

Determination of kappa number reduction in pulp and COD in bleach plant effluents using multiwavelength spectrometry and multivariate calibration

ANDERS SPARÉN, LARS RENBERG, ERIK FURUSJÖ, CHRISTINA AHLQVIST HILLFORTH, AND LARS-GÖRAN DANIELSSON

ABSTRACT: We propose a method for the simultaneous determination of kappa number reduction in pulp over a bleaching stage and chemical oxygen demand (COD) in bleach plant effluents, using multiwavelength spectrometry on the effluent and multivariate calibration. A model for kappa number reduction, based on ultraviolet (UV) spectra from a flow system, gave a mean prediction error of 0.24 K units. Models for COD gave relative errors of 2.8%-3.7% and 6%-8%, for the UV and visible/near infrared region (manual measurements), respectively. These prediction errors are similar to those expected from the manual reference measurements.

Application: The proposed test method could easily be adapted to on-line monitoring of the kappa number reduction in a pulp mill.

Several parameters are used to characterize the pulp quality, one of those being remaining lignin content. The most commonly used method to estimate this parameter is the kappa number (κ). During bleaching, the lignin is partially degraded into water-soluble organic material and thus, κ decreases.

There is, however, no direct relationship between the lignin content of the pulp and κ [1]. The classical method for determining the kappa number in pulp is operationally defined and laborious [2]. Further, recent studies suggest that it overestimates the lignin content in pulp [3]. Alternative spectroscopic methods for determining the lignin content in pulp have been proposed, using e.g. ultraviolet/visible (UV/Vis) spectroscopy [4], Fourier transform infrared spectroscopy (FTIR) [5, 6], near infrared spectroscopy (NIR) [6-9], and ^{13}C nuclear magnetic resonance spectroscopy (NMR) [6].

An alternative method to determine the lignin content of pulp could be to estimate the kappa number reduction over a bleaching stage, by correlating the spectral information from the dissolved organic material in the bleach plant effluent with the kappa number reduction. Such indirect methods have been proposed for estimating κ in pulp, by means of measurements of the UV [10] or FTIR [11] absorbance of black liquor at specific wavelengths, or its total organic carbon (TOC) content [12]. These studies, how-

ever, only used laboratory samples and calibrations based on absorbances at single wavelengths, which are likely to make the methods sensitive to interferences. In addition, some of these results have been difficult to repeat with the same degree of confidence [7].

Spectroscopic measurements of the effluents may also make it possible to simultaneously determine the chemical oxygen demand (COD), an important environmental parameter, and other parameters, such as the concentrations of sugars.

The purpose of this study was to find out whether it is possible to characterize the organic content in bleach plant effluents and predict the kappa number reduction in pulp and COD in the effluent, using a combination of multiwavelength spectrometric measurements and multivariate calibration. The study used laboratory samples, as well as samples obtained from a full-scale bleach plant at a Swedish kraft pulp mill. The suggested method has great potential of being further developed into an on-line method.

MATERIALS AND METHODS *Samples*

We included three groups of samples in this study: one sample set bleached at the laboratory (denoted laboratory samples, LS) and two sets of samples taken from a full-scale production plant (denoted plant samples, PS1 and PS2, respectively).

LS consists of about 100 pulp samples, bleached according to an experimental plan including 1-5 bleaching stages, and their corresponding bleach effluents. The bleaching procedures of the samples were denoted D, D[EO(P)], D[EO(P)]D, D[EO(P)]D[E(P)], D[EO(P)]D[E(P)]D, indicating which bleaching stages were included. The step in rounded brackets was optional and samples with and without the (P) step were included. We measured the bleach effluents with UV spectrometry and determined the kappa number for the corresponding pulp samples.

Each of the sample sets PS1 and PS2 consists of 60 samples of bleach plant effluents. Each set constitutes two subsets of 30 samples from two different bleaching stages, D0 and E1. The D0 subsets are marked with an A, while the E1 subsets are marked with a B, so that the part of the PS1 set coming from the D0 bleaching stage is denoted PS1A, and so on.

