Predicting strength characteristics of paper in real time using process parameters

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ABSTRACT: Online paper strength testing methods are currently unavailable, and papermakers have to wait for manufacture of a complete reel to assess quality. The current methodology is to test a very small sample of data (less than 0.005%) of the reel to confirm that the paper meets the specifications. This paper attempts to predict paper properties on a running paper machine so that papermakers can see the test values predicted in real time while changing various process parameters.

This study was conducted at a recycled containerboard mill in Chicago using the multivariate analysis method. The program provided by Braincube was used to identify all parameters that affect strength characteristics. Nearly 1600 parameters were analyzed using a regression model to identify the major parameters that can help to predict sheet strength characteristics. The coefficients from the regression model were used with real-time data to predict sheet strength characteristics.

Comparing the prediction with test results showed good correlation (95% in some cases). The process parameters identified related well to the papermaking process, thereby validating the model. If this method is used, it may be possible to predict various elastic moduli (E11, E12, E22, etc.) in the future as the next step, rather than the traditional single number "strength" tests used in the containerboard industry, such as ring crush test (RCT), corrugating medium test (CMT), and short-span compression strength test.

Application: The information presented in this paper is useful for operators to track sheet properties as the paper is being made. It also helps them to understand the effect of each parameter change they make in their day-to-day operation and how it impacts sheet quality.

The only way to measure destructive strength properties of paper today is after it is made by testing it in the laboratory, either using bench top equipment or using automated testing machines. Every jumbo reel takes at least 30–40 min to build, depending on machine speed and various other factors. Conditioning of paper samples and testing takes 15–20 min. During this period, the paper continues to be manufactured without papermakers knowing if it meets customer specifications. If, for instance, this paper does not meet the specifications, then it has to be either downgraded or discarded, thereby resulting in losses for mills. Also, only 0.005% of the total paper is typically tested and that, too, is on the top of the jumbo reel. It is assumed that the paper manufactured during the production of a jumbo reel has not changed in its structure or composition and will produce the same results as it does on top of the reel. This is an assumption on which paper is being manufactured and sold today. However, there could be numerous changes in the papermaking process that might affect the paper quality, either positively or negatively. These changes cannot be traced and related to the sheet properties at present. In a recycled paper mill, these variations might be huge in magnitude, such as, for example, variations in raw material being fed on the furnish conveyors.

Traditionally, the only method of knowing continuous real-time sheet properties was limited to using a scanner that measures basis weight, moisture, caliper, brightness, color, and some special scanners measuring tensile stiffness orientation (TSO) angle. In addition to this, the variation in testing from laboratory to laboratory and person to person will introduce certain errors to mills, as all mills add a safety factor to meet grade specifications. Attempts have been made in the past to utilize real-time adaptive predictions for process and quality optimization to make informed decisions, detect changes, and tune by machine learning principles [1]. Other researchers have used modeling to reduce testing in the mills, mainly by using predictive models after the paper is made. Once the paper is made, the models predict the sheet strength properties that can be used to sell paper. The periodic testing of the paper by technicians ensures the models are in line with the testing equipment. These types of models have reduced testing frequencies and improved quality decision-making. However, this method is not as preventive as the models, because when applied, the paper has already been made [2]. There are also attempts using an online sensor in the scanner to measure extensional stiffness. Due to some unknown reasons, this sensor has not been widely implemented to date [3]. Other research involved in modeling uses sheets produced on the machine with various process variables and studies in the laboratory. Then, using modeling, this method relates these properties to the paper machine process as to what major variables affect the sheet properties, including press loading, refining energy, freeness, etc. The results were verified with laboratory measurements and experimentation [4]. The combination of laboratory experimentation data and actual sheet tensile strength measurement were also used to potentially predict tensile strength of paper. But without integrating dynamic paper machine conditions, the models are ineffective. Simulations have been used to imitate dynamic conditions for input into tensile strength models [5]. There are other equipment suppliers who use advanced laboratory results for fiber furnish by conducting high-definition image analysis of fiber fibrillation, fiber length distribution, fines content, freeness, and other key morphology to use as soft sensors in dynamic conditions for predicting sheet strength properties. These strength parameters are then compared with the automated paper laboratory and correlated with paper machine process parameters like refining energy, rush/drag, chemical additions, etc., to predict the sheet properties. However, these soft sensors are expensive and need dedicated manpower to maintain and calibrate them [6].

The objective of this paper is to predict sheet strength properties in real time using dynamic paper machine process parameters. The method applies statistical analysis and papermaking knowledge to arrive at simple mathematical models that will allow operators to achieve sheet strength properties that meet customer specifications in real time. Another advantage of this method is that the sheet strength property is continuously derived in real time, thereby ensuring the quality is met throughout the process of making a jumbo reel.

