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Moving from Descriptive to Prescriptive Analytics Using AI: Success Stories in Papermaking

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ABSTRACT

A new approach to modernizing papermaking operations is available by using artificial intelligence (AI) and predictive analytics to provide real-time measurements and feedback to optimize production quality and efficiency. Unlike traditional papermaking operations that rely on laboratory tests conducted over time OR periodically, this approach uses machine learning algorithms that provide instant feedback on key process indicators. Instantaneous feedback allows operators to make informed control decisions and appropriate and timely adjustments to improve efficiency and reduce off-quality production.

This paper discusses how AI can be used in papermaking operations, how it can be used to inform control decisions, and what its potential benefits are. Specifically, the team will discuss how AI enables predictive analytics by providing a real-time understanding of indicators such as speed changes, kappa swings, and chemistry changes. The authors also explore the potential use of AI for utilizing existing data from laboratory tests to further refine predictive accuracy. Finally, the team presents an example case study from a large paper mill that implemented this approach and discusses their results, including efficiency gains and quality optimization.

AI and predictive analytics can bring greater efficiency to paper machines. By using wet tensile tests, it is possible to adjust wet strength chemistry for optimization and to adjust strength targets for better control. Moreover, strength, smoothness, and basis weight measurements, in tandem with caliper measurements, enable efficient basis weight optimization. Lastly, using predictive analysis for spore tests, which require more than two days to complete, results in more efficient microbiological (MB) control. AI and predictive analytics, when successfully implemented, have great potential to optimize paper machines.

Overall, this paper provides a comprehensive overview of how AI can be applied for predictive analytics in papermaking operations and discusses its potential benefits for improving machine efficiency and optimizing quality control. It is intended for those who are interested in understanding the impact of advanced technologies on modernizing papermaking.

Keywords: Artificial Intelligence, Process Control, Predictive Analytics

INTRODUCTION

Many methods exist for determining product quality, but the method used most often is periodic laboratory testing. Even if a laboratory analyst could test every paper reel produced, the time between test results would be significant because of the time it takes to produce a reel of paper and the laboriousness of sample preparation, testing, and data recording. Additionally, making machine control decisions based on periodic laboratory tests has many inherent limitations, such as low frequency of data, lack of machine direction (MD) data, and the existence of both measurement error and human error in laboratory tests. Acquiring quality data after the production of a reel of paper is too infrequent for the papermaker to proactively make process adjustments, leading to increased off-quality product and material and energy waste. Furthermore, testing the quality of a single MD location in a paper reel is an incomplete representation of the product and can lead to downstream issues, such as low converting efficiency and increased customer complaints. Making machine control decisions using laboratory measurements that combine both high measurement accuracy and human error induces unwanted variability into the papermaking process.

Real-time prediction models provide high-frequency and timely data every 15–30 seconds, thereby creating a MD quality profile. However, a prediction model built without considering the unique process it is simulating may result in high prediction error. Using an inadequate or erroneous prediction model to make control decisions can induce more process variability than using the laboratory test. Thus, a valuable prediction must introduce no more error than the laboratory test it is simulating. A useful prediction model must use methodologies that reflect the process being simulated. In this paper the teams demonstrate how to establish accurate, real-time, and adaptive predictions for strength parameters such as tensile, Ring Crush and Mullen. The authors discuss the structure of paper machine quality data and process information, highlight appropriate methods for creating quality predictions (mentioning novel techniques when appropriate), define simple metrics to measure prediction accuracy, describe how importance applies machine learning to maintain prediction accuracy, and exemplify how real-time strength predictions can be valuable in packaging manufacturing.

METHODS FOR CREATING AN ADAPTIVE AND REAL-TIME PREDICTIONS MODEL

Creating an adaptive and real-time predictions model is a multi-step process that begins with collecting data, includes developing the predictive model and concludes with implementing the model and evaluating the results. The type of data to be collected and how it is collected is generally very similar across paper mills but may vary from mill to mill. Likewise, how the predictive model is developed and how its challenges are overcome are also similar across mills; however, how it is implemented and the results it delivers may be very mill specific. This discussion concludes with an example of the implementation of a predictive model in a particular mill and includes details of the results and benefits achieved by using the AI predictive model.