We obtained PS1 and PS2 samples from the same locations in the same plant, but the PS2 set was collected approximately 6 months after PS1. We measured the samples with spectrometry in the UV range (PS1) and the Vis/NIR range (PS2), respectively. The kappa number was determined for the corresponding pulp samples of PS1, while COD was determined on bleach effluents from both PS1 and PS2. The samples were frozen and stored at -18°C ($\sim 0^{\circ}\text{F}$) in 50 or 100 ml polyethylene containers until analysis.

Reference analysis

Kappa number was determined according to SCAN C1:77 [1], while COD was determined with the ISO 6060-1989 method.

UV measurements

Preliminary experiments performed on laboratory samples showed that the absorbances in the UV range, using an optical path length of 10 mm, were extremely high. Dilution of the samples was impractical; it also changed the pH values of the samples and thus, the absorbances. For these reasons, we developed a flow system (Fig. 1) that made it possible to perform the measurements directly on undiluted samples. The samples were pumped by means of a peristaltic pump (Gilson Minipuls 2) at a speed of 2.4 ml min⁻¹ and filtered on-line through a 45 µm filter. They were then transported to a Spectra Focus Optical Scanning Detector (Spectra-Physics), equipped with a fused silica capillary with an inner diameter of 0.53 mm as the flow through cell. Measurements were made directly across the capillary, on which a 10 mm long window had been obtained, by burning off the polymer coating. We used a spectral operating range between 200 and 360 nm, in even intervals of 2 nm. The absorbance data obtained were transferred to a computer equipped with the Autolab Software (Spectra-Physics).

Vis/NIR measurements

For the PS2 sample set, Vis/NIR transmission measurements in the range 400-2500 nm were carried out in a 10 mm cuvette using a NIRSystems 6500 spectrometer (Foss NIRSystems, Silver Spring, Maryland, USA). Due to low light throughput, the signal above 1800 nm was very noisy in all spectra. Therefore, we did not use the 1800-2500 nm range in the multivariate modeling.

Spectral pretreatment

Particles in samples can cause "non-chemical" spectral shifts due to light scattering. Before multivariate calibration of NIR spectra, it is often beneficial to reduce or remove such effects by spectral pretreatment, since the effects are generally not related to the response(s) modeled. Commonly applied spectral pretreatment techniques for this purpose are *multiplicative scatter correction* (MSC) [13] and first or second derivative

filters [14]. In this study, we applied MSC to both UV and Vis/NIR spectra for this purpose.

Software

All computations were performed with the computer programs *Simca-S for Windows 5.0* (Umetrics, Sweden), *the Unscrambler* (versions 6.11b and 7.5, CAMO, Norway) and *MATLAB 4.2c* (Math Works, Inc., Natick, Massachusetts, USA) equipped with Barry Wise's "PLS Toolbox" (Eigenvector Technologies, Manson, Washington, USA).

Multivariate modeling

In this work, we used the multivariate techniques *principal component analysis* (PCA) and *partial least squares regression* (PLS), with which the vast information in multivariate (spectroscopic) data can be compressed to a few so-called "latent variables" that explain most of the variance in the original data. The general purposes of the techniques are to simplify the interpretation of the original data (PCA) and to find relationships between spectral data and chemical information (PLS) by reducing the number of variables and eliminating the collinearities common in spectra. These techniques have been more closely described by Martens and Naes [15]. For validating the models, we used cross validation [15], with leave-one-out segmentation, if not otherwise stated. We also validated a few models with external test sets, the samples of which had not been present in the calibration sets. The prediction errors of the models were estimated with the *root mean square error of prediction* (RMSEP), as defined in equation (1) [16]

$$RMSEP = \sqrt{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}} \quad (1)$$