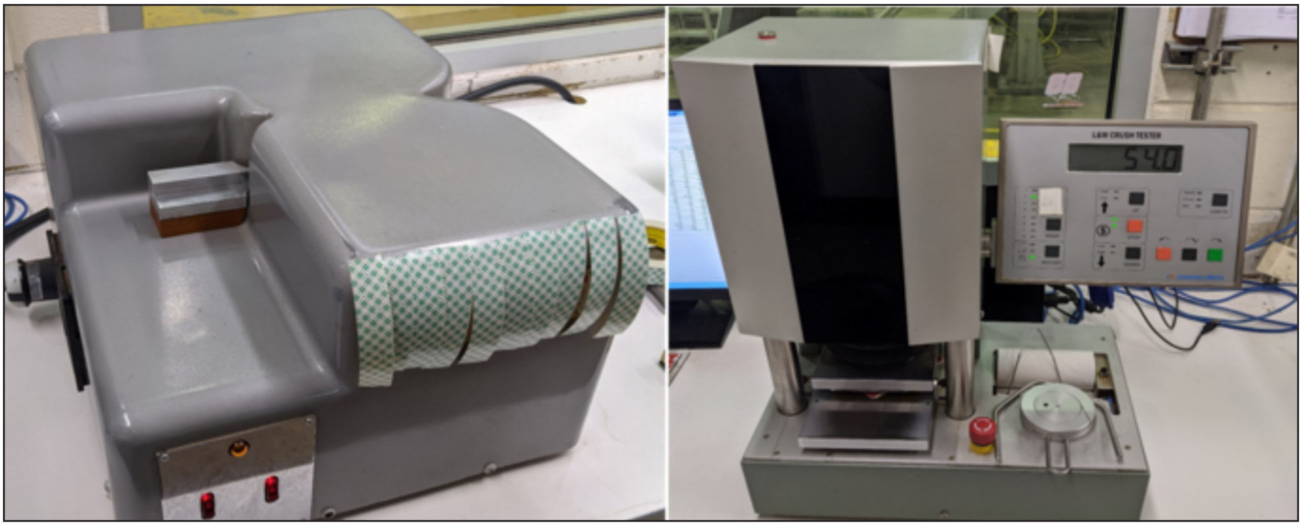
METHODOLOGY

Alsip MiniMill (Alsip, IL, USA) was originally built in 1969 as a newsprint/fine paper mill and was converted to manufacture containerboard in 2015 with a clear vision that it will produce the highest quality containerboard in the United States with the help of a "data-driven culture." The project vision included significant investment in measurement of process variables; a high level of focus on paper physics; automated testing on ABB L&W Autoline 400 (ABB; Zurich, Switzerland); and an integrated quality database by Siemens (Munich, Germany) and Panther (Vancouver, WA, USA) that allows advanced statistical analysis by a software firm such as Braincube (Issoire, France). These are the pre-requirements for the mill's methodology. Prior to implementation, it also requires thorough understanding of the mill's design parameters all the way down to pump curves and equipment capacities.

The offline testing of paper was conducted using bench top equipment for ring crush test (RCT), Concora corrugating medium test (Concora), and short-span compression strength test (SCT). The tensile stiffness index machine direction/cross-machine direction (TSI MD/CD) ratio was obtained through the mill's ABB L&W Autoline products. **Figure 1** shows the Autoline equipment installed in the mill to measure basic paper properties like basis weight, moisture, porosity, TSI, and tensile stiffness orientation (TSO). **Figure 2** shows the Concora tester (ABB L&W Crush Tester Code 248) along with the fluter (Concora Medium Fluter, Liberty Engineering; Roscoe, IL, USA) for the flat crush test of corrugating medium. TAPPI Standard Test Method T 809 om-06 "Flat crush of corrugating medium (CMT test)" is used to measure Concora. The ABB L&W Crush Tester is also used to measure RCT using TAPPI T 818 "Ring crush of paperboard (flexible beam method)." The SCT is performed using an ABB L&W Compressive Strength Tester to measure compressive strength of the corrugating medium according to TAPPI T 826 "Short span compressive strength of containerboard."

1. ABB L&W Autoline automated paper and board testing system used by the Alsip MiniMill.

A very simplistic method was used to develop the predictive models for sheet strength properties. Six months of data from each strength property that was tested using bench top equipment or ABB Autoline was collected, along with the process parameters when the paper was manufactured. The ABB Autoline measures the entire width of the sheet for every reel at 12 points. So, each property for the reel is an average of 12 points across the width of the paper machine. For RCT and SCT, the mill takes an average of 12 points across the width of the paper machine. The values used for developing the model are an average of 12 points across the width of the paper machine. Approximately 1600 variables in the process are used to conduct a multivariate analysis using Braincube software. Process variables from the pressure transmitter, consistency transmitters, flow transmitters, freeness analyzers, and so forth are collected every minute in the database. The multivariate analysis statistically provides process parameters that highly impact



2. ABB L&W fluter (left) and ring crush test (RCT)/Concora tester (right) used by the Alsip MiniMill.

the sheet property being analyzed. Papermaking and paper engineering knowledge is then applied to these process parameters to ensure they make sense. Some data cleaning is required to eliminate blanks or unrecorded entries. The high impact process parameters are selected based on papermaking knowledge and statistics. These parameters are then subjected to multivariate regression analysis. From the statistics, it becomes possible to identify the parameters that have a linear relation to the sheet property under study. This method is iterative, as only the parameters that meet the 95% confidence limits are selected for further analysis. With these coefficients, it is now possible to arrive at an equation that will help to predict the sheet property. Each process variable's coefficients are then used in real time with the process parameter to arrive at the predicted sheet property. The predicted sheet property value is compared to the actual value after the laboratory testing to determine the coefficient of determination (R^2) value to validate the accuracy of the model. Error calculations are also performed to ensure the results are well within the 10%–15% range seen in laboratory-to-laboratory and person-to-person testing variation.

