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Predicting the Cutting Time of Cottage Cheese Using Backscatter Measurements

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PREDICTING THE CUTTING TIME OF COTTAGE CHEESE USING LIGHT BACKSCATTER MEASUREMENTS

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ABSTRACT. *An automated system for monitoring culture growth and determining coagulum cutting time is needed for cottage cheese manufacturing. A light backscatter measurement system was designed and installed in a local cottage cheese manufacturing plant. A cutting time prediction algorithm was developed using parameters generated from the backscatter profile. The cutting time prediction algorithm, $T_{cut} = T_{max} + \beta_2 S$, used two time-based parameters generated from the backscatter profile (T_{max} and S) and one operator selected parameter, β_2, to predict the coagulum cutting time, T_{cut}. The standard error of prediction for the algorithm was 6.4 min and was an improvement over the standard error of 8.7 min previously reported (Payne et al., 1998). The algorithm is more robust than that used by Payne et al. (1998) because it predicts cutting time based on a measure of coagulation kinetics, S, and eliminates the uncertainty of the culture starting time from the algorithm. In addition, a method was proposed for continuous monitoring of culture growth during the first 210 min of the process.*

Keywords. *Coagulation, Sensor, Fiber optic, Milk, Cheese.*

Improved automation is needed to ensure that U.S. food processing facilities, including dairy facilities, remain competitive in the world economy and to improve product consistency, quality, and safety. Process control allows for tighter production tolerances, increased consistency of food properties, process optimization, improved quality, and savings in raw materials, energy, and waste disposal. The lack of suitable sensors for characterizing the properties of liquid particulate food materials is hindering the implementation of modern process control technologies. One important application is the use of optical sensors to monitor and control cheese-making operations where milk is converted from a liquid to a gel.

Fiber optic sensors have been developed for monitoring the changes in backscatter (diffuse reflectance) during the enzymatic coagulation of milk (Payne et al., 1993; Payne, 1995), as well as the culture of cottage cheese (Payne et al., 1997, 1998). During milk coagulation light scattering changes as a result of changes in particle size distribution and protein crosslinking (gelatinization).

Cottage cheese is formed by acid coagulation of skim milk using either lactic acid fermentation or direct acidification. Traditionally, the curd cutting time is determined by the cheese maker and based on appearance, texture, and pH. Cutting the curd at the right pH is the most important factor in producing a high quality cottage cheese, because cutting time pH correlates to specific physical characteristics of the curd (Emmons and Beckett, 1984; Perry and Carroad, 1980). Cutting the curd at the wrong time has destroyed many cottage cheese batches. The optimum time to cut the curd is when the pH is near 4.7, the isoelectric point of casein, so that casein is most insoluble and easily precipitated (Eck, 1986). Curd cut at pH values above 4.8 is overly firm curd and high in solids content. On the other hand, curd cut at pH values below 4.6 is high in moisture content (Emmons and Beckett, 1984).

Unfortunately, pH is difficult to measure consistently because of the inherent variability of pH meters. Furthermore, when pH is used to monitor the progress of the curd formation, failures of the starter culture may not be discovered in time to save the batch. Failure of the bacterial starter may be caused by bacteriophage, antibiotic residues, residual sanitizing or cleaning compounds, and natural inhibitors present in the milk (Varnum and Sutherland, 1994).

Interruption of curd growth due to bacteriophage attack is still a major concern within the dairy industry (Passos et al., 1994). Bacteriophage attacks can become a problem because cheesemaking is a non-sterile process in an environment where bacteriophages are virtually always present. In addition, once a bacteriophage has found a susceptible host, the bacteriophage population will increase very quickly because of short latent periods and large growth rates (Moineau et al., 1993). Therefore, a method to detect possible bacteriophage contamination would be useful in the cheese industry so that precautionary measures could be taken to minimize or prevent economic losses (Moineau et al., 1993).