Collecting Data

To accurately predict paper quality, meaningful historical process data must be collected for 6 to 12 months. Instrumentation on paper machines has made gathering this information easier; however, not all data is useful for predicting paper strength. Figure 1 shows important data sources that will help build accurate predictions.

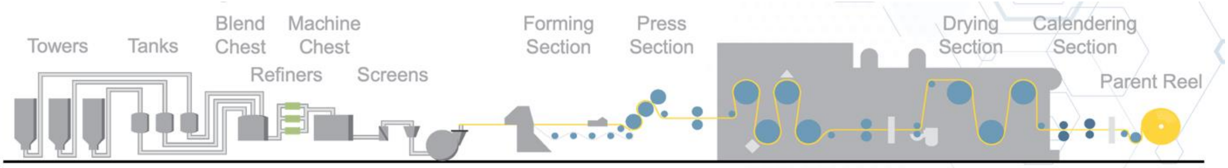


Figure 1. Important data collection points on a paper mill

Developing the Predictive Model

After the historical data is collected and surveyed, the predictive model is built. Making paper-quality predictions requires developing a supervised learning model where historical data is used to "teach" the model based on past outcomes. However, the underlying process complexity requires a novel approach to developing a predictive model. Predicting paper quality measurements in real-time presents major challenges.

High dimensionality

The number of sensors in a mill can range from hundreds to thousands. These sensors continuously collect data resulting in a high-dimensional and high-frequency data stream. Additionally, sensors are added and removed over time, which leads to temporally dynamic high-dimensional data.

Complex Spatial and Temporal Correlation

The variables in the data stream are spatially and temporally correlated. Spatial correlations exist between variables measured at the same time; temporal correlations are found within or between variables observed at different points in time. These dynamics can be linear or nonlinear, which makes their estimation extremely difficult.

Nonstationary dynamics. Due to the intrinsic dynamic nature of paper-making processes, the generated data streams have nonstationary behavior, meaning that their probabilistic distributions change over time. This makes predictive modeling challenging because a trained predictive would not be valid after a short period of time.

Measurement errors

The response variable, which is typically a quality measurement related to paper strength (e.g., tensile, Ring Crush, Mullen, etc.), is measured in a laboratory. These measurements commonly contain non-random errors, often because of human data entry errors. Because the process indicators are tested infrequently, identification and isolation of the measurement error is difficult.

Observational data

Although experimental data is preferred to identify the causal relationships between variables, it is difficult to obtain because of the exceptionally high cost of experimentation in paper mills. Consequently, only observational data is available for modeling.

Overcoming Predictive Model Challenges

By using novel approaches, the challenges of predicting paper quality measurements in real-time can be overcome.

Regularization in spatial and temporal domain

Having too many variables in a prediction model results in poor accuracy. Therefore, regularization techniques, for example, L_0, L_1, or L_2, are often employed in high-dimensional processes [1]. Regularization yields a smaller set of the most important variables for prediction (variable selection). However, most conventional regularization techniques have two limitations, namely that they work in the spatial domain and on linear relationships between variables. A nonlinear correlation estimator was needed and thus developed [2]. Subsequently, a novel regularization approach that used this estimator in the temporal space to overcome these limitations also was developed. Note that the correlation estimator can also find a linear correlation. Additionally, to aid the variable selection, a causal relationship graph is required. Estimating this is rather straightforward with experimental data. However, because of the availability of only observational data, an approach using a constrained graphical lasso method was developed.

