

Chip size distribution for an ultra-high-yield sulfite process

P. TESSIER, G. BRODERICK, AND C. DESROCHERS

IN PULP AND PAPER MILLS WHERE THERE are large differences in temperature between summer and winter, some variations in wood chip moisture and in chip size distribution are large enough to affect the quality of pulp and the paper made from it. We have analyzed chip quality data archived at a commercial newsprint mill. Our purpose was to gain insight into the effect of seasonal changes on chip quality and to quantify the impact of these changes on the quality of the mill's ultra-high yield sulfite pulp.

This mill produces different grades of newsprint from a mixture of groundwood, recycled fiber, and ultra-high-yield sulfite pulp. The sulfite pulp is produced as the main strengthening agent in the furnish. At a yield of about 85%, three batch digesters cook black spruce chips with a sodium bisulfite liquor. The softened chips are subjected to two stages of atmospheric refining that apply a total specific energy of about 1600 kW·h/ton of pulp.

Winter operation has historically produced pulp with lower tensile strength, accompanied by reductions in tear index. Although most paper-makers point to seasonal changes in chip furnish as the cause, no formal analysis has ever been performed to confirm the cause and quantify the effects.

Our objective in this study was to assess quantitatively the impact of chip length and thickness on the properties of handsheets made from this ultra-high-yield sulfite pulp. We applied multivariate statistical analy-

sis to archived data spanning 16 months and used the results to construct an empirical model linking chip size fractions to handsheet quality. This model serves as the basis for a numerical optimization problem whereby we identify the chip size distribution that simultaneously maximizes tensile energy absorption (TEA), tear index, and burst strength.

BACKGROUND

Seasonal changes in chip size distribution have long been observed in mills. These changes in chip quality have a direct impact on mechanical pulp strength. The shive content increases in the winter, while TEA and tear strength drop. The reduction in paper strength leads to more paper breaks and to poorer press runnability, which printers have complained about for a long time.

Chipping reduces the average chip size and allows the pulping liquor to penetrate rapidly and uniformly. However, wood fibers may be damaged in the process, resulting in a weaker pulp. The ideal chip size distribution is a compromise between good liquor impregnation and pulp strength. The thickness of the chip and the uniformity of this thickness determine how completely and uniformly the liquor penetrates.

Previous studies show a lack of agreement in data published on the effects that different chip size distributions have on chemical treatment (1-10). Most of these studies have dealt with only one chip dimension, either length or thickness, without both descriptors being looked at to-

ABSTRACT

Data archived as part of a mill's routine for monitoring chip quality were used to quantify the effects of seasonal changes in chip size distribution on the handsheet properties of an ultra-high-yield sulfite pulp. Multivariate statistical analysis indicated that at least one third of the seasonal variation in pulp quality is directly linked to changes in raw material characteristics. An empirical PLS model was used to numerically optimize the chip size distribution in both length and thickness. Optimization results showed that an increase in the proportion of long chips, thicker than 4 mm, would provide the best combination of tear strength, burst index, and TEA.

Application:

Finding the best chip size distribution can help reduce strength loss during the winter months.

gether. Our purposes were to quantify the effects of chip thickness and length on pulp strength and to identify promising distributions of chip size for the furnish.

MILL DATA

The chip quality data were weekly averages computed from the mill's data archives for the period extending from January 1995 through April 1996. Weekly averages were appropriate because we wanted to identify seasonal variations rather than distinguish between individual suppliers.

Table I summarizes statistics for each of the handsheet properties of the ultra-high-yield sulfite pulp and for each of the chip quality descriptors. The results for the coefficient of variation, or the ratio of the standard deviation to the mean, indicate that there is quite a lot of variation in the weekly averages for chip size distribution and for dryness. Standard deviations in each of the chip fractions