where

$\hat{y}$ = The value of sample i , predicted with the model

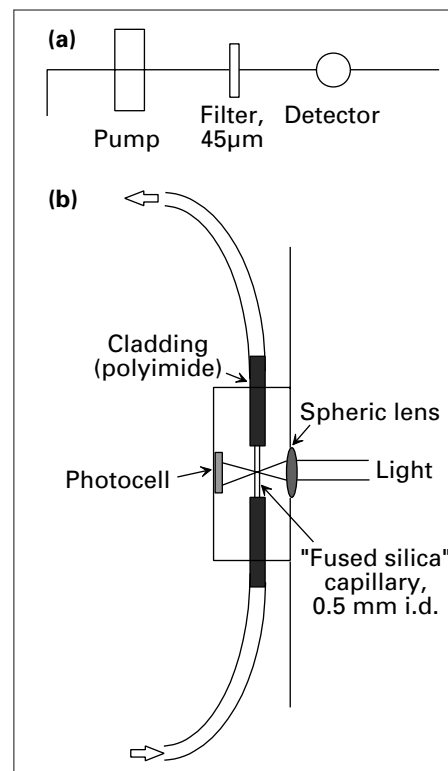
y_i = the reference value of sample i

N = the number of samples in the calibration or prediction set.

RESULTS AND DISCUSSION

Sample handling

Since sampling and reference analyses were carried out at one site and spectral measurements at another, the samples



1. The flow system used for recording UV spectra: (a) the flow system set-up; (b) an enlargement of the fused silica capillary used as the flow through cell.

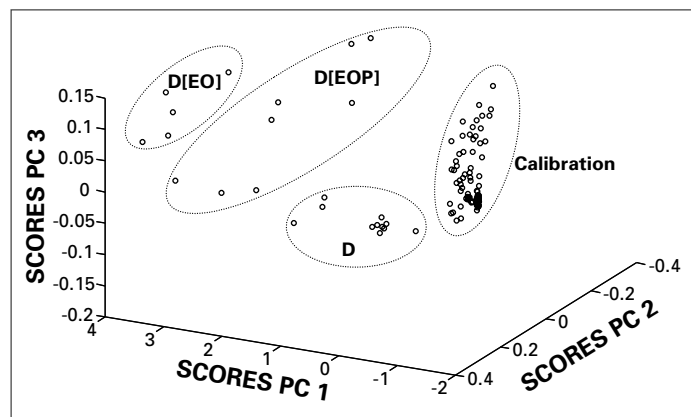
were frozen and stored at -18°C (~0°F). To ensure that freezing and thawing did not have any significant effect on the spectral information, we compared the spectra of fresh samples with those of frozen and thawed ones and found no significant differences. Nor did storage at room temperature for up to four days have any significant effect on the spectra.

Linearity of the UV measurements

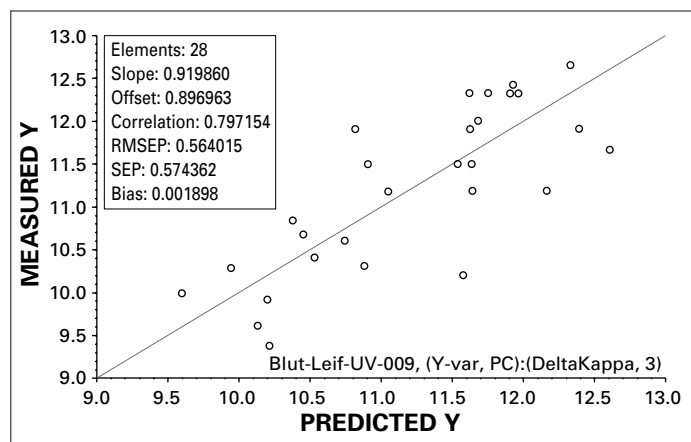
A common problem when applying spectrometric methods in the UV/Vis range to industrial samples is the extremely high absorbances obtained. This may lead to non-linear responses, which complicate calibration. The principal solutions to this problem include the following:

1. dilute the samples
2. use a sufficiently short optical path length to avoid non-linear responses
3. leave out or down-weight spectral regions with highly non-linear responses
4. mathematically transform the

KAPPA MEASUREMENT



2. Classification of samples with PCA, based on UV spectra of bleach effluents from the laboratory study. Clusters in the scores plot correspond well with the different bleaching stages in the process. Ellipses only mark the groupings, they do not indicate statistically significant classes.