Adaptive and evolving model

Paper manufacturing is a continuous process that changes over time. These changes can occur slowly or abruptly. For example, a change in a raw material or the degradation of a machine part leads to a slow process shift. On the other hand, at or near the time of a paper break or grade change, the process rapidly experiences a shift. These scenarios lead to two considerations, namely historical data becomes obsolete quickly and the predictive model must be updated frequently. Thus, a continuously evolving and adaptive model is required. The predictive model evolves over time as newer data is collected and older data loses its relevance. The prediction system is built such that it automatically uses the knowledge gathered from the old data and combines it with the new data to construct an evolved (relearned and more accurate) model. Additionally, the prediction system adapts to process changes. For the model adaptation, the data science team performs the best prediction model selection, and its retuning, periodically and on-demand. The periodic runs are to ensure nothing is missed by the triggers. The on-demand is triggered automatically whenever a process shift is detected. Data with measurement errors are identified in real-time using F-tests and are isolated from the training data. These adaptation features of the model are computationally intensive. To deploy them in real time, the team parallelized the processes through multiple processing units. The parallel processing enables the delivery of accurate predictions in real-time every 30 seconds.

Figure 2 shows the outcome of a predictive model that uses an off-the-shelf approach without considering the unique characteristics of the papermaking process compared with a model using a tailor-made, advanced approach such as the one discussed previously. The oversimplified model depicted in Figure 2a does not mirror the true process, while that of Figure 2b considers the complexity of the papermaking process and clearly delivers predictions that are more accurate.

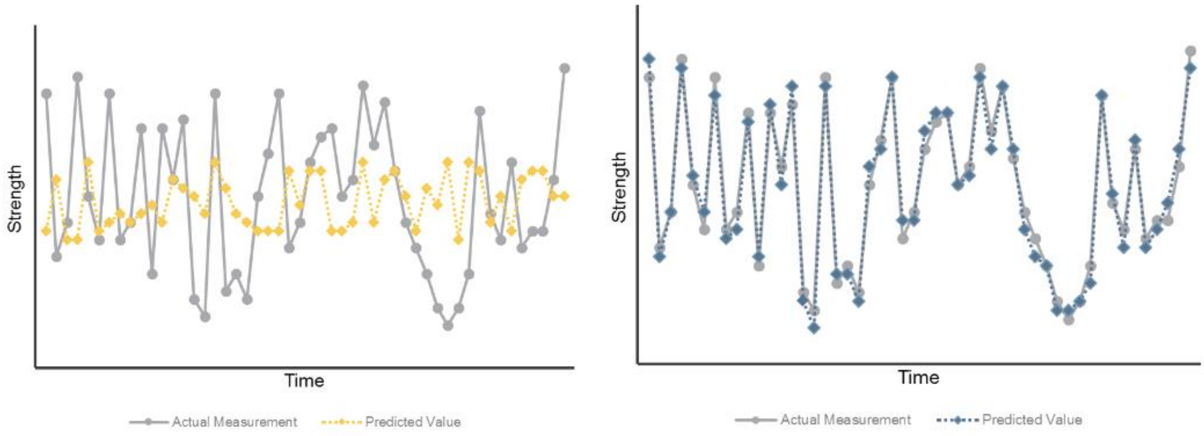


Figure 2. (a) Predictive strength model using poor prediction techniques that oversimplify the process; (b) Predictive strength model with the same data using advanced techniques capable of handling paper machine process data

Implementing the Predictive Model Using Closed-Loop Control

After the predictive model is built, with the aid of subject matter experts, a recommendation engine is built for each paper machine. The engine, once configured, recommends chemistry adjustments that, when taken, improve process control and reduce quality variations. Recommendation engines range in complexity from the simplest one-variable recommendation to the most complex, multi-variable, cost-optimized recommendations, which are shared from the cloud to a dashboard. The dashboard is accessible through a web browser and through an Internet of Things (IoT) edge device. The edge device provides the final connection to complete the loop of the closed-loop control.

Closed-loop control is essential to extract full value from the predictive model. Open-loop recommendations extract a fraction of the value of closed-loop control. The most successful open-loop implementation enacted 30% of issued recommendations. OPTIX™ closed-loop sites are taking 90% or more of recommendations issued.