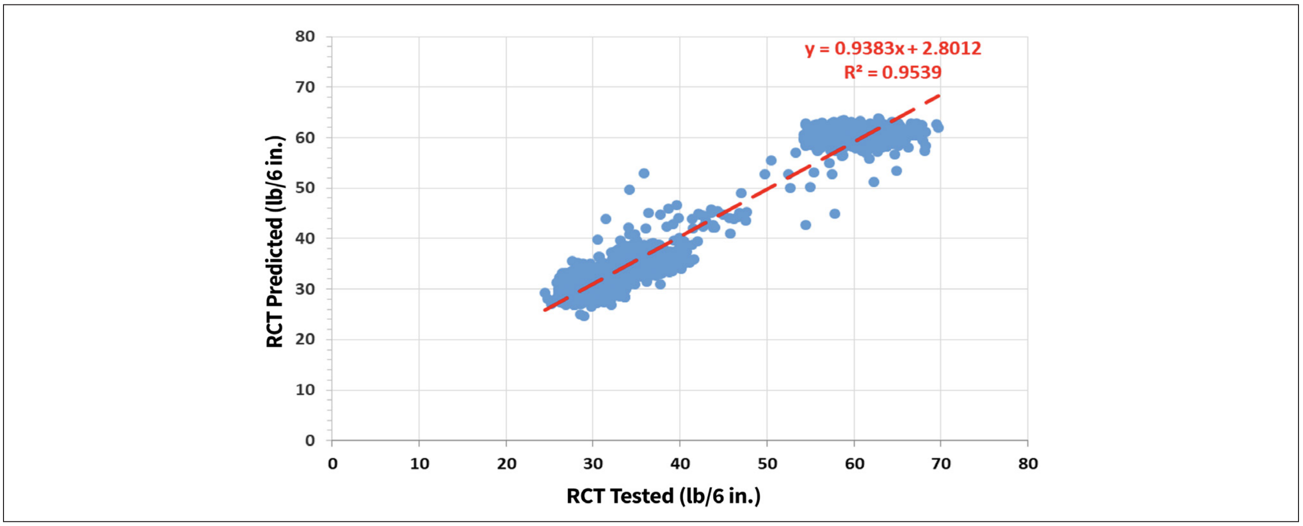
The error percent notifies mill personnel when the predicted model moves away from the actual value, thereby showing when the model needs to be carefully examined. These equations are then entered into the mill's live database to examine whether it can accurately predict the properties. By trending the calculated sheet property with the operator tested property, it was evident that the mill had a model that could accurately predict the sheet properties. Observing the process parameters, it became easy to see how the sheet property changed with process changes. The process parameters used to develop the model were indicative of whether the paper would meet the specifications for the grade. The data was validated for the past data from the historian and also the present ongoing manufacturing data. From both the trends, it became evident that that the mill was able to predict sheet strength properties accurately. This process also identified the key parameters and their operating ranges to meet the sheet quality requirements.

RESULTS AND DISCUSSION

Ring crush test prediction

Ring crush test is one of the main quality parameters that is measured in the mill's process and is used to grade paper. The mill would benefit greatly if it could control and predict this sheet property when the paper is being manufactured. The operators perform RCT every reel and enter it into the mill quality system with the timestamp for when the reel was produced. Six months of the process data during the manufacture of the reels in real time is used to perform multivariate analysis and use the top parameters that can predict the RCT. **Figure 3** shows the correlation between the actual values tested by the operator using laboratory equipment on the X-axis compared to the predicted value through statistical analysis on the Y-axis. The data clearly show a strong correlation between the lab-measured value and the value obtained by the mill's model. The R2 value was 0.95, which shows that the model used to predict RCT is reliable and accurate. The graph shows a grouping of two major data points, mainly due to the different grades manufactured at the mill. Moreover, one single model was able to predict all the grades manufactured on the machine.

The major parameters that showed a strong correlation to predict RCT are shown in **Table I**. Basis weight, headbox static head, rush/drag, and wet suction box-1 vacuum on the Fourdrinier table were the major parameters that affect RCT. It is evident that the sheet strength will always depend on basis weight, which forms the basic structure. The wet-suction box-1 vacuum on the Fourdrinier table is the vacuum element on the mill's Fourdrinier table where the sheet consolidates ("dry line"). It is also evident how the headbox operations are important in obtaining the desired RCT by controlling the rush/drag for fiber orientation and headbox



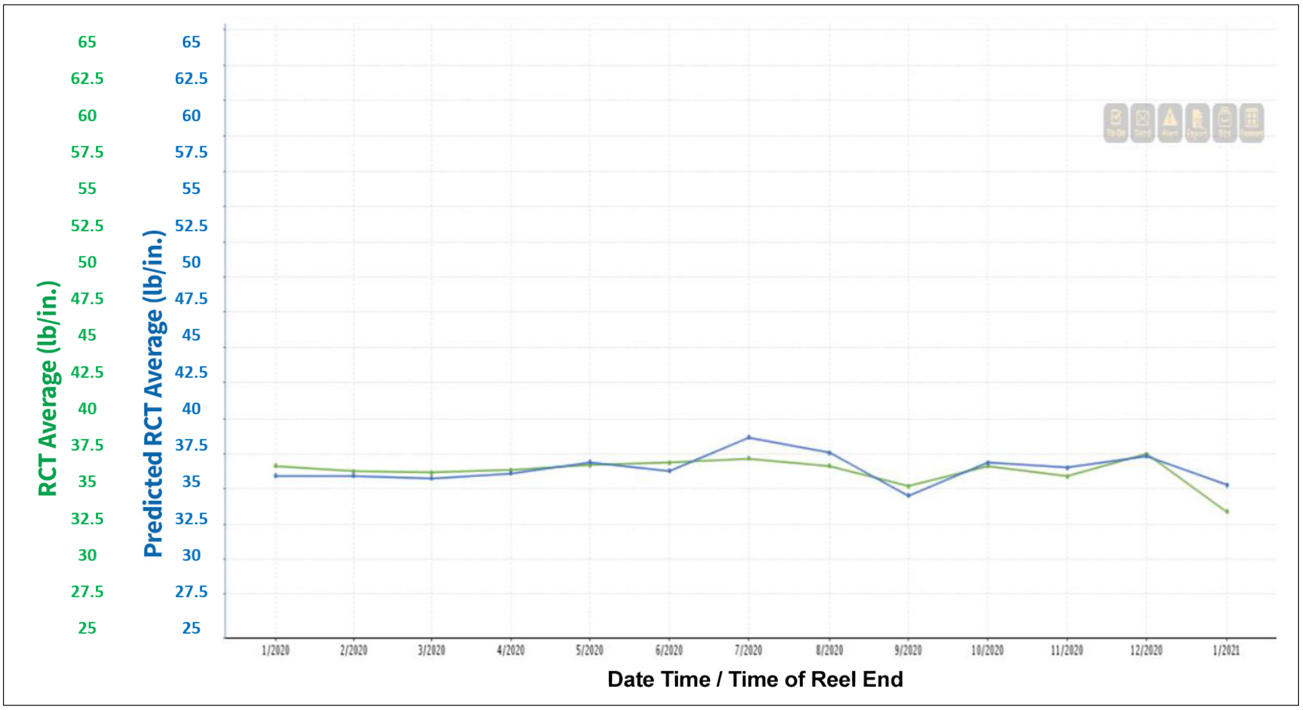
3. Correlation between RCT tested in the laboratory vs. RCT predicted using the model.