Payne et al. (1998) developed a cutting time prediction algorithm by correlating parameters generated from the light backscatter profiles with the actual cutting time as

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determined by the operators. The sensor system measured light backscatter using a fiber optic sensor. A computerized data acquisition system calculated the backscatter ratio (backscatter sensor response divided by the initial sensor response) and the slope of backscatter ratio. A typical graph of the measured light backscatter during the coagulation of cottage cheese and its slope can be seen in Payne et al. (1998). The profile parameters T_{max} (time of maximum slope) and the slope of backscatter ratio at T_{max} were correlated with cutting time. The resulting cutting time prediction algorithm was as follows:

$$T_{cut} = \beta_o + \beta_1(T_{max}) + \beta_2(\text{slope at } T_{max}) \qquad (1)$$

where β_o, β_1, and β_2 are regression parameters. This model predicted cutting time with a standard error of 8.7 min. This standard error was viewed as most likely too large to be used to automate the cutting time selection (Winchester Farms Dairy, Winchester, Ky.). These significant errors were attributed to the variability in operator initiation of the data acquisition system when culture was added.

The algorithm parameters (T_{max} and slope at T_{max}) were generated directly from the backscatter profile. The "slope at T_{max}" is a response-based parameter and is affected by product composition such as solids and fat content. Time-based parameters, based on the experience of the second author, are desired for predicting time events, such as cutting time, because they are less affected by composition factors and sensor design features. A time-based parameter is desired to replace "slope at T_{max}" in the above cutting time prediction algorithm.

The current study was undertaken in an attempt to improve the performance of the light backscatter monitoring system and develop a technique for monitoring culture growth to give operators an early warning of a slow growth culture.

Objectives

The current study objectives were to develop and validate an improved prediction algorithm. The specific research objectives were to:

1. Develop a time-based measure of "slope at T_{max}" that is independent of backscatter response.
2. Develop an improved cutting time prediction algorithm.
3. Validate the improved algorithm.
4. Determine if backscatter ratios can be used as an indicator of culture growth.

Materials and Methods

Based on input from plant personnel at a commercial dairy plant (Winchester Farms Dairy, Winchester, Ky.) the computerized data collection equipment was redesigned from that described by Payne et al. (1998) to improve the precision of the system and permit more accurate predictions. The system was redesigned to: automatically collect the light backscatter data with minimum operator intervention, present a graph of the backscatter ratio and slope to the operators for convenient determination of culture status, and alert the operators of an approaching cutting time by activating a strobe light.

Data Acquisition and Control System

A computerized data acquisition and control system was developed to monitor and record the backscatter ratio during the culture process, alert the operator to the predicted cutting time, and present the output to the operator. The system consisted of a fiber optic backscatter sensor, a control box, a computer, and two monitors as shown in figure 1. The optics, electronics, and fiber optic probe were designed and fabricated by the Biosystems and Agricultural Engineering Department at the University of Kentucky. The data acquisition portion of the system consisted of a personal computer (486, 33 MHz) equipped with a Keithley-Metabyte CTM-05/A counter timer board and programmed for data acquisition using Visual Basic 4.0 (Microsoft Corporation, Redmond, Wash.) and VTX 1.1 (Keithley-Metabyte, Cleveland, Ohio).

The system was installed in a commercial dairy facility (Winchester Farms Dairy) in May of 1997. The sensor and control box were installed on vat number 8 and connected to a computer and monitor. The control box included a flashing strobe alarm and three push buttons: Culture Add, Enzyme Add, and Alarm Recognition, as well as a signal driver for the sensor. The computer was located one floor above the vat room but connected to a second monitor located in the control room easily seen by the operator from vat number 8. The sensor probe was suspended from overhead supports to eliminate mechanical contact with the vat that could transmit vibration during mixing. The probe was designed to rotate out of the vat for cleaning. The fiber optic probe, shown in figure 2, consisted of one fiber for light emission into the milk and one fiber for transmitting backscattered light from the milk to the photodetector. The optical fibers from the probe were routed to the control box where they were connected to the emitter and detector. The control box was installed above the vat. Backscatter was measured with an optical sensor (TSL235, Texas Instruments, Austin, Tex.) mounted to the fiber. The TSL235 output was a digital pulse (50% duty cycle) with the pulse frequency proportional to light irradiance. An infrared LED light (880 nm) was used as the light source.