4. Prediction of $\Delta\kappa$, using a cross-validated PLS model with 3 PLS components, and leave one out cross validation.

spectral data into linear data that could be handled with linear calibration models

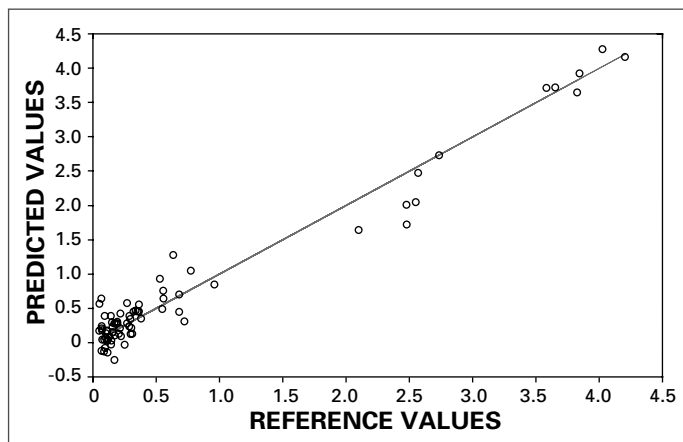
5. apply non-linear multivariate calibration models.

For this study, we used the first three methods.

With the flow system including on-line filtration and an optical path length of 0.5 mm, the maximum absorbances obtained were below 1.7 absorbance units (a.u.). Linearity tests of the measuring system using synthetic solutions of ascorbic acid showed a linear response up to about 1.7 a.u. The on-line filtration had no significant effect on the absorbances, but made the measurements more repeatable. The relative standard deviations for four consecutive measurements on the same sample were 0.1%-1.0%, varying with the amplitude of the signal at different wavelengths.

Modeling $\Delta\kappa$

Choice of response parameter. The content of dissolved organic matter in the effluents of a given bleaching step relates to how much lignin was dissolved from the pulp during that step. There should, therefore, be a relationship between the spectral information obtained from the aqueous phase and the differ-



3. Prediction of $\Delta\kappa$, using a cross-validated PLS model with 6 PLS components. Data pre-treatment: Mean centring. Solid line denotes slope 1.0. Model characteristics: RMSEP = 0.24; $r^2 = 0.98$.

ence in kappa number over a bleaching step. We call this difference 'kappa number reduction' ($\Delta\kappa = \kappa_{in} - \kappa_{out}$).

Laboratory bleached samples

A feasibility study, using diluted samples and spectra obtained with a 10 mm cuvette showed that the idea of predicting the kappa number reduction from UV spectra of bleach plant effluents was promising. A more thorough study, including both samples from a bleach plant of a Swedish kraft pulp mill and laboratory bleached samples, was performed, using the flow system described earlier. We applied principal component analysis to the UV spectra of the bleach plant effluents. The samples grouped into clusters that correspond well to the bleaching stages from which the samples originated (Fig. 2). Based on this classification, samples belonging to the bleaching stages D and D[EOP] were excluded from the quantitative PLS models; the rest were included in the calibration model. This selection of samples improved the quality of the models dramatically.

Figure 3 shows the correlation between values predicted with a typical PLS model using six PLS components and corresponding values obtained with the standard reference method on laboratory samples. The agreement between the two methods proved to be good, with a high correlation coefficient (r) for the regression line ($r=0.99$), a slope not significantly different from 1.0, and an intercept very close to 0. The prediction error (RMSEP) of the model was 0.24 κ units. We also tested this model with external test sets. It showed high stability and good prediction ability (data not shown).