	Mean	Coeff. of var., %	Min.	Max.	
Wood Chip Characteristics					
Dryness, %	60.190	5.77	55.875	69.314	
Density, tons/m ³	0.420	1.68	0.401	0.438	
Bark content, %	1.112	45.28	0.241	2.245	
Dust content, %	0.664	83.00	0.245	3.439	
Distribution by fraction, %					
<u>Length</u>	<u>Thickness</u>				
All 35 mm	<2 mm	3.876	39.85	1.755	7.933
<35 mm	2–4 mm	28.956	18.80	18.411	45.792
>35 mm	2–4 mm	0.226	121.55	0.0433	1.879
<35 mm	4–6 mm	28.995	8.97	23.848	35.969
>35 mm	4–6 mm	1.430	57.14	0.413	3.622
<35 mm	6–8 mm	18.267	17.06	10.792	24.343
>35 mm	6–8 mm	2.828	46.42	1.010	5.841
<35 mm	8–10 mm	5.342	33.58	2.106	8.965
>35 mm	8–10 mm	1.855	31.96	0.889	3.135
<35 mm	>10 mm	3.687	32.78	1.055	5.896
>35 mm	>10 mm	3.813	31.91	1.663	6.759
Handsheet Properties					
Freeness, mL	527.656	3.97	479.94	571.08	
Bulk, cm ³ /g	2.417	2.76	2.245	2.57	
Burst, kPa	3.068	8.96	2.504	3.572	
Tear, mN m ² /g	12.163	4.71	10.689	13.452	
TEA, J/m ²	46.307	9.17	37.259	54.376	
Shives, %	0.513	42.07	0.206	1.479	
Brightness, % ISO	57.760	1.59	55.935	59.899	

I. Chip quality and handsheet property data

generally represent over 30% of the overall mean values for this 16-month period.

Figure 1 shows the weekly average moisture content of the chips from January 95 through April 96. The chip moisture content averages about 42% in the winter and 32% in the summer. The bark and fines contents are significantly higher in the winter, as Figs. 2 and 3 show. Bark content exceeds 1.5% in winter but is commonly less than 0.5% in summer. As for the chip size distribution, as shown in Fig. 4, the chip fraction measuring less than 4 mm thick increases significantly in the winter, as the frozen chips become more brittle. Similar trends were reported by Fuhr and Tyrvaenen (11, 12).

These seasonal changes in chip

quality have a direct impact on the quality of the sulfite pulp and handsheets. The shives content increases, while TEA, burst, and tear strength drop in the winter, as Figs. 5–8 show. These findings are in agreement with those of Tyrvaenen and Fuhr, except that Fuhr reported an increase in burst strength under winter conditions (11).

The values in Table I for the coefficient of variation for the handsheet properties indicate, however, that this shift in pulp strength is less dramatic than the relative changes in chip size. These values result partly from the influence of the operators, who control the operating conditions to dampen the variability in the outgoing pulp and maintain quality as consistently as possible.

In addition, minor variation may arise from other sources, such as water quality and equipment wear, but we did not include these factors because no mill data were available. More importantly, the confidence limits for random error are much tighter when averages are being compared instead of single values. As these are not individual test samples but weekly averages, a 10% seasonal change in tensile strength is definitely not negligible.

ANALYSIS

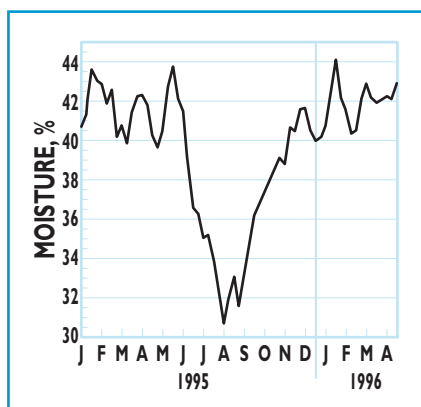
Pulp quality was measured by the seven handsheet properties in Table I and was modeled in terms of the fifteen chip quality descriptors that are also presented in the table. The relationships between chip quality and handsheet quality were mapped with multivariate statistical analysis.

Traditional regression analysis was not appropriate because of the interdependent nature of the data. Just as handsheet properties are extensively interrelated, there are significant interactions between the measurements of chip quality.

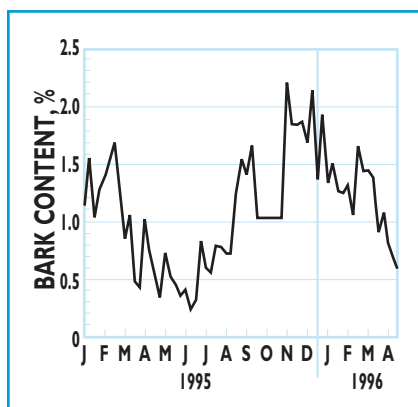
Multivariate statistical modeling

Collinearities, or interdependencies between regressors, cause severe problems with ordinary least-squares regression. The difficulty is one of assigning relative importance to a set of regressor variables in a single predictive equation, when the same underlying effect on the response is caused more than once.