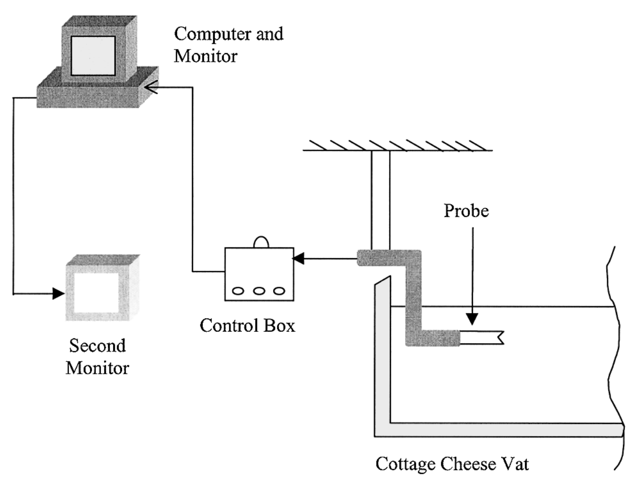

Figure 1–Schematic of the cottage cheese culture monitoring system installed at Winchester Farms Dairy.

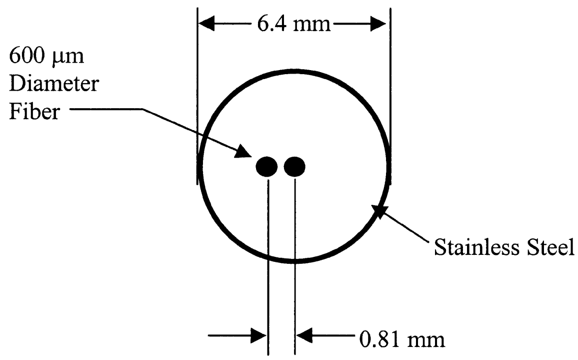

Figure 2–Schematic of the probe tip used to monitor the light backscatter during the coagulation of cottage cheese. The optical fiber located in the center emits light into the milk and the fiber located 0.81 mm from the center transmits the light scattered back to a photodetector.

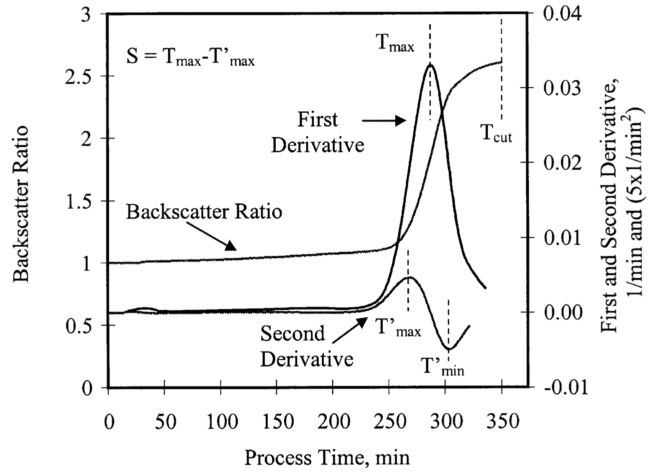

Figure 3–Backscatter ratio profile with the corresponding first and second derivative curves with curve parameters T_{cut}, T_{max}, T'_{max}, and T'_{min} identified. The second derivative curve has been scaled for emphasis.