Plant samples 1

Figure 4 shows the correlation between the reference values of kappa number reduction and the values predicted with a PLS model using three PLS components, for samples obtained from a Swedish kraft pulp mill. The agreement is slightly worse than for the models based on laboratory samples. The main reason for this is probably the limited range of the $\Delta\kappa$ in this sample set, which makes calibration difficult. It is thus clear that efforts should be made to extend the range of $\Delta\kappa$ covered by the calibration set.

Modeling COD

UV measurements. Principal component analysis of UV spectra from the PS1 sample set shows that two principal components

(PCs) are sufficient for explaining 99.9% of the variance in both PS1A and PS1B when these are modeled separately. The amount of variance explained by two PCs is somewhat lower for the combined data sets. Scores from this combined PCA model show that the samples are grouped with respect to sampling location, *i.e.* bleaching stage. The grouping indicates that it might be beneficial to treat the subsets separately, also in the calibration of COD.

For the PS1 sample set, measured in the UV range, the approximate range of COD values are 1000-1500 for the D0 samples (PS1A) and 1500-3000 for the E1 samples (PS1B). We removed two samples, one each from PS1A and PS1B, due to obviously erroneous COD determinations, leaving 29 samples in each subset.

Table I shows data for three calibration models developed for the UV spectra from the PS1 sample set. The prediction error (as RMSEP) and the number of PLS components were determined by leave-one-out cross validation. For subset A, one PLS component is sufficient for satisfactory prediction of COD, while subset B requires two PLS components. The prediction error is higher for the model for subset B, but the COD range is approximately three times wider for subset B than for subset A, hence the higher correlation for the subset B model. As indicated by the PCA analysis of the spectral data, a higher model complexity is required when subsets A and B are modeled together. The performance of the model in terms of prediction error is similar to that of the models developed for the separate subsets (see **Fig. 5**).

All calibration models described above are built using the full spectral range of the data, *i.e.* 200-360 nm. The predictive ability of the models decreases slightly if data from wavelengths in the region 280-360 nm is removed. If data from the low wavelength region is removed on the other hand, a larger decrease in predictive ability is observed, indicating that this region is important for the prediction of COD from UV data.

Vis/NIR measurements

Vis/NIR measurements were carried out for the PS2 sample set. As for PS1, this sample set consists of two subsets of 30 samples each. **Figure 6** shows the spectra from subset PS2A. The COD range is larger for subset B (samples from the E1 bleaching stage) than for subset A from the D0 stage. COD lies between 1000 and 2000 for subset A and between 1500 and 3000 for subset B, except for the extreme sample PS2B-2 that has a COD value of 5500. We removed this sample as an outlier in all models discussed below.

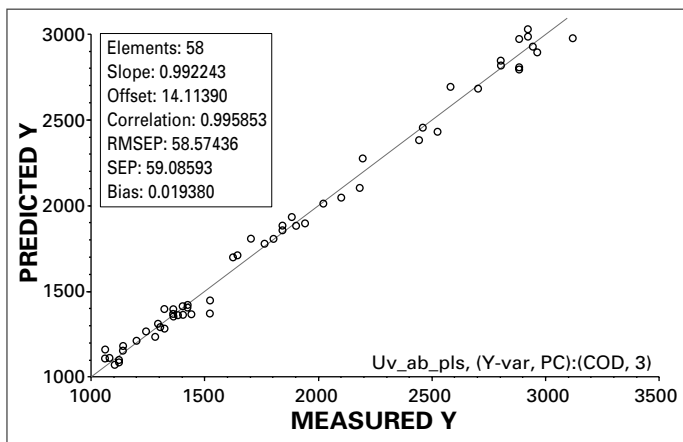
PCA of the spectral data reveals that the Vis/NIR data has a significantly higher complexity than the UV data discussed above. A large number of principal components are needed to describe the major part of the variance in the data. As for the UV spectra from PS1, a grouping is visible in scores when PCA is applied to Vis/NIR spectra from both subsets of PS2 simultaneously.