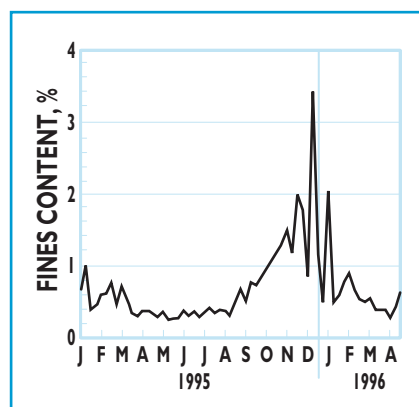
Performing multiple least-squares regression with this type of data will produce misleading and erroneous results. Mathematically, collinearities inflate the error associated with estimating the regression coefficients. Biased regression methods such as partial least squares (PLS) counter this problem by computationally suppressing the effects of collinearity. More detailed discussions of the mathematical treatment of collinear-



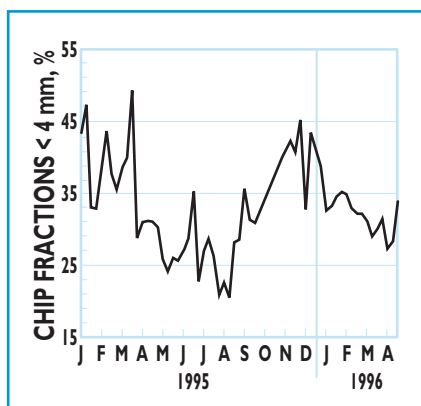
1. Weekly average for chip moisture content (1/95 – 4/96).



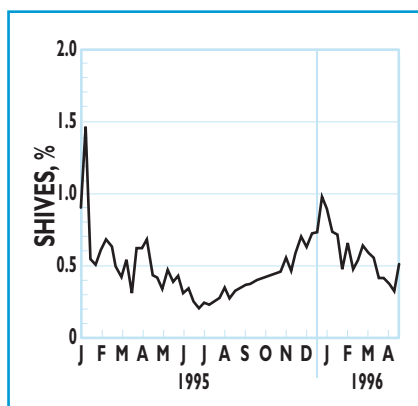
2. Weekly average for chip bark content (1/95 – 4/96).



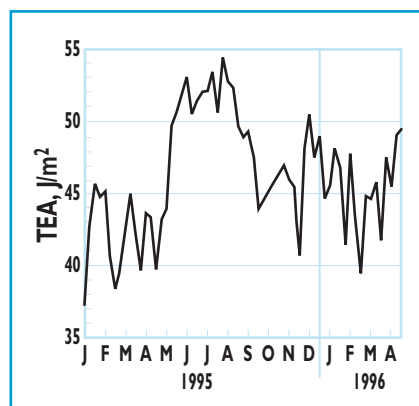
3. Weekly average for chip fines content (1/95 – 4/96).



4. Weekly average for the sum of chip fractions with thicknesses less than 4 mm (1/95 – 4/96).



5. Weekly average for shive content in ultra-high-yield sulfite pulp (1/95 – 4/96).



6. Weekly average for handsheet TEA of ultra-high-yield sulfite pulp (1/95 – 4/96).

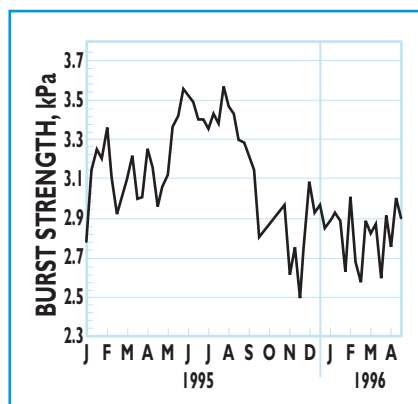
ities are found in Broderick *et al.* (13) and Jackson (14).

Latent vector analysis is a data compression technique that defines a new coordinate system by combining the original variables. The new system consists of a number of composite variables that are distinct and mutually independent.

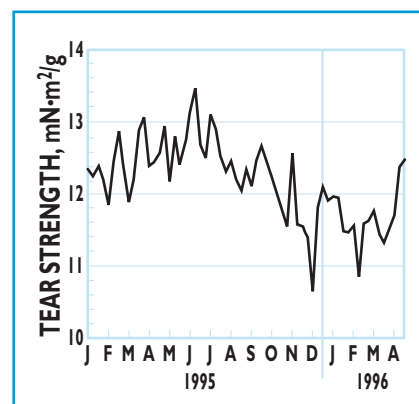
The original variables are scaled to a variance of 1.0 to eliminate the effect of unit magnitudes. As a result, each variable is assigned equal importance in the latent vector calculations. In essence, latent vector regression will sequentially provide the least squares solution to the best fitting line, plane, and hyperplane through the swarm of observations.