Closed loop is configured like many of the other important control loops in a paper mill. Machine operators can always retake control. Closed-loop predictive control essentially elevates the machine operator to a supervisory role. An AI virtual operator is now enabled with a simple mouse click by the machine operator. Much like autopilot in an airplane or cruise control in an automobile, with the AI predictive model the machine operator can assume control at any time.

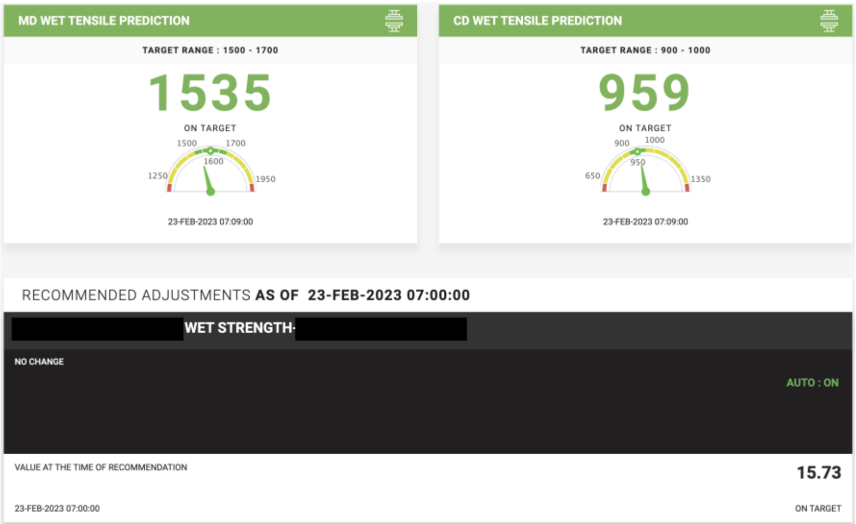
RESULTS IN WET STRENGTH

A large North American liquid packaging mill was interested in reducing wet tensile variation and improving wet tensile quality adherence. This mill employed a typical wet-end chemical dosage strategy practiced throughout the industry of waiting for dry-end quality laboratory tests to be completed or validated by re-testing before chemical setpoints were changed. These delays typically forced operators to run higher chemical feed rates to ensure no off-quality board would be produced.

Implementation

The predictive model was developed and implemented using customer and digital resources to ensure its accuracy. The team then built a recommendation engine that used the model predictions to drive optimization. The recommendation engine used key levers to drive the predictions and process to the desired quality. The recommendation engine interpolates how changes to the recommended levers will affect the system and issues a cost-optimized result.

Mill staff was trained on the system and key objectives were established for the project. Machine operators were provided with a customized dashboard. This dashboard can be integrated into the current machine's digital control system (DCS). The dashboard, as shown in Figure 3, displays the key predictions, recommendations, and current status of the process.


MD WET TENSILE PREDICTION
TARGET RANGE : 1500 - 1700
1535
ON TARGET
23-FEB-2023 07:09:00

CD WET TENSILE PREDICTION
TARGET RANGE : 900 - 1000
959
ON TARGET
23-FEB-2023 07:09:00

RECOMMENDED ADJUSTMENTS **AS OF 23-FEB-2023 07:00:00**
[redacted] WET STRENGTH- [redacted]
NO CHANGE
AUTO : ON
VALUE AT THE TIME OF RECOMMENDATION 15.73
23-FEB-2023 07:00:00 ON TARGET

Figure 3. Sample machine operator dashboard displaying key predictions (selectable), recommended adjustments, and current status

The color coding allows operators to understand quickly the current state of the process. Green indicates no changes needed, yellow indicates minor changes, and red indicates major changes.

Trials were initially run in an open loop to build confidence. Operators were asked to accept the recommendations as given by the system. The purpose of these trials was to confirm that the engine was working correctly and to allow the operators to build confidence in the solution. After training was completed, closed-loop trials were begun.

Closed-loop trials involved sending recommendations directly to the DCS to drive adjustments in the identified levers. These trials were longer and were used to fine-tune the recommendation engine and evaluate the overall value of the autonomous control. Operators acted in a supervisory role. Rather than manually entering the recommendations, they simply ensured that the process was driving to the desired target. After these closed-loop trials were completed successfully, the system was implemented. Additional changes and tuning were explored to drive additional value.