If only the Vis range (400-700 nm) is studied, the complexity of the data is lower, but still higher than for the UV data. The higher complexity might result from factors in addition to the different spectral ranges. Samples studied with UV and Vis/NIR spectroscopy were not exactly the same. Although separated in time, PS1 and PS2 samples did come from the same locations in the same plant and should thus be similar in composition. In

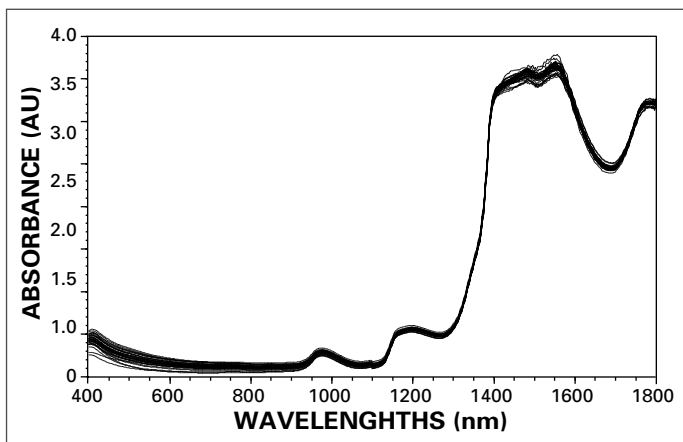
SUBSETS	PLS COMP. ^a	RMSEP ^a	r ^b
A	1	46.7	0.940
B	2	62.8	0.992
A+B	3	58.6	0.996

^a Determined by leave-one-out cross validation
^b Correlation between measured and predicted COD.

I. PLS calibration models for COD in the PS1 sample set from UV spectra. One sample from each subset was removed in all models.



5. Predicted vs. measured COD values for the PLS model built on UV spectra from subsets PS1A and PS1B, see Table I.



6. Vis/NIR spectra from subset PS2A.

addition, a higher complexity of spectral data in the NIR region can be expected, since more chemical species absorb radiation in this region as compared to the UV range. This also indicates that more information might be extracted from the spectral data. Results of investigations aiming at predicting the concentrations of specific groups of organic species in the samples that contribute to COD (sugars and fatty acids) indicate that this is a difficult task.

Table II lists PLS calibration models developed for the PS2 spectral data. Prediction of COD is possible, but the prediction errors are higher in all cases than for the UV calibration models previously discussed. When the subsets are modeled separately, more PLS components are needed for subset A than for subset

KAPPA MEASUREMENT

SUBSETS	MSC	RANGE [nm]	OUTLIERS ^a	PLS COMP. ^b	RMSEP ^b	R ^c
A	no	400-700	3	3	135	0.74
	yes	400-1800	4	7	120	0.74
	yes	400-700	5	5	122	0.84
B	no	400-1800	4	2	142	0.88
	no	400-700	4	1	143	0.88
	yes	400-1800	4	1	140	0.88
A+B	yes	400-700	4	1	144	0.88
	no	400-1800	7	5	157	0.94
	no	400-700	7	5	135	0.96
	yes	400-1800	7	2	152	0.95
	yes	400-700	6	5	146	0.96

^a Number of samples that were removed from the calibration as outliers.
^b Determined by leave-one-out cross validation.
^c Correlation between measured and predicted COD.

II. PLS calibration models for COD in the PS2 sample set from Vis/NIR spectra.

B, which only requires one component if MSC pre-treatment is used. When both subsets are modeled simultaneously, slightly higher prediction errors are obtained than for separate subset models.

The selection of spectral range and whether or not MSC pre-treatment is used has some effect on predictive ability, but no firm conclusions can be drawn from this investigation on the optimal choice of range and pre-treatment. The results do, however, indicate that the Vis region contains the most information on COD. When only the NIR range (700-1800 nm) is used, the predictive ability is significantly lower than for all models in Table II.