The standard model for a single block of variables is given in Eq. 1:

$$_N[X]^K = _N[T]^A _A[P']^K + _N[E]^K \quad (1)$$



7. Weekly average for handsheet burst index of ultra-high-yield sulfite pulp (1/95 – 4/96).



8. Weekly average for handsheet tear index of ultra-high-yield sulfite pulp (1/95 – 4/96).

where X is the matrix of N trials conducted using K variables. The scores matrix T contains the coordinates of each observation with respect to the new system of A latent vectors. The loading matrix P describes the rotation of these latent vectors with respect to the original system. The

residuals from the least squares fit are found in matrix E .

In PLS, the latent vectors are computed for two blocks simultaneously: a set of K predictor variables X and a set of M response variables Y . As for the X block, the latent vector model for Y may be written in matrix form:

PLS latent vectors	Variability in chip quality, % (X block)		Variability in handsheet quality, % (Y block)	
	Individual	Cumulative	Individual	Cumulative
1	32.97	32.97	26.62	26.62
2	23.93	56.90	10.79	37.41
3	11.56	68.46	6.73	44.15
4	7.69	76.15	3.17	47.32
5	7.58	83.71	1.12	48.44

II. Decomposition of variability in chip and pulp quality in terms of latent vectors in the PLS model

$${}_N[Y]^K = {}_N[U]^A {}_A[C']^K + {}_N[F]^K \quad (2)$$

Equations 1 and 2 are the outer relationships.

The objective of PLS is to predict Y from X . PLS is used to search for a line, a plane, or a hyperplane that well approximates the observations in X , while having the additional property of correlating well with the corresponding line, plane, or hyperplane in Y space.

The principal components of each block are not calculated independently. Information is exchanged between both sets to rotate the components slightly in both blocks to minimize their deviations from the regression line described by the inner relationship:

$$U = T + H \quad (3)$$

In the actual calculations performed in this study, we made use of the NIPALS algorithm (nonlinear iterative partial least squares) (15). This algorithm introduces an exchange of scores which rotates the X -block latent vectors and alters the loading from the original P matrix to the matrix of PLS weights W . Combining Eqs. 1–4 leads to the mixed relationship in which the residuals F^* are to be minimized:

$$\begin{aligned} Y &= T B C' + F^* \\ &= X \beta + F^* \end{aligned} \quad (4)$$

The resulting matrix of biased coefficients can be calculated from the matrix of PLS weights W as follows:

$$\beta = W(P'W)^{-1} C' \quad (5)$$

An important step in developing a PLS model for a system is determining the proper dimensionality A , or selecting the appropriate number of latent vectors. Various stopping rules exist, ranging from simple scree plots to significance tests of the system's eigenvalues. For this work, we used a cross-validation scheme that involves the PRESS statistic (16, 17). Note that this approach differs from canonical correlation, in which predictor and response variables are not recognized as such.

Assessing model performance

How well does a model approximate the information from a data set? A common way to assess a model's performance is to consider how much of the initial variance is accounted for.

The overall variance in the response block Y can be broken down to show the increment in variance S_a^2 modeled for a given response Y_m at each PLS dimension a as follows:

$$\% S_{Y_m}^2 \text{ explained} = 1 - \frac{S_m^2}{S_{Y_m}^2} \quad (6)$$

The variance $S_{Y_m}^2$ in any response Y_m is 1.0 because all responses were scaled to unit variance before the PLS calculations were performed. For a PLS model consisting of A components, the residual variance S_m^2 for any particular response is calculated from the $N \times M$ residual matrix F as follows:

