rho - \rho_{corr}$, was 0.17 kg/m³.

The density of milk-water mixtures follows simple physical rules. The density is determined by the fraction of serum, milk fat and water:

$$\rho = x_{serum} \cdot \rho_{serum} + x_{fat} \cdot \rho_{fat} + x_{water} \cdot \rho_{water} \quad (\text{Eq. 7})$$

where

$$\rho_{serum} = 1036.6 - 0.09773 \cdot t - 0.003663 \cdot t^2$$

$$\rho_{fat} = 928.8 - 0.6652 \cdot t$$

$$\rho_{water} = 1000.3 - 0.02251 \cdot t - 0.004403 \cdot t^2$$

The values given above are tabulated in the literature (Walstra & Jenness, 1984 and Handbook of Chemistry and Physics, 1974) and t is the temperature in °C. The error in the literature data model was considered small, as compared with the error in the process instruments.

3.1.3. Turbidity

The output of the optical instrument used was not an unbiased measure of the well-defined physical property, turbidity, as it was affected by the geometry of the sensor. Therefore, no absolute calibration is possible.

The calibration of the optical instrument with milk-water mixtures is simple but the most time consuming. For the calibration, triplicate measurements were made at all combinations of four fat concentrations, eight milk concentrations and eight temperatures. Figure 5 shows the effect of milk concentration at 0.1 and 3.0% fat and at 20 and 70°C. The increased turbidity at higher temperatures might be due to increased voluminosity of the casein micelles at higher temperatures. Above 60°C the increase is irreversible and strongly time dependent, due to denaturation of β -lactoglobulin. The denatured β -lactoglobulin forms complexes with κ -casein at the surface of the casein micelles (Journink, 1992). Since no theoretical relationships are known and it was found difficult to describe empirically the three-variable calibration functions by simple parametric functions, the data from the calibration of the optical instrument were represented as a data table. Intermediate values were interpolated from the table using the Matlab 6.5.1 (The MathWorks, Inc., Natick, Massachusetts, USA) interpolation function, *interp3*, with spline interpolation using default parameters. The accuracy of this implicit calibration function was given a value suitably positioned between the upper and lower bounds. The lower bound was given by the variation observed between replicates, and an upper bound was estimated from the residual variation around a fitted second-order polynomial.

3.2. Multivariate evaluation

Three sensors were used for the determination of milk and fat contents of a sample. Two sensors would have been sufficient to give a unique result, but three sensors will increase the precision and make it possible to detect anomalies. However, it means that a more sophisticated estimation/prediction method must be used, *weighted nonlinear least squares* (for use in multivariate calibration, see Clarke, 1992, and Sundberg, 1999). For given measurements (signal values) this method determines the milk and fat contents as the values minimizing the following function.

$$f(\text{milk}, \text{fat}) = \frac{(s_{\text{turb}} - m_{\text{turb}})^2}{v_{\text{turb}}} + \frac{(s_{\text{cond}} - m_{\text{cond}})^2}{v_{\text{cond}}} + \frac{(s_{\text{dens}} - m_{\text{dens}})^2}{v_{\text{dens}}} \quad (\text{Eq. 8})$$

Here s_{turb} is the observed turbidity sensor signal, m_{turb} is the calculated signal as a function of milk and fat contents using the calibration of this sensor, and v_{turb} is the statistical variance of the measurement. The subscripts cond and dens denote the corresponding values for conductivity and density. Note that the variances may also be functions of temperature and milk and fat contents. In order to find the milk and fat contents minimizing Eq. (8), MATLAB's constrained minimum search routine *fmincon* with default settings was used.

For assessed values of milk and fat contents in the function f , the fitted sensor m -values are compared with the actual measured signals, s . The value of f for the best combination of milk and fat contents indicates how well the model is able to explain the observed sensor data. If the variances are correctly determined, the minimum f -values should be of magnitude 1 (degrees of freedom=3-2=1). A much higher value indicates that the model does not fit. The reason might be that the tubing is only partially filled, a sensor error, or some other kind of process malfunction.

The statistical precision of the milk and fat determinations can be estimated approximately by local linearization of the nonlinear model functions. More precisely, if J denotes the 3x2

Jacobian matrix of derivatives of the model functions and V is the variance-covariance matrix of the sensor measurements (a diagonal matrix with v_{turb} etc. on the diagonal), then the variance-covariance matrix expressing the uncertainty in the determinations is given approximately by $J' V^{-1} J$, where $'$ denotes the matrix transpose. We used this variance-covariance matrix to construct uncertainty ellipses for the milk and fat determinations as later shown in Figure 9.