Sources of error

A possible source of error in multivariate calibration is the quality of the reference values. Many manual methods are fairly imprecise. The standard method for measuring kappa number has a reasonable average repeatability (relative standard deviation, RSD ~3.8%) for kappa numbers between 10 and 20, and a good repeatability (RSD ~1.2%) for kappa numbers between 20 and 190 [2]. In our laboratory study, the measured kappa numbers (before calculating $\Delta\kappa$) were below 6, for the samples included in the model. In addition, taking the difference between two reference values when calculating $\Delta\kappa$ will increase the error (by a factor of $\sqrt{2}$). Thus, it is reasonable to assume that the precision of the reference analyses is limited, *i.e.* an RSD around 4% or greater, which is in the same range as the RMSEPs found in Figs. 3 and 4.

The models proposed for COD determination also yield prediction errors in

the same range as the precision of the reference method (COD_{ref}), which in a recent Swedish intercalibration was estimated to be 6%-8% [17]. Lower RMSEP values than the precision of the reference method should not be expected in a multivariate calibration. This does not imply, however, that the *precision* of the multivariate method is limited to that of the reference method [18].

The analytical performance of both $\Delta\kappa$ and COD measurements based on spectroscopy and multivariate models are thus similar to those of the corresponding manual reference methods. However, the measurement system is very stable and in a given process situation, it should be possible to detect even very small changes in those parameters.

Apart from the errors in the reference analyses, it is essential that the bleach plant effluents investigated can be correctly assigned to certain portions of pulp. In laboratory milieu, the samples are carefully rinsed between two bleaching stages and no real problems are envisioned. In a production plant the correct assignment of a portion of filtrate to a pulp sample is more difficult due to carry-over of filtrate with the pulp from the previous stage.

Applicability

An interesting question is whether the proposed methods can be applied to on-line analysis within a pulp mill. Using the flow system described, we have minimized the manual work involved in the measuring procedure. A critical point, however, may be whether the narrow fused silica capillary ($d_i=0.53$ mm) is usable for on-line analysis. Even though

the capillary is narrow, the manifold does not contain any sharp bends that would increase the risk of clogging. In order to minimize this risk, we used on-line filtration through a rather crude filter (45 μm). These precautions have been sufficient for the samples we have studied and the filter lasted for quite some time (a single filter was used during the whole study on laboratory samples). If necessary, it is probably possible to insert an even cruder filter. Whether this would be sufficient for on-line monitoring in full-scale pulp production needs to be tested.

CONCLUSIONS

The kappa number reduction in pulp can be successfully predicted, using a combination of spectral information from the aqueous phase of bleach plant effluents and multivariate statistical models. A rapid, easy to handle flow system that includes sample preparation, requires small sample volumes and gives repeatable results will facilitate measurements. Determination of COD in bleaching effluents from spectroscopic measurements and multivariate calibration is feasible. UV spectroscopy seems superior to the Vis/NIR range for this purpose, giving estimated prediction errors of approximately 60 COD units. Further investigations are needed to decide whether it is advantageous to model the different bleaching stages separately or to build one model covering samples from several stages. Our investigations show no significant difference in performance.

In order to use the proposed method for on-line monitoring of the kappa number in a pulp mill, the flow system must be tested on-line, to confirm that it is robust enough to monitor real samples for a longer period of time. Clogging of the optical cell might be a problem, even though that is not our experience. **TJ**

ACKNOWLEDGEMENTS

We thank the following persons for their contributions that made this work possible: Hans Johansson, Solvej Herstad-Svård, Lennart Andersson, Max Rosén, Delphine Marel, Leif Johansson, Greger Andersson, and Mikael Karlsson. In addition, we thank Foss Sweden for kindly providing an NIR instrument.