$$S_m^2 = \sum_{i=1}^N \frac{f_{i,m}^2}{(N-A-1)} \quad (7)$$

Note that the PLS method models the responses as a group. Adding a

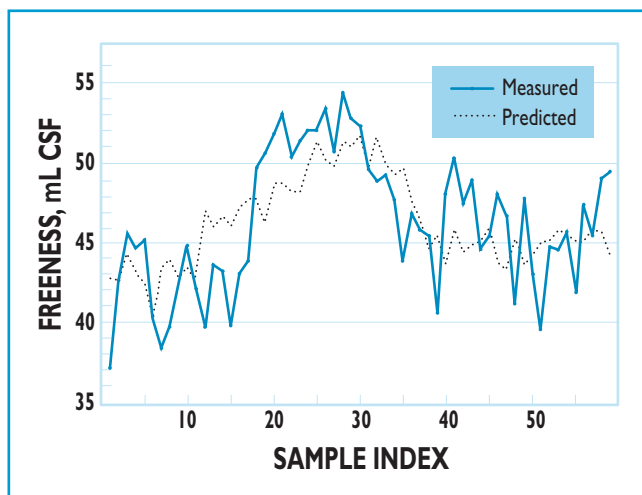
dimension to the PLS model will decrease the residual error for the responses as a group. On an individual basis, however, this new dimension may represent noise for a specific response, and for this particular response the consequence of adding a dimension is a loss of explained variance. To put it another way, if we add new dimensions that fail to reduce the residual error in a specific response, then this residual error is distributed over progressively fewer degrees of freedom. This effect leads to a decrease, or negative increment, in explained variance for this response.

Optimizing for the best combination of properties

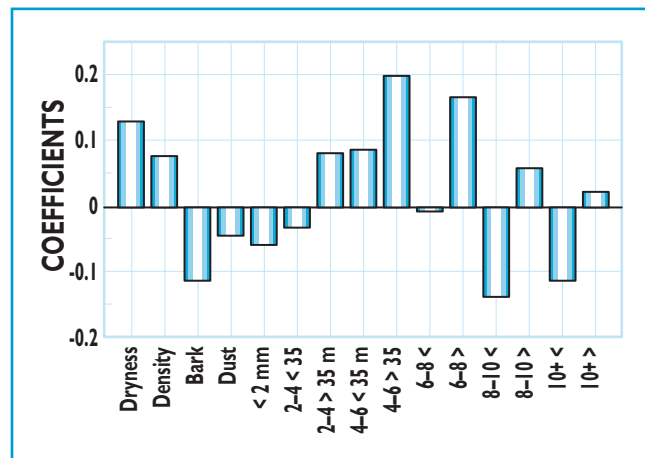
The PLS model we constructed from mill data was used in an optimization scheme to calculate the chip size distribution that would lead to the best combination of TEA, burst, and tear strength. Two objective functions have been used in the optimization. The first one consists of an overall quality index similar to a geometric average and is defined in Eq. 8. An index value of 1.0 indicates a quality that is equivalent to the average pulp quality produced at the mill from January 1995 through April 1996.

The second objective function is a weighted average quality index. In this index, the individual terms are weighted based on their coefficients of variation. The function used is defined in Eq. 9.

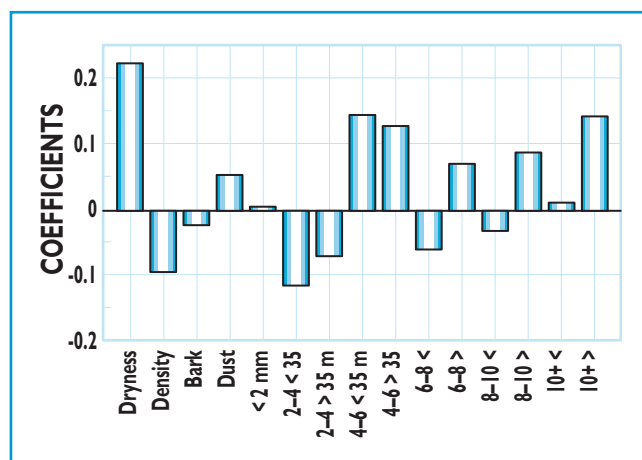
We used a sequential quadratic programming (SQP) optimization technique to identify the chip feed that maximizes the multiplicative objective function in Eq. 8. At each major iteration of the algorithm, a quasi-Newton method was used to approximate the Hessian matrix. We applied this approximation to solve a quadratic programming subproblem. The solution of this subproblem provides a search direction along which a line search is applied as the final step.



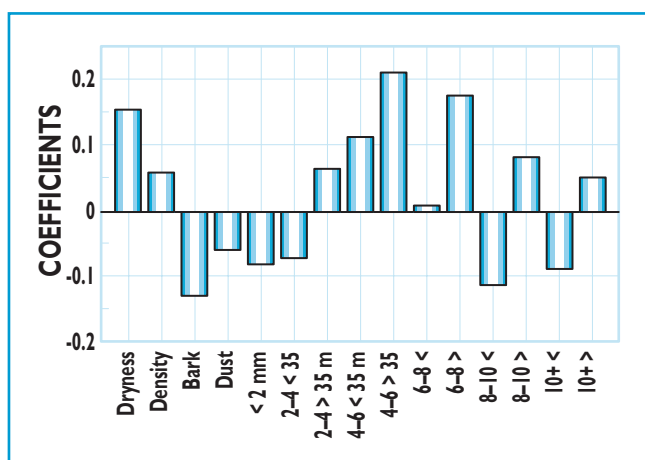
9. Weekly average for pulp freeness and PLS model prediction based only on chip quality (1/95 – 4/96).