Parameters	Influence/Impact
Basis weight average	+ High
Wet suction box No. 1 vacuum	+ High
Rush/drag value	+ Medium
Headbox static head control	- Low

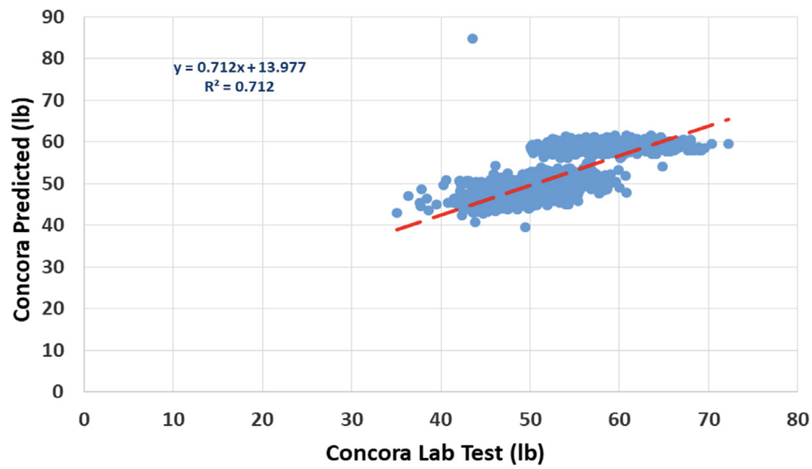
I. Process parameters that affect RCT.

static head for headbox flows. The combination of all these process parameters will ensure the mill achieves the desired RCT. Note that a strong correlation of refining energy or freeness as a parameter that affects RCT was not seen. The refining energy applied at this mill is a constant, and hence was not a major factor in developing RCT.

Once the model for RCT was developed, the operators could manipulate the corresponding variables to achieve the required RCT target for the grade. Also, when making process changes for any reason, they can see the impact of each variable and the trend of RCT to ensure it is in the right direction. The operators also have trends available for watching these individual variables with statistical pro-



4. Trend between RCT tested in laboratory vs. RCT predicted using the model.



5. Correlation between Concora tested in the laboratory vs. Concora predicted using the model.

cess control charts to ensure they are within the parameters to achieve the grade specifications. This has also helped the mill to optimize various items, such as basis weight and steam usage per ton, to obtain the desired results, leading to consistent operations and cost reduction. This makes quality decisions easier for achieving the desired RCT for the entire reel, for example. One result achieved using these models and their variables was to avoid "over-refining," which affects drying and production rates. The predicted RCT from its variables has resulted in increased speed and optimized basis weight and prevented unnecessary refining energy use.

Comparing the predicted calculated values for a one-year period, it was evident that the model accurately predicts the RCT (**Fig 4**). This accuracy is enough to guide the operators in real time to control and make changes to the process to achieve desired results. They can also troubleshoot RCT problems before the entire reel is manufactured by making necessary changes to the right process parameters to achieve the grade targets. This model also guides them if the changes made are in the right direction. This type of prediction not only helps the mill to meet grade specifications all the time and make prime paper but also optimizes basis weight, reduces refining energy, and increases throughput.

Table II shows the statistics for a period of one year. This confirms that the RCT-predicted value through the mill's models can be used reliably. This statistic represents 9900 reels manufactured during the period.

Concora flat crush of corrugating medium prediction

Concora, as evaluated by TAPPI T 809 om-06, is another important paper property for the mill that is used to meet grade specifications. For grades where the CD property RCT and MD property Concora are both requirements for meeting grade specifications, it becomes imperative for the mill's operators to watch and control these properties to optimize the results. Since both of these properties are attained at the cost of each other, it is a constant challenge to balance between MD and CD direction sheet properties.

Figure 5 shows the correlation between the actual Concora values tested by the operator in the lab on the X-axis compared to the predicted value using the mill's statistically derived model on the Y-axis from real-time process parameters on the paper machine. The R^2 value of 0.71 shows that the model can reliably predict Concora using the real-time process parameters. The mill believes that the R^2 value is slightly lower due to laboratory variation in testing Concora.

With recycled furnish, it becomes more challenging due to the inherent variability of wastepaper, as the process is highly dependent on variations in the raw material used. In order to help the operators, the Concora predictor is used to guide operators to ensure the mill meets grade specifications. With the multivariate analysis, it was found that Concora is dependent on more process variables compared to the RCT. All the process variables were machine parameters. **Table III** shows the process

	Minimum	Maximum	Average	Deviation	1st quartile	Median	3rd quartile
Predicted RCT	32	36.2	33.9	1	33.2	33.8	34.4
Laboratory RCT	30.9	35	33.7	0.997	33.4	34.1	34.2

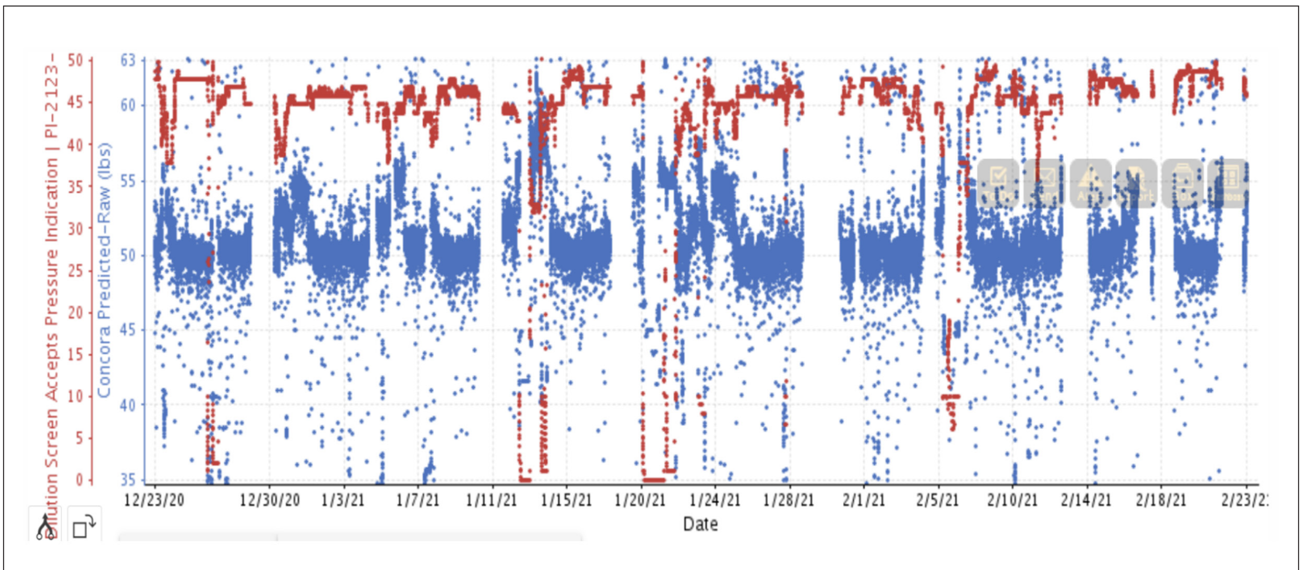
II. Statistical comparison of laboratory test values vs. predicted values for RCT.

