Effects of Some Wood Chip Properties on Pulp Quality

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Abstract: As the raw material, wood chips influence pulp and paper quality. On-line detection and evaluation of the intrinsic properties of wood chips are therefore a basis for quality control. Following CMS measurement of some properties of the chips, a series of TMP experiments were performed at the CIPP pilot plant. A PLS analysis demonstrated that CMS measurements can be used to predict some pulp properties.

Wood chips being the raw material in pulp and paper making, their properties, such as wood species, freshness, moisture content, and size, are the most important factors affecting pulp quality [1, 2]. Variations in the wood raw material and its fibres may give rise to 30-40% variations in pulp properties [3]. Continuous variations in wood basic density and moisture content occurring in the chip flow tend to cause variations in refining consistency, which, in turn, affect pulp uniformity and energy consumption [4]. Homogeneous chip size distribution and low fines content produce good pulp strength while knots and bark content decrease pulp strength and brightness [5]. Unfortunately, the industry does not have an efficient method to predict pulp quality from wood chip properties due to the lack of on-line measurement technology.

In this research we used CRIQ's CMS (chip management system) to measure some chip quality parameters before the chips entered the thermo-mechanical pulping (TMP) process. The CMS has been implemented in several mills for on-line monitoring of chip unloading and TMP pulping. Chip brightness (or luminance) has been considered a synthetic function of chip properties [6, 7]; and we also found that it could be used to reduce bleaching agent consumption [6]; this was not enough, however, to estimate pulp quality. For this reason, CRIQ developed two new soft sensors (a virtual screen and a virtual bark content detector) and added them to the CMS. With the new soft sensors, CMS measurements became more powerful and included more important chip properties such as aging, wood species ratio, chip size distribution, bark content, etc. By applying a principal component analysis (PCA) method, we were able to find an inherent relationship between wood chip properties and CMS measurements, which gave us a better interpretation of some chip properties.

A series of TMP experiments were performed at CIPP’s TMP pilot plant, and some pulp properties were measured. By comparing chip and pulp properties, and using projections to latent structures (PLS) analysis, we were able to demonstrate that on-line CMS measurements can be used to predict some pulp properties.

It should be pointed out that the focus of this paper is to show how CMS measurements can be used to predict some pulp properties. This prediction will suggest ways to control chip quality so as to ensure pulp quality. We tried to explain some important chip properties included in the measurements, but did not try to model them.

EXPERIMENTAL

Materials

For basic raw materials, we selected a mixture of balsam fir and black spruce in varying proportions, and then added jack pine and yellow birch. The ten-chip sample protocol involved these four pure species and six mixtures of these species in different proportions. Chip aging is one of the important parameters involved in TMP. In order to evaluate aging impact, initial testing involved chips of a known age, and the test was repeated five times with chips of up to six months of age. The chips were stored outside under ambient air conditions, thus aging occurred naturally.

Chip Measurement

Before entering the refiner, the wood chips were measured by the CMS and its new soft sensors. The CMS is a multi-sensor system that includes principal and auxiliary sensors [6]. The former, e.g., artificial vision sensor and near infrared sensor, measure chip optical properties and moisture content. The latter, e.g., distance sensor and air conditions sensor (air temperature, velocity and relative humidity), etc., provide information to extend measurements by the principal sensor, and stabilize...
the system. CMS measurements provide extensive information on chip properties that we can use to evaluate chip quality.

Pulping
Chip measurement and pulping were performed at CIPP’s TMP pilot plant. The first phase of refining was performed under steam pressure (128°C) and the second under atmospheric pressure. During the test, four samples based on freeness/refining energy indices were prepared and evaluated. The pulp properties were measured by different sensors, such as: FQA (fibre quality analyzer), to measure fibre length distribution; and Pulmac, to measure shives content, etc.

RESULTS AND DISCUSSION
Chip Aging State
Chip freshness is a very important parameter for the TMP process because fresh wood chips are brighter than older chips. Chip aging is a very complex phenomenon that depends on the wood species, log and chip storage, ambient air conditions, etc. It would be very difficult and unnecessary to estimate chip age from their aging state. As mentioned in the Experimental section, ten samples were measured five times (tests A, B, C, D and E) by the CMS during natural aging (about six months). Although chip brightness can provide an indication of chip aging, this is only useful when the wood species distribution does not vary. For an uncertain proportion of wood species, we need more information.

On the basis of laboratory and mill tests, we chose nine CMS measurement parameters, i.e.: moisture content, darkness, six optical parameters, and standard deviation of luminance.

Using PCA (principal component analysis), which involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components, to analyze the CMS measurements, we developed an inherent relationship for chips at different aging states. As shown in Fig. 1, the variations are well explained and predicted by two components [Comp(1) and Comp(2)], where X are variables, R²X(cum) is the cumulative sum of the squares of all the X values explained by all extracted components, and Q²(cum) is the cumulative Q² value for the extracted components. In the PCA, the R² is the goodness of fit, that is the fraction of the sum of squares of all the X values explained by the current component and the Q² value is the goodness of prediction, that is the fraction of the total variation of the X values that can be predicted by a component.

Figure 2 shows the plot obtained when plotting the scores of the two first principal components. From the first component, we divided the tests into 3 groups. Group 1 was formed of test A; Group 2 was formed of test B, and tests C, D and E were superimposed to form Group 3. From the second component, we were barely able to separate test E from tests C, D and B.
Taking the test conditions into account, we found that tests C and D had been performed in the winter of 2001; the chips were frozen, thus aging had almost stopped. Test E was performed in the spring of 2002; the measured results had changed only slightly, indicating that chip aging tended to stabilize. It is clear that the chip aging state information was reflected in the CMS measurements.