Cottage Cheese Production

The cottage cheese production procedure was identical to the procedure described in Payne et al. (1998) with the following additional steps. Once the pH of the skim reached 6.0, eighty-five grams of rennet was added to the cheese vat and the operator pressed the "Enzyme Add" button to record the enzyme addition time. The data acquisition program activated the strobe alarm approximately 10 min prior to the predicted cutting time. The operators were able to deactivate the strobe alarm by pressing the "Alarm Recognition" button. The operator determined the appropriate cutting time based on pH measurements and a subjective evaluation of the curd texture. The actual cutting time was recorded when the curd cutting mechanism physically toggled a microswitch installed on the mixer rail. The toggling of the microswitch also terminated data collection and reset the Visual Basic program for the next test.

Data Analysis

Data collected and automatically stored by the computer during the culture process included process start time, process end time, and the light backscatter measurements from the fiber optic probe. Light backscatter measurements were collected every six seconds within the Visual Basic program and the average of 10 measurements (1 min of data) was recorded. Backscatter ratio (BR) was calculated by dividing the measured backscatter by the initial backscatter (averaged over the first 10 min after culture addition). The first derivative of the backscatter ratio was calculated using linear least squares regression on the most recently collected 31 backscatter ratio data points. The calculated slope was assigned to the midpoint of this data set. Thus, the first derivative calculation trailed the backscatter ratio by 15 min. The process time when the first derivative reached a maximum, T_{max}, was determined and used to predict the cutting time. Winchester Farms Dairy also provided skim milk processing data sheets and cottage cheese setting information sheets. The information gathered from these data sheets included casein content, initial pH of the milk, and milk solids (SNF).

The backscatter ratio profiles for each test were analyzed using a spreadsheet to determine potential process parameters. A typical profile and description of the parameters generated from the process curves are shown in figure 3. The time from culture addition to the maximum of the first derivative, T_{max}, the minimum and the maximum of the second derivative, T'_{min} and T'_{max}, and finally the difference between T'_{max} and T_{max}, denoted as S, were determined. The parameter S was an inverse measure of coagulation kinetics induced by the combined effect of culture growth and enzyme kinetics.

The validation tests were conducted by adding additional data analysis steps to the Visual Basic program to calculate the second derivative and determine S. Additionally, as discussed later, a new cutting time prediction algorithm and a culture growth algorithm were tested.

Results and Discussion

Algorithm Development for Cutting Time Prediction

Data were collected during the commercial culture of 49 vats of cottage cheese between 20 July 1997 and 30 October 1997. The data is summarized in table 1, given in terms of means and standard deviations. Casein content data were available in 18 tests and total nonfat solids data were available in 30 tests. The process parameters T_{max}, T'_{min}, T'_{max}, and S were calculated from the backscatter ratio profiles for the 49 tests. Regression analysis was conducted using the GLM procedure in SAS® (1995) on all the dependent variables listed in table 1. The parameters T_{max} and S were consistently found to be the better descriptors of cutting time throughout the various linear regression models tested. The following cutting time algorithm:

$$T_{cut} = \beta_1 T_{max} + \beta_2 S \qquad (2)$$

yielded parameters $\beta_1 = 1.045$, $\beta_2 = 2.453$, an uncorrected R^2 of 0.9997, and a standard error of prediction of 6.32 min. In the linear regression models tested, β_1 in equation 2 was very close to unity and typically between 1.03 and 1.05. Because a one-parameter algorithm is easier for operators to implement in the plant, β_1 was set to unity [regression conducted on $(T_{cut} - T_{max})$] and β_2 determined

Table 1. Summary of data collected at Winchester Farms Dairy between 20/7/97 and 30/10/97