Parameters	Influence/Impact
Bone-dry basis weight +	+ High
Headbox static head control +	+ High
Second press draw +	+ Medium
Rush/drag value -	+ Low
Paper machine dilution screen accepts pressure indication -	- Low
Suction pick-up roll-holding zone vacuum -	- Medium
Headbox stilling chamber pressure -	- High

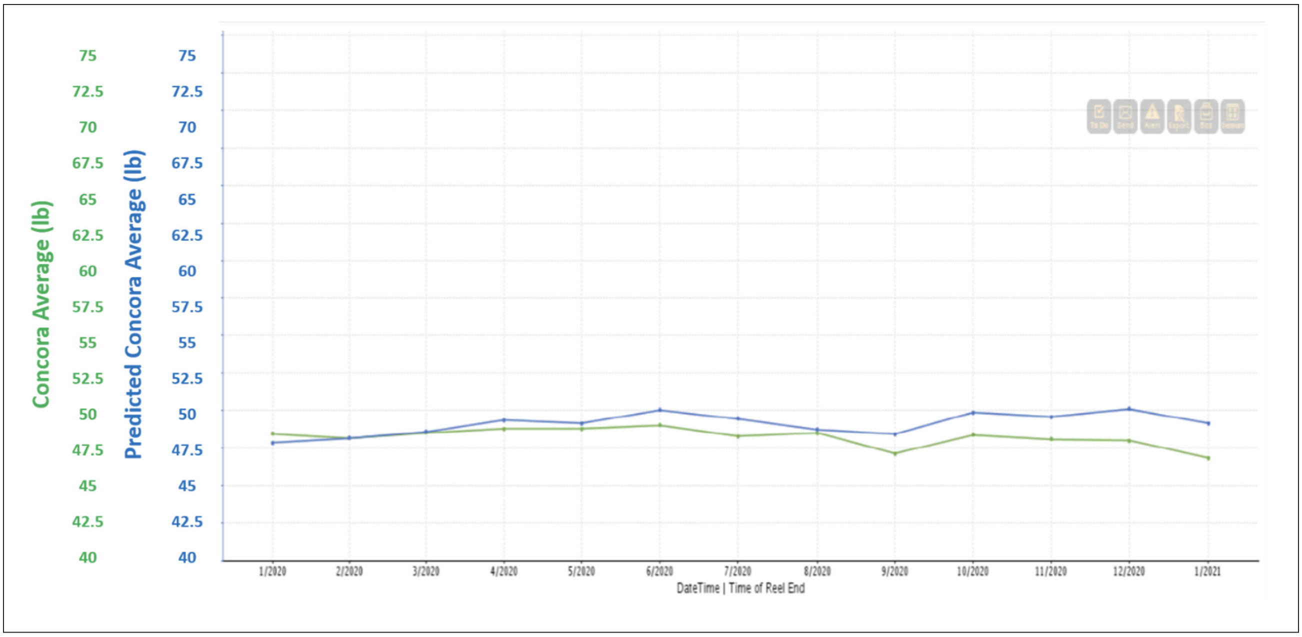
III. Process parameters that affect Concora or flat crush medium test (CMT).

variables that have impact on Concora and are used in the model to predict Concora on the paper machine. The major parameters that showed the influence on the Concora test were basis weight, headbox operations, and suction pick-up (PU) roll holding zone vacuum. As stated earlier, basis weight will always be the major parameter that affects sheet strength.

It was also evident how headbox operations were important to control the fiber orientation to achieve Concora values. The mill's paper machine is equipped with a dilution headbox where the paper machine (PM) dilution screen feeds the low consistency (LC) header. It was observed that when the dilution screen accepts pressure was high (>46 PSIG), we would see a drop in the Concora values. Dropping this pressure by 2 PSIG saw an increase in Concora values. Investigating this further, it was evident that the design of the ModuleJet headbox (Voith; Heidenheim, Germany) confirms that it affects the fiber orientation, based on the description in the patent [7]. This PM dilution screen controlled the pressure on the LC header of the headbox, which in turn maintained the differential pressure between the LC header and stilling chamber; the higher the differential pressure, the greater the disturbance in fiber orientation. The second press draw also appeared as an important parameter for obtaining Concora; the higher the draw, the higher the Concora, until the sheet breaks. The second press draw is where the sheet is transferred to the second press with a sheet solids of 37%–38%. Here, the sheet is still consolidating, and any pull at this point changes the fiber orientation and lowers TSI CD strength. This helps to improve Concora only if the force is not enough to cause a sheet break or weak spots in the sheet. The first press is a Valmet (Espoo, Finland) Combi Press (ceramic roll against PU roll nip). The holding zone vacuum is important, because this determines how the sheet is sealed and how the water is drained in the first press section. This also impacts the sheet solids coming out of the press section. This is the only open draw on the paper machine. Again, the refiner outlet freeness or refiner specific energy did not show up as an influential process parameter. This



6. Data showing the influence of the mill's low consistency header pressure on Concora.



7. One-year trend for laboratory-tested Concora values vs. the predicted Concora values derived from the model.

shows that the mill's sheet properties might not be directly affected by the refining process, because this refining process is stable, with minimal changes. However, the vacuum on the suction PU roll was a factor that shows some relation with refining. However, by using other variables like PM dilution screen pressures, which can be manipulated using the LC header recirculation flow, the mill was able to produce the desired Concora values. This eliminated the use of high refining energy, which impacted the mill's drying rates.