Wood Species Information
Wood chip species is another important variable for the TMP process. Optical test methods [8, 9] and chemical vapour analysis [10] have been applied in the laboratory or for on-line monitoring of single wood species. But these sensors cannot be used to evaluate a mixture of more than two species.

Using PCA to analyze the CMS measurements, we obtained a good explanation and prediction of variations from two components as shown in Fig. 3.

Figure 4 shows a scatter plot of $t_1$ vs. $t_2$. The four wood species, i.e. spruce, balsam fir, jack pine, and birch scattered in different positions. If a mixture is close to a point corresponding to a pure species, one can conclude that the mixture contains a higher proportion of this particular species. The distances from the mixture point to different pure species points represent the proportions of these species in the mixture.

Although the chip aging state did not influence this conclusion, it did affect the different species' positions in the $t_1$-$t_2$ plane (see Fig. 2). Therefore, the chip aging state is an auxiliary parameter for recognizing wood species. We concluded that the wood species information implicated in the CMS measurements. It should be noted that this analysis was based on four known wood species; we did not try to model species identification. For future modeling, we think that much additional testing and research will be required because of the variability of chip properties.

Chip Size Distribution and Bark Content Indices
There are about 12 different types of chip classifiers available for off-line laboratory testing, and a few on-line discontinuous measurement systems [11]. Size measurements are based on only one portion of the wood chips, which is not really representative. The identification of bark in wood chips is a manual operation conducted in the laboratory. In order to perform on-line chip size and bark content measurements, we developed two soft sensors: a virtual screen and a virtual bark content detector, both based of the CMS system. The virtual screen is a granulometry tool based on mathematical morphology; it simulates chip sifting through screens of increasing mesh sizes, which is what is done to compute size distribution in real tests. The virtual screen calculates the percentage of pixels for chips of a certain size (such as width, length, diagonal and area) in relation to total pixels in an image. This is different from the Williams classifier, which calculates the percentage by weight of the different chip sizes in relation to total chip weight. The two methods cannot be compared directly, but a relationship can be established with PLS modeling. The PLS is a regression extension of PCA; instead of finding the hyperplanes of minimum variance, it finds a linear model describing some predicted variables in terms of other observable variables. Validation test results (width) for the four wood species are plotted in Fig. 5.

The virtual bark detector was based on a colour classifier that identifies zones in the image having the color of bark. As there are no basic colours for bark, the classifier had to be trained to identify bark despite variations in colour, luminance and shadows. In the laboratory tests on the four pure wood species chips, detection accuracy for sound chips was about 95%; for the bark, it was about 80%. The test samples included 50% fresh chips and 50% old wood chips. The percentages represent the number of pixels of sound chips or bark in relation to total pixels in the images. With these two new soft sensors, the CMS can therefore provide additional information on chip size distribution and bark content.

Fibre Length Prediction
As previously discussed, the CMS measurements were now able to provide much more implicit information about wood chip properties. Our purpose was not to develop a tool for estimating these
properties, but to use these measurements to evaluate some pulp properties. If this challenge can be met, TMP model predictive control can be achieved. In order to study the effects of CMS-measured parameters on the TMP process, we tried to find a relationship between CMS measurements and some pulp properties. The pulp properties that can be measured on-line are: freeness, shives content, and fibre length distribution, including: long fibre content, fines content, and mean fibre length (arithmetic, length weighted or weight weighted), etc. In this research, we considered freeness, specific energy, and CMS measurements as inputs; and shives content and fibre length distribution as outputs of the TMP. Outputs were measured by the Pulmac and FQA methods respectively.

Using the test results from the CIPP pilot plant, we developed a PLS model. Figure 6 shows a plot of cumulative $R^2_Y$ and $Q^2$ values for individual responses, where $R^2_Y$ (cum) was the cumulative sum of squares of all Y values explained by all extracted components, $R^2_Y$ was the fraction of the sum of squares of all the Y values explained by the current component, and Y represented predicted variables. Obviously, the explained and predicted variations of the model were very good.

An example of the predictions of the model for fibre length (lw) is shown in Fig. 7. It is clear that the prediction is excellent.

CONCLUSIONS
The CMS is an excellent on-line chip measurement sensor. With the assistance of PCA analysis, it allows for interpretation of some implicit chip properties such as chip aging state, species ratio, and moisture content. By integrating two new soft sensors into the CMS, we were also able to evaluate chip size distribution and bark content. Using PLS modeling, we demonstrated that the CMS measurements can provide enough information to predict some pulp properties. In future studies, we will use CMS measurements to define chip quality and refining parameters according to the pulp quality desired.

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LITERATURE

Résumé: Les caractéristiques de la matière première, les copeaux, influencent la qualité de la pâte et du papier; la détection et l'évaluation en continu des caractéristiques intrinsèques des copeaux représentent donc une base pour le contrôle de la qualité. Après avoir mesuré les caractéristiques des copeaux avec le CMS, nous avons effectué divers essais de PTM à l'usine pilote du CIPP. L'analyse de PLS démontre que les mesures du CMS peuvent être employées pour prédire certaines caractéristiques des pâtes.


Keywords: CHIP QUALITY, ONLINE DETECTION, QUALITY CONTROL, PULP QUALITY PREDICTION, PLS