Data	Mean	S.D.	N	Min.	Max.
Casein	2.65	0.14	18	2.41	2.83
SNF	9.64	0.24	30	8.98	10.16
Initial pH	6.59	0.02	49	6.52	6.64
pH at T_{cut}	4.70	0.01	49	4.68	4.73
T_{max}	292.2	20.9	49	248	348
BR at T_{max}	1.82	0.04	49	1.75	1.90
T'_{max}	273.4	20.2	49	232	326
BR at T'_{max}	1.28	0.02	49	1.23	1.34
T'_{min}	308.0	21.1	49	263	365
BR at T'_{min}	2.32	0.04	49	2.23	2.41
T_{cut}	351.8	25.4	49	294	431
BR at T_{cut}	2.55	0.04	49	2.45	2.65
BR at T = 60 min	1.012	0.005	49	1.003	1.027
BR at T = 90 min	1.018	0.006	49	1.005	1.035
BR at T = 120 min	1.027	0.008	49	1.010	1.046
BR at T = 180 min	1.055	0.011	49	1.030	1.078
BR at T = 210 min	1.072	0.012	49	1.045	1.094
BR at T = 240 min	1.114	0.074	49	1.062	1.510
BR at T = 270 min	1.389	0.360	49	1.077	2.489
BR at T = 300 min	1.998	0.440	48	1.116	2.535
BR at T = 330 min	2.385	0.263	40	1.359	2.630
BR at T = 360 min	2.483	0.114	13	2.186	2.635
BR at T = 390 min	2.488	0.138	5	2.253	2.595

SNF = Solids Non-fat.
T_{max} = Time at which the first derivative is maximum.
T'_{max} = Time at which the second derivative is maximum.
T'_{min} = Time at which the second derivative is minimum.
T_{cut} = Operator-selected cut time.
BR = Backscatter ratio.
T = 0 min at culture addition.

from regression. The resulting cutting time algorithm after rearranging was as follows:

$$T_{cut} = T_{max} + \beta_2 S \quad (3)$$

Linear regression with this algorithm and the collected data using the GLM procedure of SAS® (1995) resulted in the following:

$\beta_2 = 3.16$	$SE(\beta_2) = 0.0485$	$P = 0.001$
SEP = 6.34 min	N = 49	$R^2 = 0.989$

where
- β_2 = least squares regression coefficient
- $SE(\beta_2)$ = standard error of estimate for β_2
- P = probability that F-critical will exceed the F-test statistic for the linear model
- SEP = standard error of prediction
- R^2 = coefficient of determination based on sum of squares uncorrected for the mean
- N = number of data used in the regression

A plot of actual versus predicted cutting times is shown in figure 4.

Algorithm Development for Growth Monitoring

The mean backscatter ratio continuously increased during the first 210 min of culture. The standard deviation about the backscatter ratio mean was relatively small. Figure 5 shows the backscatter ratio, taken from table 1, with error bars representing ±1 standard deviation plotted as a function of process time. It was postulated that this information could be used to monitor culture growth.

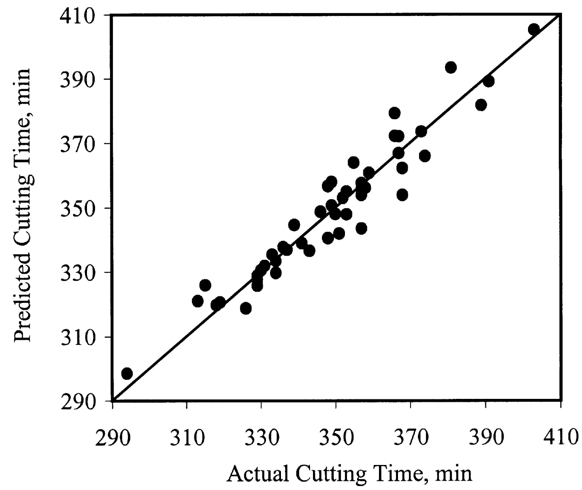

Figure 4–Plot of actual and predicted cutting times for the data collected July through October 1997 using the algorithm $T_{cut} = T_{max} + \beta_2 S$.