Based on the predicted parameters for influencing Concora, **Fig. 6** shows one of these parameters that negatively influences Concora. As the paper machine dilution screen accepts pressure increases, feeding the LC dilution header of the headbox increases, the Concora decreases and vice versa. This pressure increase or decrease can be managed by using the LC header recirculation valve. This parameter is now used to maintain the Concora specifications. Prior to developing these models, increasing refining energy and increasing recirculation flow of the refined stock were the ways to maintain Concora. This resulted in adverse effects on the paper machine drying capacity, leading to slowdown of the paper machine. Statistical modeling with papermaking knowledge proves to meet Concora specifications, and at the same time, improve productivity.

Figure 7 shows a one-year trend for laboratory-tested Concora values vs. the predicted Concora values derived from the model. It can be clearly seen that the predicted models accurately follow the trend, but the actual values might differ slightly due to various reasons, including variation in paper testing. It can be concluded that the mill was able to predict the Concora values using process parameters.

Table IV shows the statistics for measured values of Concora and the predicted value for 9900 reels manufactured during the period. This confirms that the Concora predicted value from the mill's models can be reliably used.

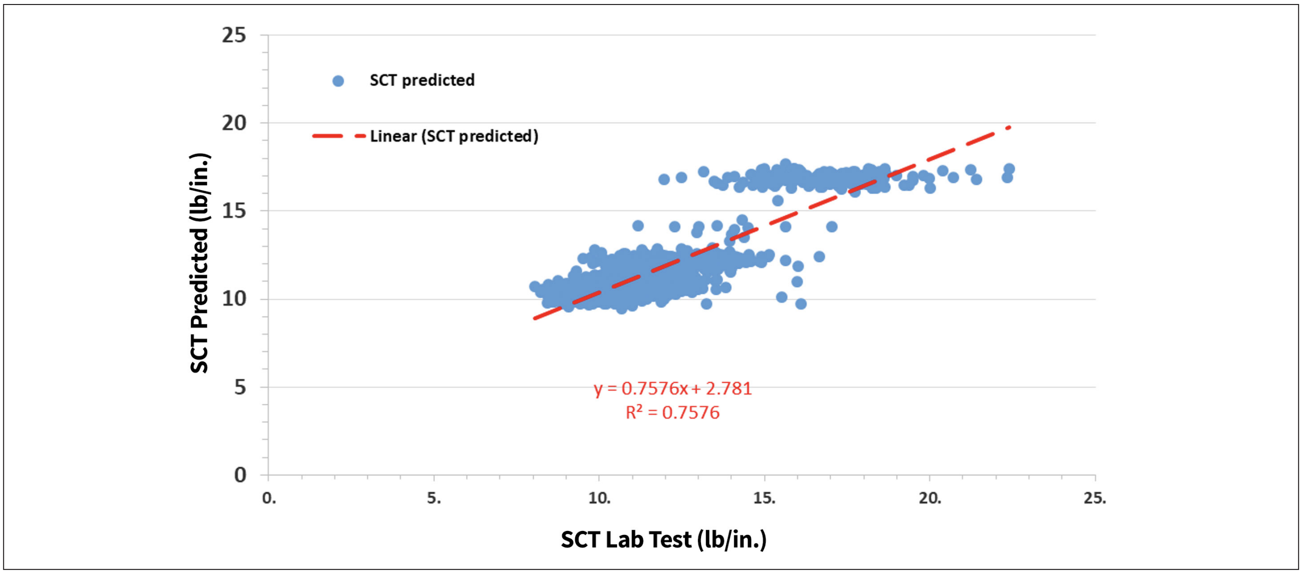
Short span compression test prediction

By further investigating sheet properties, the mill was also able to develop a statistical model for predicting SCT using process parameters. There were several iterations to the model to arrive at the right model based on statistical interpretation and papermaking knowledge. The SCT was found to be dependent on only two variables; namely, basis weight and rush/drag. All the other variables had negligible or no impact on the outcome of SCT. This might also be machine dependent and process dependent and vary from mill to mill and machine to machine.

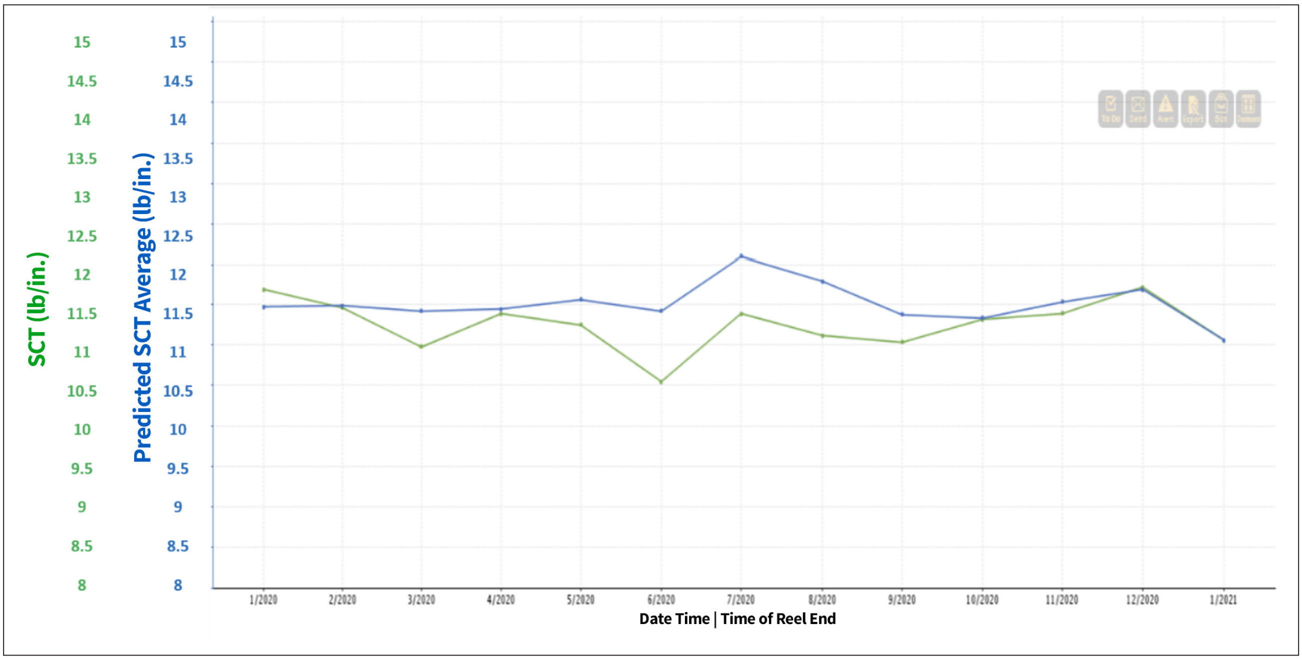
Figure 8 shows the correlation between SCT tested on bench top equipment and that was obtained with the