Value Generated

Laboratory test variation and target adherence were used to evaluate the value of the closed-loop control. First, the distributions of the test parameters predicted were tracked and plotted. When action is taken more frequently using a measurement that has less error, then laboratory variation in test values is expected to decrease.

Figure 4 shows the cross-directional (CD) wet tensile laboratory tests before and after implementation. The blue curve shows tests from a baseline established before the predictive control model was implemented. The green curve contains all tests performed after the predictive control model was implemented. The curves show a significant reduction in variation and a shift towards the target, which confirms that the system is reducing error in the process by reducing variability in the laboratory or wet tensile test.

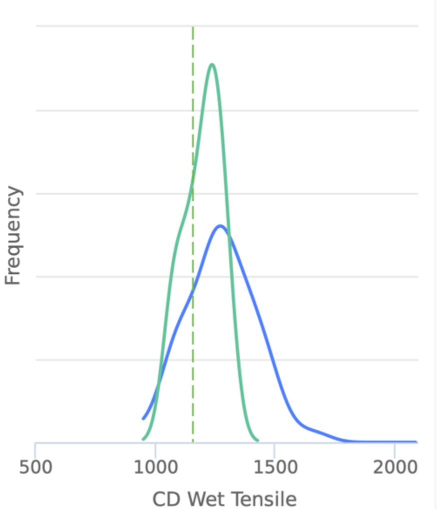
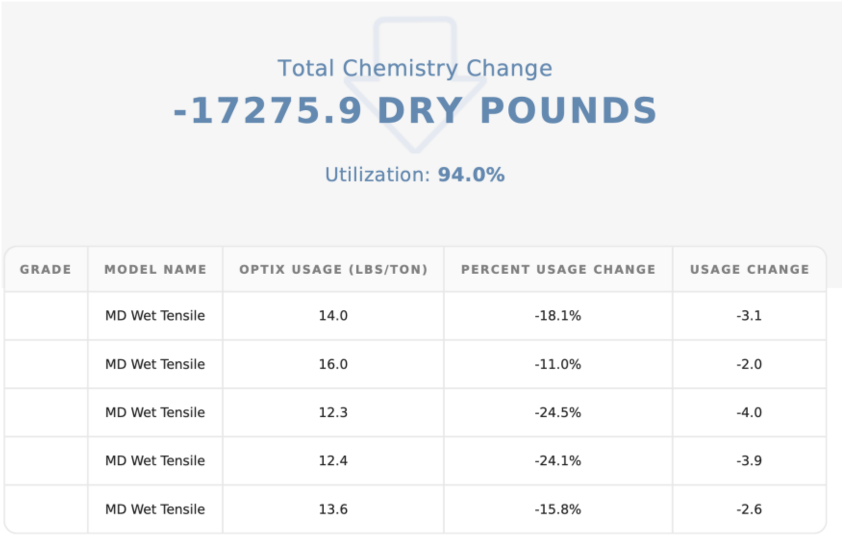


Figure 4. Smoothed histogram of lab tests comparing time ranges of closed-loop control in green and baseline in blue

Second, the optimization of the levers driven by the recommendation engine was tracked. Similar to the laboratory test distributions, a baseline was established to track progress. Values for the different levers were tracked while autonomous control was enabled and then compared to the baselines. These changes and the optimization generated by the system were reported. This optimization was broken down by grade to better understand the performance. Figure 5 shows a sample of the report.



Total Chemistry Change

-17275.9 DRY POUNDS

Utilization: **94.0%**

GRADE	MODEL NAME	OPTIX USAGE (LBS/TON)	PERCENT USAGE CHANGE	USAGE CHANGE
	MD Wet Tensile	14.0	-18.1%	-3.1
	MD Wet Tensile	16.0	-11.0%	-2.0
	MD Wet Tensile	12.3	-24.5%	-4.0
	MD Wet Tensile	12.4	-24.1%	-3.9
	MD Wet Tensile	13.6	-15.8%	-2.6

Figure 5. Report of the value generated by enacting closed-loop control

Reports were generated weekly and monthly to identify the benefit of the system, and they identified improvements in chemistry, energy, fiber, and sustainability, thereby confirming that the paper machines were achieving their optimization goals.