LITERATURE CITED

1. "SCAN-C 1:77: Massa, Kappatal," *Scandinavian Pulp, Paper and Board*. Caslon, Stockholm (1977).
2. In *Tappi Test Methods 1992-1993*. TAPPI, Atlanta, Georgia, USA. (1992).
3. Jiebing, L., "Towards an Accurate Determination of Lignin in Chemical Pulps. The Meaning of Kappa Number as a Tool for Analysis of Oxidizable Groups," *Ph.D. Thesis*, The Royal Institute of Technology, Stockholm, Sweden (1999).
4. Kubulnieks, E., Lundqvist, S.-O., and Pettersson, T., *Tappi J.* 70(11): 38(1987).
5. Schultz, T.P., Templeton, M.C., and McGinnis, G.D., *Anal Chem.* 57: 2867(1985).
6. Wallbäcks, L., Edlund, U., Nordén, B. and Berglund, I., *Tappi J.* 74(10): 201(1991).
7. Birkett, M.D. and Gambino, M.J.T., *Tappi J.* 72: 193 (1989).
8. Easty, D.B., Berben, S.A., DeThomas, F.A., and Brimmer, P.J., *Tappi J.* 73(10): 257(1990).
9. Olsson, R.J.O., Tomani, P., Karlsson, M., et al., *Tappi J.* 78(10): 158(1995).
10. Bobier, W.D., Poniatowski, S.E., and Walkinshaw, J.W., *Tappi J.* 64(10): 122(1981).
11. Michell, A.J., *Tappi J.* 73(4): 235(1990).
12. Genco, J.M., Hassler, J.C., and Busayasakul, N., *TAPPI 1983 International Pulping Conference Proceedings*, TAPPI PRESS, Atlanta, p. 11.
13. Geladi, P., MacDougall, D., and Martens, H., *Appl Spectrosc.* 39(3): 491(1985).
14. Savitzky, A. and Golay, M.J.E., *Anal Chem.* 36(8): 1627(1964).
15. Martens, H. and Naes, T., *Multivariate Calibration*, John Wiley, New York (1989).
16. Naes, T. and Isaksson, T., *NIR News* 2(4): 16(1991).
17. Lagerman, B. and Sköld, E., "Provningsjämförelse 1999-2 - AOX, BOD₇, COD_{Cr}, COD_{Mn}, TOC, pH", *ITM-rapport 79*, Institute of Applied Environmental Research, Stockholm, Sweden (2000).
18. Fearn, T., *NIR News* 7(2): 3(1996).

Received: January 2, 2001
Revised: September 25, 2001
Accepted: October 6, 2001

This paper is also published on TAPPI's web site <www.tappi.org> and summarized in the January *Solutions! for People, Processes and Paper* magazine (Vol. 86 No. 1)

INSIGHTS FROM THE AUTHORS

During the last decade or so, on-line analysis has become an important tool for increasing efficiency in pulp mills both in R&D and in production-scale mill operations. Since our research has focused on process analytical chemistry since the early 1990s, this area of application seemed a natural choice for further study.

This work is related to our previous work on various aspects of sulfide chemistry during kraft cooks and the production of polysulfides. Although not directly linked, the analytical systems developed all facilitate direct on-line control of important parts of a pulp mill.

Initially we expected problems with the fibers occurring in the samples. Varying fiber loads could easily make complicated filtration systems necessary. However, it turned out that a simple coarse filtration was sufficient for the samples we tested. A very simple and straight flow path eliminated most possibilities for capture of flowing debris that could lead to clogging.

One of the more surprising discoveries of our study was

the ruggedness of the spectroscopic sampling system. The capillary without cladding is very fragile, but in the holder in the spectrophotometer, it is rugged. The original capillary is still in use several years after it was first inserted.

The most direct benefit for mills is probably that the system can substantially ease process development in pilot plants or in the lab. However, the system is rugged enough for use in production should there be a reason to do so.

—Lars-Göran Danielsson

Sparén and Danielsson are with AstraZeneca, Tablet Production Sweden, SE-151 85 Södertälje, Sweden; Renberg is with Eka Chemicals, Bohus, Sweden; Furusjö is with IVL Swedish Environmental Research Institute, Stockholm, Sweden; and Hillforth is with Cellchem AB, Stockholm, Sweden; email Danielsson at lars-goran.danielsson@astrazeneca.com.



Sparén



Renberg



Furusjö



Hillforth



Danielsson