	Minimum	Maximum	Average	Deviation	1st quartile	Median	3rd quartile
Predicted Concora	47.8	50.1	49.1	0.688	48.4	49.1	49.6
Laboratory Concora	46.8	49	48.2	0.601	48	48.4	48.5

IV. Statistical comparison of laboratory test values vs. predicted values for Concora.



8. Correlation between laboratory-tested short-span compression strength test (SCT) values vs. SCT predicted using the model.



9. One-year trend for laboratory-tested SCT values vs. the predicted SCT values derived from the model.

mill's predicted model. The R^2 value of 0.76 shows that the model can accurately predict the SCT value using process parameters. Comparing RCT and SCT, which are both CD-oriented tests, it was surprising to see that more variables are required to predict RCT compared to SCT. The explanation for this difference is unknown, as the same parameters were used for multivariate analysis and also during the same period. The R^2 value of 0.758 suggests that this is a reliable model.

Figure 9 shows the trend for a period of one year using laboratory-tested data and predicted values from our model. It is also important to note that the mill does not test SCT values for every reel. Based on these trends, it can be concluded that the mill's model can reliably predict SCT values.

Table V shows the statistics for laboratory-measured and predicted values of SCT for 3500 reels manufactured during a period of one year. This confirms that the SCT predicted value through the models can be reliably used.

Tensile stiffness index ratio prediction

Further applying the methodology, the mill looked at the process parameters affecting TSI MD/CD ratio. **Table VI** shows the process parameters that affect TSI MD/CD ratio. It was found that the TSI MD/CD ratio was dependent on the machine draws, low vacuum on the fourdrin-

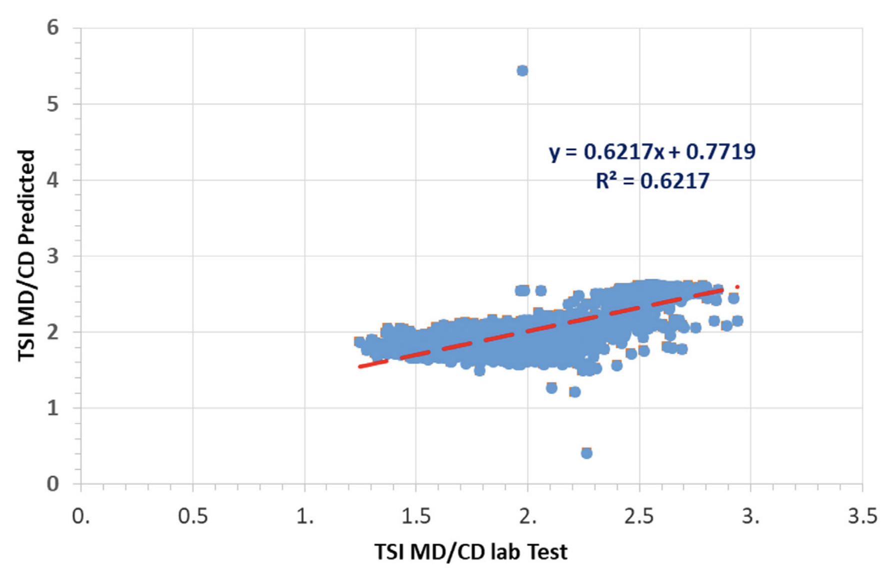
	Minimum	Maximum	Average	Deviation	1st quartile	Median	3rd quartile
Predicted SCT	11.06	12.1	11.52	0.24	11.38	11.47	11.57
Laboratory SCT	10.5	11.7	11.3	0.305	11	11.3	11.4