10. Scaled and centered biased coefficients of the PLS model for predictions of handsheet burst index.



11. Scaled and centered biased coefficients of the PLS model for predictions of handsheet tear index.



12. Scaled and centered biased coefficients of the PLS model for predictions of handsheet TEA.

$$\text{Quality Index \#1} = \frac{\text{TEA}}{\text{mean TEA}} \times \frac{\text{Tear}}{\text{mean Tear}} \times \frac{\text{Burst}}{\text{mean Burst}} \quad (8)$$

Quality Index #2 =

$$\frac{\text{TEA}}{\text{mean TEA}} \cdot \frac{\text{mean coeff. var.}}{\text{coeff. var. TEA}} + \frac{\text{Tear}}{\text{mean Tear}} \cdot \frac{\text{mean coeff. var.}}{\text{coeff. var. Tear}} + \frac{\text{Burst}}{\text{mean Burst}} \cdot \frac{\text{mean coeff. var.}}{\text{coeff. var. Burst}} \quad (9)$$

SQP and related algorithms guarantee superlinear convergence rates. Overviews of the SQP algorithm can be found in Fletcher (18) and in Powell (19). In the case of the weighted sum objective defined in Eq. 9, the algorithm for the quadratic programming sub-problem is collapsed to a

linear programming step.

RESULTS

Impact of individual chip fractions

The results in Table II describe how the overall variability in chip and handsheet quality is decomposed

over five latent vectors. Each latent vector can be interpreted as a new layer of information that contributes a new and distinct increment to the model resolution. The results tabulated indicate that the most significant portions of the variability in the system are captured by the first two

			Solution		Mill	
Range			Eq. 8	Eq. 9	8/95	2/96
Wood Chip Characteristics						
Distribution by fraction, %						
Length	Thickness					
All 35 mm	<2 mm	0–15	0	0	1.98	3.6
<35 mm	2–4 mm	10–60	10	10	18.8	31.1
>35 mm	2–4 mm	0–5	5	0	0.2	0.1
<35 mm	4–6 mm	15–50	50	50	30.4	27.1
>35 mm	4–6 mm	0–10	10	10	2.50	0.5
<35 mm	6–8 mm	5–40	5	5	23.2	19.7
>35 mm	6–8 mm	0–10	10	0	4.7	1.4
<35 mm	8–10 mm	0–15	0	0	6.0	6.2
>35 mm	8–10 mm	0–10	0	0	2.3	1.2
<35 mm	>10 mm	0–10	0	10	4.2	4.8
>35 mm	>10 mm	0–15	10	15	5.3	3.1
Handsheet Properties						
Decker burst, kPa			4.67	3.86	3.57	2.60
Decker tear, mN m ² /g			16.73	14.71	12.3	11.5
Decker TEA, J/m ²			66.78	71.72	54.4	41.0
Decker freeness, mL			558	585	558	490
Decker bulk, cm ³ /g			2.63	2.37	2.38	2.30
Decker brightness, %ISO			57.1	56.5	58.0	58.6

III. Optimal chip size distribution for maximal burst, tear, and TEA

or three latent vectors.

For the sake of simplicity and since we are mainly interested in examining seasonal changes, we have retained only the first two latent vectors in this work. As the results in the table indicate, roughly 38% of the quality variations in ultra-high-yield sulfite handsheets can be associated statistically with variations in chip quality.

Figure 9 illustrates the degree of fit obtained with the PLS model to the data catalogued for pulp freeness from January 1995 to April 1996. This figure illustrates that the variability in pulp handsheet quality related to changes in chip quality is a seasonal change of low frequency. The high-frequency changes in measured pulp quality logically correspond primarily to rapid changes in operating conditions and, to a lesser extent, to random test variability. Although these results are based on correlation, they appear to be in agreement with causal observations from a number of fundamental studies.

An indication of the sensitivity of handsheet strength to changes in individual chip properties can be inferred from the biased coefficients in the PLS regression model. These coefficients are presented graphically in Figs. 10–12 for handsheet burst index, tear index, and TEA, respectively.