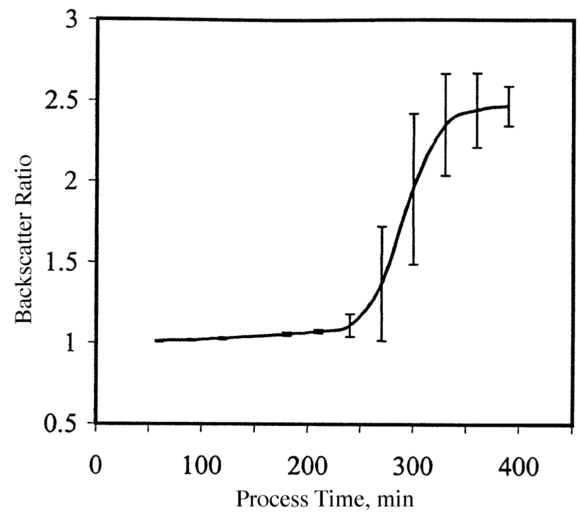

Figure 5–Average backscatter ratio for data collected July through October 1997, shown with one standard deviation error bars.

Analyses were performed with BRs from the first 210 min of culture. The mean backscatter ratio was found by regression to be described as a function of culture time by the following relationship:

$$BR = \beta_0 + \beta_1 t^2 \quad (4)$$

where $\beta_0 = 1.0062$ and $\beta_1 = 1.456 \times 10^{-6}$ (both parameters significant with P = 0.001) with an R^2 of 0.9998 and standard error of estimate of 0.00042. The variability of the standard deviation, s, with culture time was found by regression to be described by the following relationship:

$$s = \beta_0 + \beta_1 t \quad (5)$$

where $\beta_0 = 0.001599$ and $\beta_1 = 5.388 \times 10^{-5}$ (both parameters significant with P = 0.001) with an R^2 of 0.9917 and standard error of estimate of 0.00035.

The culture growth algorithm was constructed using these relationships to calculate the expected mean and standard deviation of BR for culture times between 60 and 210 min. The algorithm would indicate high, normal-high, normal, normal-slow, or slow growth if the calculated BR was > 2s, 2s > BR > s, s > BR > –s, –s > BR > –2s, or –2s > BR, respectively. Consider the BR at 180 min, it had an average of 1.054 and had a standard deviation of 0.011. Thus, 95% of the time the BR at 180 min fell above 1.032. If the BR were to fall below this value the algorithm would label the culture growth as slow.

Unlike the algorithm for predicting the cutting time, the algorithm for growth monitoring is not based on the relationship between data taken during a single run. For this reason, the two algorithms were validated separately.

Algorithm Validation for Cutting Time Prediction

Data were collected during the commercial culture of nine vats of cottage cheese between 25 March and 5 May 1998 to validate the improved cutting time prediction algorithm. A summary of the collected data is tabulated in table 2. The monitoring system was reprogrammed to calculate the second derivative in addition to calculating the backscatter ratio and the first derivative. The prediction algorithm was updated to the cutting time algorithm described by equation 3. Prior to data collection, the operators were instructed to use the sensor predicted cutting time as a guide for selecting the appropriate cutting time. The value of β_2 was set to 3.0 so that the cutting time alarm would be activated early and provide the operator adequate time to evaluate the readiness of the curd for cutting.

The standard error of prediction of the cutting time prediction algorithm (eq. 3) was 6.4 min for the nine validation tests. A plot of the predicted versus the operator selected cutting times is shown in figure 6. To quantify the fit of the model, analysis was performed to determine if there was a significant difference between the predicted and actual cutting times. The data were fit to a line and a standard F test was used to test the null hypothesis, Ho: intercept = 0 and slope = 1 (Teng, 1981). With a resulting F statistic of 0.5895 and a F_{crit} (α = 0.05) of 4.74 (Snedecor and Cochran, 1989), the null hypothesis cannot be rejected. Based on this evidence, it was concluded that the predicted and actual cut times are not significantly different and the model can be considered a good fit.