V. Statistical comparison of laboratory test values vs. predicted values for short-span compression strength test (SCT).

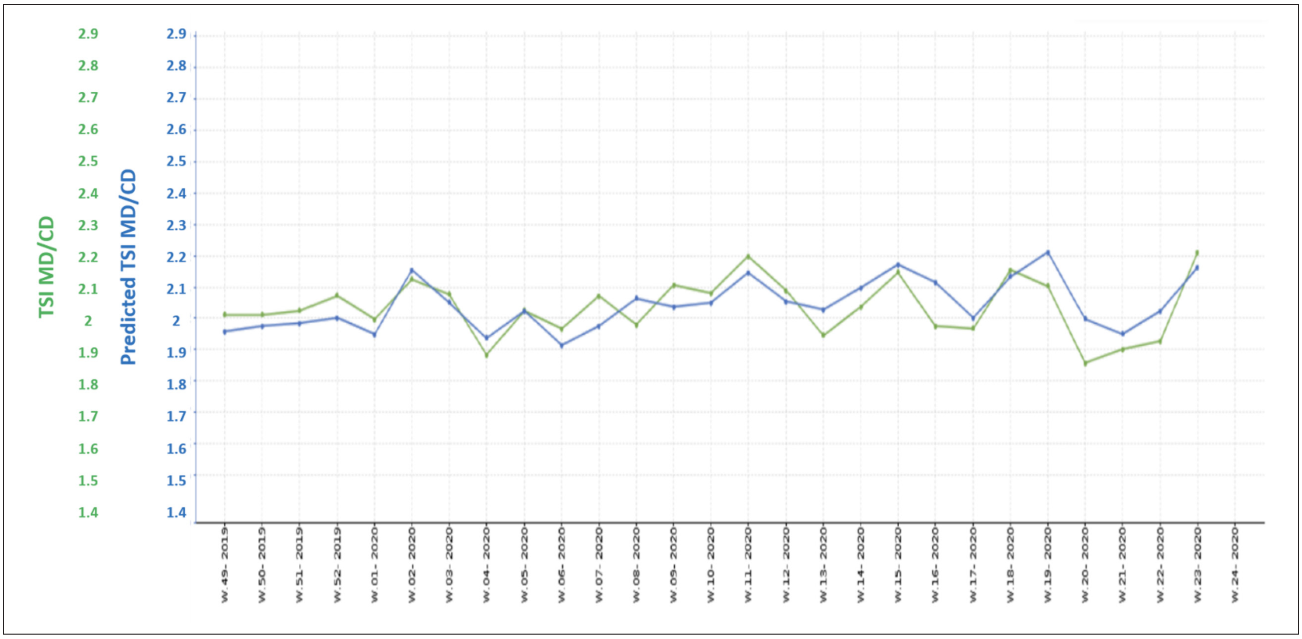
Parameters	Influence/Impact
Second press draw percentage +	+ High
Basis weight average +	+ Medium
Step foil box No. 3 separator vacuum +	+ Low
Machine speed +	+ Low
First press draw percentage -	- Low
Rush/drag value -	- Low
Suction pick-up roll-holding zone vacuum -	- Low
After-dryer draw percentage -	- High
Wet suction box No. 1 separator vacuum -	- High
Headbox stilling chamber pressure indication -	- High

VI. Process parameters that affect tensile stiffness index machine direction/cross-machine direction (TSI MD/CD) ratio.

ier table, and headbox operations. In fact, one of the draws was the mill's long open draw between the pre-dryer section and after-dryer section due to the absence of the old size press. The model developed showed satisfactory correlation and was dependent on 10 variables. The R^2 value was slightly lower at 0.61. The mill believes that the lower TSI MD/CD is due to the challenge to meet both CD direction strength RCT and MD direction strength Concora. The model would predict more accurately if CD strength and MD strength are maintained independently of each other. **Figure 10** shows the correlation between the laboratory-tested TSI MD/CD ratio using Autoline with that calculated using the mill's statistical model.



10. Correlation between TSI MD/CD ratio in the laboratory vs. TSI MD/CD predicted using the model.



11. Trend between TSI MD/CD ratio in the laboratory vs. TSI MD/CD predicted using the model.

	Minimum	Maximum	Average	Deviation	1st quartile	Median	3rd quartile
Predicted TSI MD/CD	1.98	2.15	2.06	0.049	2.01	2.05	2.11
Laboratory TSI MD/CD average	1.9	2.21	2.25	0.701	1.97	2.06	2.11

VII. Statistical comparison of laboratory test values vs. predicted values for TSI MD/CD.

Figure 11 compares the six-month trend between TSI MD/CD ratio in the laboratory to that obtained by the predicted statistical model. Most of the time, the trend is identical, but the magnitude varies slightly.

Table VII shows the statistics for laboratory-measured and predicted value of TSI MD/CD for 9900 reels manufactured during a period of one year. This confirms that the TSI MD/CD predicted value through the mill's models can be reliably used.

Key performance indicators

The authors gained confidence in the methodology used for predicting sheet strength properties using multivariate analysis. To take it to the next level, the began to apply the same principles to identify the major process indicators that govern key performance indicators (KPIs). The KPIs studied were stock preparation production rates, refiner freeness, press uhle box flows, freshwater flows, production rates, etc. It was evident that these parameters could be accurately modeled and predicted in real time. The major advantage of performing this modeling was to identify the key process parameters that control or affect these KPIs. Controlling these key process parameters using statistical process control will lead to better quality, improved cost, and increased productivity. The mill is now in the process of controlling these process parameters using statistical process control to reap these benefits.

CONCLUSION

In order to improve quality, cost, and productivity, there is a need to use a "data driven decision-making" process in the manufacturing environment in real time. This paper demonstrates the use of statistical data combined with subject matter expertise to achieve desired results. The major focus of this project continues to provide real-time data to the operators and tools to control and optimize the papermaking process. Process parameters obtained using this method resulted in a perfect guide for operators to ensure the process is optimized to provide the best quality to customers and reduce costs by improving efficiency. Further applying this methodology to predict KPIs resulted in improved cost and productivity. **TJ**

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ABOUT THE AUTHORS

In this study, we were trying to understand the interactions of various process parameters and how they affect sheet strength. What are the tools that the operators need to watch to stay on quality all the time? We decided to use statistics and papermaking knowledge to arrive at a conclusion.

There are some researchers who have tried to use process parameters for predicting sheet strength, but everyone's methodology is different. Here, we provide a simplistic tool to develop these models, which can be modified if any process changes happen.

Arriving at the model and selecting the parameters from the statistical analysis was a challenge. We had to dive deep into papermaking knowledge to ensure the statistics matched with papermaking theory.

The most surprising part of this finding was the R^2 values for our models. We did not imagine that these values would work out this well, as any industrial data correlations have very low R^2 values.

The tool described here is very simple to use and can be adopted by any mill if it has a good data historian. With this tool, we are not waiting for the paper reel to be manufactured to know the sheet strength. Loss of paper due to poor quality can be avoided.

Mills can also use this tool for tracking not just quality, but also various KPIs. We are seeing great success with this method.

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