Figures 10 and 11 indicate that the burst and tear indexes will react similarly to changes in chip quality. In both cases, increased bark content is detrimental to the development of these handsheet properties. This observation stands to reason because bark has poor bonding properties. Tear strength is generally compromised by the addition of fine particles unless these particles belong to the fraction containing the longer chips (>35 mm). The same condition applies to the effect of coarse particulate matter on both tear and burst strength. If the proportion of chips with thicknesses between 8 mm and 10 mm is increased, tear and burst strength will decrease unless these

chips are not only coarse but relatively long as well. Chip length would therefore appear to be the principal factor in tear and burst strength in a high-yield pulp.

Figure 12 presents the biased regression coefficients for the PLS model of handsheet TEA. This pattern differs from the patterns for burst and tear strength. One of the main differences is the opposite effect of chip density on TEA. Lower chip densities will result in higher TEA values but will be detrimental to both burst and tear. Perhaps the lower densities lead to more flexible fibers that lend themselves more readily to interfiber bonding.

Another distinctive feature is the generally positive effect that increases in coarse particles have on the development of TEA. Once again, surface development is thought to be at the heart of this behavior. Presumably, coarser fibers are more apt to generate fine material in addition to developing more extensive surface fibrillation during refining.

Interestingly enough, these findings seem to depart from previous work such as that by Broderick *et al.* (13) that shows burst index and TEA following similar trends. However, our study focuses on the effect of changes in chip quality under relatively constant cooking and refining conditions. In contrast, Broderick and coworkers used constant chip quality in that earlier study, which was aimed specifically at identifying the effect of changes in refiner operation on handsheet strength.

Basically, the same type of chip feed that will promote better tear strength will also promote better burst index. However, refiner operating conditions that provide better burst index are quite different from those which increase tear strength. Consequently, it may be possible to combine chip feed characteristics with a refiner operation that exploits this behavior to achieve a better bal-

ance of handsheet strength properties.

Pulp quality optimization

As the results indicate, better control over the chip size distribution can improve pulp quality. To represent a more realistic commercial scenario, we used the proportions of each of the chip fractions as the only free variables in this optimization problem.

For high pulp quality, moisture content should be as high as possible, and bark content and dust should be as low as possible. As for wood density, this characteristic depends largely upon wood species and location, factors over which we have only limited control in practice.

Therefore, for this study, we set wood chip dryness, density, bark content, and dust at their average values. Furthermore, the proportion of any single chip fraction in the feed was constrained within a certain range, as shown in **Table III**. Realistically, we cannot expect the chip feed of an industrial operation to be composed entirely of chips in a single size fraction.

The ranges were chosen to be about 50% wider than the actual ranges found in the mill data for each class. The content of each individual chip fraction was allowed to vary independently, even though the fractions are correlated when delivered to the mill because of the chipping processes. We allowed the fractions to vary, so we could assess the impact of more aggressive chip screening and size fraction selection at the mill.

The results of the optimization are rounded to the closest 1% increment in **Table III** to highlight the general trends. By either quality index, in Eq. 8 or 9, the overall pulp handsheet quality is improved if we reduce the amount of the smallest fraction or reduce the amount of chips shorter than 35 mm. This improvement is valid regardless of thickness. This outcome is in agreement with mill experience.

rience.

In winter, when the amount of small chips increases, the strength properties drop dramatically. The optimum solution seems to favor the addition of wood chips longer than 35 mm and thicker than 4 mm. There is little difference in tear and brightness, and there is a slight increase in TEA, burst, and freeness, indicating an increase in not only long fibers but also potentially coarse fibers as well. This observation is in agreement with the work from Jensen and Wiseman (20).

The optimum solutions for the two quality indexes predict values of pulp strength that are higher than those reported by the mill even in the best of summer conditions (**Table III**, Aug. 1995 data). This prediction suggests that proper chip supply and screening can make a big difference in final product quality.

Although the general trends should be quite reliable, absolute values for handsheet property predictions should be used with caution. The mill data (**Table I**) show that some fractions were below 10% and in some cases even below 5% when the PLS model was being developed. We are now finding the optimal solutions to be well above these levels; i.e., we are extrapolating the model outside the range over which it was calibrated.

SUMMARY AND CONCLUSIONS

In this quantitative analysis of mill data, we related chip quality to the strength of high-yield sulfite pulp. A PLS multivariate statistical model was constructed and used as the basis for optimizing chip size distribution. The results of this analysis led to several conclusions.