Table 2. Summary of data collected at Winchester Farms Dairy between 25/3/98 and 10/5/98

Data	Mean	S.D.	N	Min.	Max.
T_{max}	308.8	19.1	9	264	328
T'_{max}	290.9	17.8	9	249	308
S	17.9	1.7	9	15	20
Predicted T_{cut} $\beta_2 = 3.0$	362.4	23.3	9	309	388
Predicted T_{cut} $\beta_2 = 3.16$	365.3	23.6	9	311	391
Actual T_{cut}	366.3	23.0	9	313	387
BR at T = 60 min	1.003	0.002	9	1.000	1.007
BR at T = 90 min	1.007	0.002	9	1.005	1.011
BR at T = 120 min	1.014	0.003	9	1.010	1.017
BR at T = 180 min	1.023	0.006	9	1.015	1.034
BR at T = 150 min	1.037	0.013	9	1.026	1.064
BR at T = 210 min	1.054	0.021	9	1.037	1.101
BR at T = 240 min	1.073	0.035	9	1.048	1.153
BR at T = 270 min	1.172	0.248	9	1.061	1.828
BR at T = 300 min	1.608	0.369	9	1.186	2.315
BR at T = 330 min	2.343	0.210	8	2.019	2.612
BR at T = 360 min	2.663	0.051	7	2.574	2.708

T_{max} = Time at which the first derivative is maximum.
T'_{max} = Time at which the second derivative is maximum.
S = $T_{max} - T'_{max}$.
Actual T_{cut} = Operator-selected cut time.
BR = Backscatter ratio.
T = 0 min at culture addition.
Predicted T_{cut} = $T_{max} + \beta_2$.

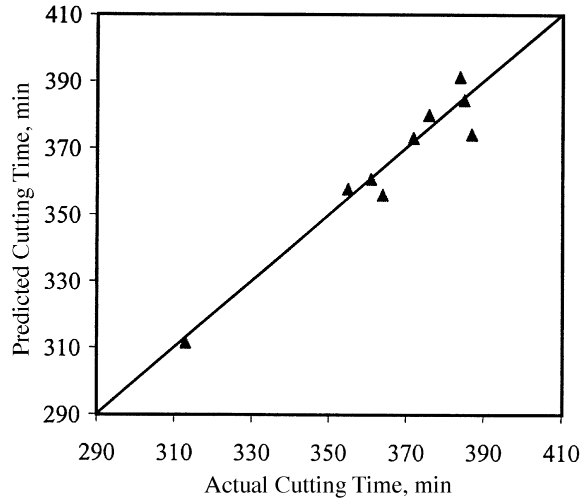

Figure 6–Plot of actual and predicted cutting times for the data collected March through May 1998 using the algorithm $T_{cut} = T_{max} + \beta_2$ S.

In the above statistical analysis, the operator selected cutting time was assumed to be the *correct* cutting time. In reality, the operator's judgement was subjective and has an unknown variability. In addition, variability due to pH and casein content may have also affected the microbial growth dynamics of the culture. The initial pH and casein content values were measured in an attempt to statistically eliminate the variability of these factors. However, there was insufficient statistical evidence to do so for two possible reasons: casein data was only available in 18 of the 49 tests and the pH readings were recorded with a single decimal place resolution.

The validation data confirm that the operators frequently selected the same cutting time as predicted. Ideally, cutting the curd at the *optimum* time would result in the highest quality and lowest losses. Yet, the operator selected cutting time may differ a few minutes from the *optimum* cutting time because of differences in operator judgment, precision of operator inspection, and the time required to manually set the cutting knives. The cutting time prediction is based on the culture behavior and may be a better estimate of the *optimum* cutting time than the cutting time chosen by the operators. This suggests that the standard error of 6.4 min may be artificially inflated.