The variances, v_{turb} , v_{cond} and v_{dens} must be assessed, and this is an uncertain procedure in itself. Hence, the figures of the uncertainty in the determinations, as described above, must be regarded as somewhat unreliable. The assessments were mostly based on the residual variation in the sensor calibrations, as described in Sections 2.1 and 2.2, but other factors also influence the uncertainty. The statistical uncertainty in the calibrated functions was assessed jointly with the residuals, (even though they often made a small contribution). However, when an instrument is used in a new environment, calibration errors might appear, and the accuracy of the calibration will also vary with the milk properties during a time period. This was compensated for by additional linear calibration for the dairy plant process, when the determinations were adjusted to give a milk contents of zero at the start, when the piping only contained water, and 100% milk when there was only milk in the system. In practice, the latter calibration can be made on the previous run of the dairy process.

A value of v_{turb} 50% higher than the average variance of the 224 triplicate measurements from the calibration was used. The reason for this was that the error arising from the interpolation of intermediate values is difficult to estimate and a value 50% higher was believed to cover this error. It is better to underestimate the precision of a sensor than overestimate it. v_{dens} is the variance resulting from the calibration of the density meter and v_{cond} the overall mean error, as described in Eq. (5).

The sensitivity of a sensor to a measured variable may vary with the composition. Figure 6 illustrates that the optical instrument was more sensitive to the milk content at low concentrations than at high concentrations. At low concentrations a small change in milk concentration will change the sensor output substantially. An incorrectly assessed milk concentration would lead to a considerable difference between the sensor output and model value, strongly affecting the penalty function f in (Eq. 8). At high milk concentration the sensitivity is smaller and a change in milk concentration will not change the sensor output as much as at low concentration and the penalty function will be less affected. Mathematically, the sensitivity of the sensor set is represented by the Jacobian matrix J , introduced earlier in this section. By choosing sensors that complement each other, sensor fusion provides a good tool with which to monitor the whole calibration range with high accuracy. By using weighting factors for each sensor, the algorithm automatically makes use of the strengths and weaknesses of the sensors in the assessment of the composition of the sample. The goodness of fit, as given by the absolute value of the penalty function, can be used to monitor deviations from the expected trajectory. For example, if a small amount of highly conductive cleaning solution would leak into the milk-water mixtures, the multivariate calculation would report a large error due to the “impossible” combination of the conductivity, density and turbidity values.

3.3. Dynamic tests

3.3.1. Dynamics of the sensors

In on-line use, the sensor response time is an important issue. We determined the instrument response times and found them to be <1 s, and hence much shorter than the time

scale of the dominant mixing process of interest. A problem in dynamic monitoring using several sensors is the time delay caused by the dead volume between the sensors. This was not a problem in the three-sensor configuration used in this study because the sensors were in so close proximity to each other that the delay was less than 0.5 s. However, in the dynamic test rig, a change in flow setting causes a compositional change which arrives at the sensors after a time delay that depends on the flow rate and the volume of the piping. This time delay had to be compensated for in evaluating our test data. The time delay between the calculated mixing conditions based on the flow and the mixing conditions estimated by the sensors was actively compensated for by $t = \frac{\text{dead volume}}{\text{volume flow rate}}$, where dead volume = 5.35 litres and the volume flow rate, which varied, was measured.

3.3.2. Results of the dynamic test

Figure 7 shows how the predicted fat concentration and milk concentration correlated with the concentrations calculated from the measured flow rates. The results show that in the range from 0 to 2.25% fat the maximum difference in prediction of the total fat concentration was 0.11%. The mean bias was 0.02%. In the range from 0 to 75% milk in water the maximum difference in the predicted milk concentration was 2% and the mean difference 0.75%. These differences include the errors arising from the sensors, in the evaluation and the errors in the flow measurements. Figure 7 (bottom) shows how the sensors predict the fat concentration of the milk for milk concentrations above 10%. The actual fat concentration of the milk was 3%.