First, close to 40% of the variability in pulp quality can be associated with seasonal changes in chip feed characteristics.

Second, the addition of fine particles will generally result in lower tear

and burst strengths unless such particles belong to the fraction containing longer chips (>35 mm). The same observation applies to the effect of coarse particulate matter on both tear strength and burst strength.

Third, lower chip densities will result in higher TEA values but will be detrimental to both burst and tear strengths. Furthermore, increases in coarse particle content lead to increased TEA. In both instances, the development of a bonding surface is thought to be responsible.

Fourth, optimal pulp strength can be achieved by reducing the amount of chips shorter than 35 mm, in particular when these are thinner than 4 mm. However, oversized chips require more energy during refining.

Although the same chip feed that promotes better tear strength will also promote burst index, refining conditions will have vastly different effects on each of these properties. It might be possible to identify and use a combination of chip feed characteristics and refiner operating conditions that would deliver a better balance of tear, burst and TEA. **TJ**

Tessier is president of ISAC Technology Inc., 5962 Signal Ridge Heights, Calgary, AB, T3H 2N8. Broderick is a senior scientist at Noranda Technology Centre, 240 Hymus Blvd., Pointe Claire, PQ, H9R 1G5. Desrochers is a process engineer at James MacLaren Industries, P.O. Box 2400, Buckingham, PQ, J8L 2X3. Correspondence should be addressed to Dr. Patrick Tessier.

*Received for review March 24, 1998.
Accepted Dec. 5, 1998.*

LITERATURE CITED

1. Broderick, G., Cacchione, E., and Héroux, Y., *TAPPI J.* 81(2): 131(1998).
2. Birchard, W. H., *Paper Trade J.* 85(12): 59(1927).
3. Stone, E. J. and Forderreuther, C., *Tappi* 39 (10): 679(1956).
4. Nye, J. W., Fitkowski, T. C., Tay, C. H., et al.,

- TAPPI 1989 *Proceedings of the 5th International Symposium on Wood and Pulp Chemistry*, TAPPI PRESS, Atlanta, 1989, p. 151.
5. Wardrop, A. B., *Tappi* 52(3): 396(1969).
 6. McGovern, J. N. and Chidester, J. H., *Technical Association Papers* 17: 292(1934) (in *Paper Trade J.*).
 7. Anderson, C. A., *Pulp Paper Mag. Can.* 47(1): 43(1946).
 8. Hagglund, E., *Svensk Papperstid.* 44(6): 102 (1941).
 9. Feiner, J. H. and Gallay, W., *Pulp Paper Mag. Can.* 63(9): 435(1962).
 10. Saunderson, H. H. and Maass, O., *Canadian Journal of Research* 10: 24(1934).
 11. Fuhr, B. J., Henry, D., Leary, G., and Smith, G., *Proceedings of the 83rd Annual Meeting*, Technical Section CPPA, Montreal, 1997, p. B443.
 12. Tyrvaïnen, J., *1997 TAPPI International Mechanical Pulping Conference Proceedings*, TAPPI PRESS, Atlanta, p. 213.
 13. Broderick, G., Paris, J., Valade, J. L., and Wood, J., *Paperi Puu* 77(6-7): 410(1995).
 14. Jackson, J. E., *A User's Guide to Principal Components*, Wiley, New York, 1991.
 15. Wold, H., "Nonlinear estimation by iterative least squares procedures," in *Research Papers in Statistics* (David, F. N., Ed.), Wiley, New York, 1966.
 16. Wold, S., *Technometrics* 20: 397(1978).
 17. Allen, D. M., "The prediction sum of squares as a criterion for selecting variables," Technical Report No. 23, Dept. of Statistics, University of Kentucky, 1971.
 18. Fletcher, R., *Practical Methods of Optimization*, Vols. 1 and 2 ("Unconstrained optimization" and "Constrained optimization"), Wiley, New York, 1980.
 19. Powell, M. J. D., "Variable metric methods for constrained optimization," in *Mathematical Programming: The State of the Art* (A. Bachem, M. Grotschel, and B. Korte, Eds.), Springer Verlag, 1983, p. 288-311.
 20. Jensen, A. and Wiseman, N., "Effect of chip quality on pulp quality and energy consumption in RMP manufacture," 1980 International Symposium on Fundamental Concepts of Refining, Institute of Paper Chemistry, Appleton, WI, p. 84.