Autonomous control successfully reduced raw material inputs by 10–25% for packaging, fine paper, and tissue mills[3]. The autonomous control also prevented the production of any additional rejects. Using intelligent predictions based on historic machine data for control allows machines to achieve levels of optimization unobtainable with machine operator control. The paper mills had a virtual operator focused on machine optimization day and night, including weekends and holidays—and it showed. Predictive technology is the next step for papermaking optimization.

NEXT STEPS

This technology can be adapted and applied to areas within papermaking beyond strength. Consider the following examples.

Closed-loop control continues to progress in complexity as the industry moves from functional chemistry control to overall machine optimization. Using AI to determine the optimal balance of multiple key machine parameters, such a basis weight, calendaring, and additives, allows for a level of production that is not consistently achievable with human control. AI makes decisions proactively instead of reactively.

Basis weight control on a bleached coated paperboard machine is being evaluated. This machine has a common problem of overweighting to achieve caliper and smoothness targets. Often a suboptimal combination of pressing, caliper, and basis weight was used to achieve overall paper quality. Operators were complacent with test values and slow to react when the opportunity for optimization presented itself. A recommendation engine that balances multiple machine predictions with cost optimization was built to provide process decisions that quickly drive value when the opportunity is available, thereby ensuring that the optimal balance of these levers are used consistently for the machine.

Predictive analytics can provide help with spore tests on aseptic board. Currently, it takes at least 48 hours to receive spore test results. Using predictive analytics, feedback is delivered immediately. Thus, excursions can be diagnosed quickly, and MB control programs can be adjusted to prevent the production of rejected paper. The team is now exploring how it can use this technology to both troubleshoot drivers for increased spore production and driving optimization in the MB chemical programs for these mills.

Predicting spore counts provides a unique challenge. Microbiological growth does not develop instantaneously; however, the growth is exponential and often is driven by processes that are not commonly measured. Some MB growth can be forecasted with inline measures of ORP (oxygen reduction potential) and pH, but many contributing factors, such as high-density tank growth and poor mixing, are challenging to measure. Using AI to understand these more complex relationships allows for a better understanding of MB growth in the papermaking process.

CONCLUSIONS

Prediction is not a novel concept. For centuries mathematicians have built and perfected predictive capabilities through modeling and simulation. Delivering value with only a prediction is challenging in the paper manufacturing environment. Machine operators are busy and must prioritize many competing tasks. Elevating the operator to a supervisory role in AI systems enables a higher level of work to be performed. Closed-loop control of paper machine processes is the next step in optimization for the papermaking industry.

Using real-time predictions calculated with real-time process data to make process control decisions removes error from the paper-making process. Removing error reduces variation and improves the quality of the produced paper. As engineers continue to search for solutions to achieve improved machine efficiencies, predictive-based closed-loop control unlocks machine optimization that was previously unavailable. This paper explains the befits of transitioning from human to autonomously control. As the technology and adoption continue to grow, the paper-making industry will see more systems elevated to autonomous control. Predictive control will lead to the digitization of the paper-making industry. In the next ten years, the team expects to see the first paper machines will be running in full autonomous control. Machines will be run remotely and will achieve efficiency targets unable to be reached currently.

References

[1] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. Cambridge, MA: The MIT Press.

[2] ProcessMiner. (n.d.). ProcessMiner/nlcor. Retrieved from https://github.com/ProcessMiner/nlcor

[3] Demboski, P. (2021). *AI-Driven Autonomous Control Reduces Paper Machine Dry End Test Variability* [Photograph]. Www.Solenis.com. https://www.solenis.com/globalassets/resources/case-histories/eqt-pk-ch-n646-0123.pdf