Algorithm Validation for Growth Monitoring

The backscatter ratios for the nine validation tests were analyzed. Bacteriophage or other processing complications did not affect the culture growth of the cottage cheese cultures during these tests. Therefore, the utility of using the growth monitoring system as an early warning of slow culture growth was not formally tested. The backscatter ratios between 30 and 210 min after culture addition for the validation tests appeared to have the same quadratic response but were offset. The average backscatter ratio at

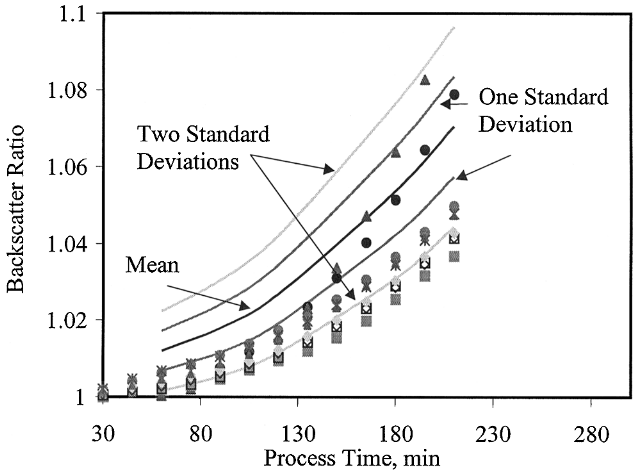

Figure 7–The backscatter ratio data collected March through May 1998 (plotted as scatter points) shown with the mean of the data collected July through October 1997 (plotted as solid lines) and standard deviation curves.

60 min was 1.012 and 1.003 for the July through October 1997 and March through May 1998 tests, respectively. This offset was considered a result of a change in calculating the reflectance ratio to eliminate the variability during the first 15 min after culture start. For this reason the backscatter ratios did not fall within the same range as those collected from July through October 1997 as is illustrated in figure 7. The backscatter ratio and its derivatives are response-based parameters and are thus influenced by sensor design and milk composition, thus limiting the usefulness of these measurements for characterizing growth. A time-based measurement of growth, independent of these factors, is needed. The change in reflectance proportional to t^2 as described by equation 4 suggests that a first order growth model may describe the change in reflectance during the early phase of culture growth. The specific growth rate parameter from a first order model may provide the time-based parameter needed to monitor culture growth and is suggested for future work.

Processing Plant and Operator Assessment

The operators reported that the system was very useful for selecting cutting time. The light backscatter monitoring system made it possible for the cottage cheese culture progress to be monitored. The operators were able to conveniently observe the culture status from the graphical presentation of the backscatter ratio, first derivative, and second derivative. The operators used the strobe light that was activated shortly before the predicted cutting time to determine when to closely monitor vat 8. The information from the system was presented to the operators in a clear and concise manner.

The cutting time prediction algorithm, as described by equation 3, was preferred over the previous algorithm. It had the advantage of removing operator variability in activating the Culture Addition button time and thus makes the prediction more robust. The algorithm essentially predicted cutting time based on a measure of the coagulation kinetics, S.

The prediction of culture growth based on an increase in backscatter ratio was not found to be beneficial primarily because bacteriophage attack was not a problem during the testing period. The presentation of the growth ratings should be reduced possibly to three: slow, normal, and high.

Conclusions

An improved cutting time prediction algorithm, $T_{cut} = T_{max} + \beta_2 S$ (where β_2 is a constant) was developed for the culture of cottage cheese, where S is a time-based parameter with less dependence on product composition than previous parameters. The standard error of prediction of the improved algorithm was 6.4 min. The operators considered the system beneficial for selecting an optimal cutting time. A growth-monitoring algorithm based on trends in backscatter ratio during the first 210 min of the culture process was developed and tested. Insufficient data were available to validate the algorithm, yet the results indicate that a specific growth rate parameter from a first order model may provide the time-based parameter needed to monitor culture growth.

The backscatter monitoring system gave an accurate, simple prediction of the cottage cheese curd cutting time and a means by which the operators could monitor the progress of the culture. The ability to automatically predict the curd cutting time may someday lead to automated curd cutting or at least free up the operators to perform other tasks.

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