3.4. Start-up at a dairy plant

In the dairy plant experiments, the baseline for the conductivity and turbidity measurements was adjusted in accordance with the readings of the instruments during steady-state conditions with rinsing water in the processing line as noted above. The reference value for milk was determined from the last values measured, where the steady-state mixing conditions were set to 100% milk concentration and 3.0% fat concentration. In a real life situation these would be known from the previous measurement.

Figure 8 illustrates the typical course of the calculated sensor output, the size of the penalty function f and the variation in composition with time during start-up, as milk first entered the system, replacing water. The high values of f in the beginning showed that something more than milk and water was present. Evaluation of the signals provided the likely explanation that there was some air in the system. After 280 s all the sensor outputs increased. The evaluation algorithm showed clearly that only skim milk was present at that time. (The apparent presence of up to 0.2% fat is an artefact of the evaluation, possibly caused by the different homogenizers used at the dairy plant and in our calibration experiment) The skim milk concentration increased at a rate corresponding to a time constant of 80 s, reflecting the mixing and dispersion in the whole process line.

The increase in fat content was delayed by 90 s. This was due to the fact that the time of passage of the cream through the homogenizer, as seen in Figure 2, was much longer than the time of passage of skim milk. The rate of increase in the fat content corresponds to a time constant of 20 s, reflecting the lower degree of dispersion in the homogenizer circuit. The steep decrease in fat concentration observed at 640 s correctly reflected a deliberate change in the fat percentage set by the operator. The concentration reading indicated that water admixture persisted up to 700 s after start-up. Our data also suggest that the fat content was not completely stabilized until at 1300 s.

Figure 9 shows uncertainty ellipses corresponding to the variance-covariance matrices at seven different measuring points. The form and size of the ellipses shows the uncertainty of the milk and fat predictions. When the milk concentration is low, the accuracy in the fat concentration prediction is low. At intermediate milk concentrations both milk and fat predictions are good and the size of the ellipses small. At milk concentrations close to 100%, fat predictions are worse. The reason for this is the same as that illustrated in Figure 6 and discussed in Section 3.2. At high milk concentrations the milk sensitivity of the optical instrument decreases and therefore also the accuracy in the prediction of milk concentration. To some extent, which is difficult to quantify, this will be compensated for by the calibration of the 100% milk level from the previous run.

4. Conclusions

It has been demonstrated that the signals from common, routinely used process instruments can be fused to monitor process conditions in terms of composition by means of multivariate calibration using a penalty function. The methodology ensures maximum use of all the information available in a system containing redundant data, as well as automatic weighting of the different sensors depending on their accuracy. The capability of the method developed has been verified in a dairy process line and it has been shown that the system could follow the dynamics in terms of milk/water composition, i.e. milk, water and fat contents, during start-up with sufficient accuracy and excellent time resolution. The method can be used to monitor dynamic changes in process conditions such as those encountered during start-up, and in diagnosing process malfunctions.

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Figure captions

Figure 1. The experimental rig for dynamic tests.

Figure 2. A schematic outline of the placement of the sensor set in the processing line with partial homogenization in dairy plant experiments (PHE = Plate Heat Exchanger).

Figure 3. The results of the absolute calibration of the conductivity meter.

Figure 4. Absolute calibration of the density meter. a) The temperature-dependent offset between the literature values and the measured density for deionised water. b) The offset dependent on the absolute value of the density of NaCl solutions at 20°C.

Figure 5. Calibration of the optical instrument with milk-water mixtures at two different fat contents of the milk. Top 20°C, bottom 70°C. The figure shows all triplicates. The differences between triplicate points are however too small to be noticed.

Figure 6. Schematic illustration of the sensitivity of the optical instrument at different milk concentrations.

Figure 7. The dynamic test of sensor fusion. Milk (top), total fat (middle) concentration and fat concentration in the milk (bottom).

Figure 8. Start-up of a milk pasteurizer with partial homogenisation: sensor output (top left), predicted milk and total fat concentration (bottom left), predicted fat concentration in milk (top right) and the residuals of the penalty function, f (bottom right).

Figure 9. The uncertainty ellipsis at seven different measuring points. The size of the ellipsis corresponds to the uncertainty of the milk and fat predictions.

Figure 1. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

Figure 2. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

Figure 3. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

Figure 4. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

Figure 5. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

Figure 6. Sensor fusion as a ... Henningsson, Östergren, Sundberg & Dejmek

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