Application of AI-based approach to control the papermaking process

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ABSTRACT: This paper explores AI's role in revolutionizing the pulp and paper industry, and specifically in predicting wet tensile strength (WTS) for specialty-grade papers. Leveraging eLIXA technology, a 90-day study achieved a 15% reduction in chemical dosage and an 80% decrease in wet tensile standard deviation. The real-time dosage prediction led to optimizing the wet strength resin (WSR) consumption and improved process reliability. The self-learning models exhibited adaptability to changing variables, ensuring their robustness.

Overall, this study highlights AI's transformative impact on efficiency, cost savings, and product quality within the dynamic landscape of papermaking. The approach used for wet strength optimization has been used to optimize other aspects of pulp and paper production.

Application: This paper will benefit papermakers, process engineers, and mill management professionals through better utilization of available data in predictive process control capabilities. Impacts of the predictive algorithms will benefit production cost, efficiency, and reduction off-spec product.

The history of the pulp and paper industry stretches back more than 100 years. The processes were developed then with the status quo of ample resources and limited technological advancements in mind. With time, immense progress has been made on the technological front, and resource availability has changed.

All industries constantly try to reduce energy, water, and other resource consumption. These efforts are in response to increasing competition, price pressure, and increased environmental awareness. Efficiency is a must to navigate any competitive market, and the pulp, paper, and packaging industry, a significant energy and water consumer, is no exception.

The industry is opting to improve its efficiency by adapting to technological advancements, accommodating newer sources of raw materials, and continuously innovating the papermaking process. When we zoom into technological advances, we see that artificial intelligence (AI) is crucial to Industry 4.0. Artificial intelligence and machine learning (ML) enable industries to unlock the value of the enormous amounts of data that manufacturing machines create. Leveraging data via AI can lead to cost savings, enhanced safety, supply chain efficiencies, and a set of other benefits.

This paper does not intend to discuss the fundamentals of AI technology. Instead, we present the results of its specific use in the optimization of the wet strength resin (WSR) application. Multiple factors affect WSR performance and are included in the model predicting the value of wet tensile strength (WTS). The success of the deployment of AI is measured by the ability to predict the WTS and control the system variables to reduce off-spec products and minimize the cost of WSR application.

ARTIFICIAL INTELLIGENCE AND PAPERMAKING

The pulp and paper industry has a wide array of AI applications, from sourcing raw materials to delivering the final products to customers. A large number of publications discuss the AI approach to industrial process control [1,2]. Papermaking systems with their intrinsic complexity will benefit from the AI approach and receive increasingly more attention in this area [3-5]. Some practical applications linking process variables with the stabilization of the wet-end operations [6] were recently discussed. Real-time monitoring and communication between machines will improve the quality of human intervention. Labor hours can be directed towards tasks of higher importance, and repetitive tasks can be automated. This aids in improving the industry's overall effectiveness. Data-driven decision-making and actions carried out with the implementation of AI ensure accuracy, faster decision-making, and timely efforts to improve system performance and end-product quality [7-9].

The future of AI applications lies at the core of papermaking. Papermaking involves numerous variables that impact the paper machine's efficiency and the product's final quality. Whenever there is a variation in efficiency or any desired rate, the challenge is to identify the cause and devise strategies to prevent such deviations in the future. To conclude, substantial data sets need to be analyzed. This effort most often happens reactively to the observed problem.

Historically, most of this data was collected via laboratory tests at predefined intervals. There was a need for a subject matter expert who could then comprehend and correlate data via manual calculations or fundamental statistical analysis to derive the trends and sources of variation. However, this often could not suffice, as data for several other parameters may not be available or included in the analysis. An intermediary data collection meant the sample space was relatively small to spot the right cause. In addition, the process relied heavily on the ability of the experts to recognize trends. Hence, no conclusive corrective action could be taken to prevent such errors in the future.

Today, real-time data can be collected and analyzed with the development of online, continuous sensors. Analyzing the relationship between variables and proactively controlling them to achieve the desired result would help unleash the industry's full potential. To list a few, properties like wet tensile, sizing, and dry strength are influenced by furnish composition, refining, additives, retention, and water chemistry. Manually controlling these highly fluctuating parameters in a reactive manner may result in a loss of the entire reel of produced paper if the papermaker misses the target's specification value and, most likely, a loss of a minimum of one of the consecutive reels. The alternative of applying a higher dosage of chemical additives to ensure meeting specifications would drastically drive up the costs, affect profitability margins, and lead to other runnability issues. Therefore, it is essential to rely on the estimates made from previous experience to achieve a critical parameter and apply it in an ongoing fashion to proactively drive (not respond to) quality checks and cost. We are now able to leverage AI to navigate such challenges. One can monitor relevant conditions in real time and predict the quality of interest.

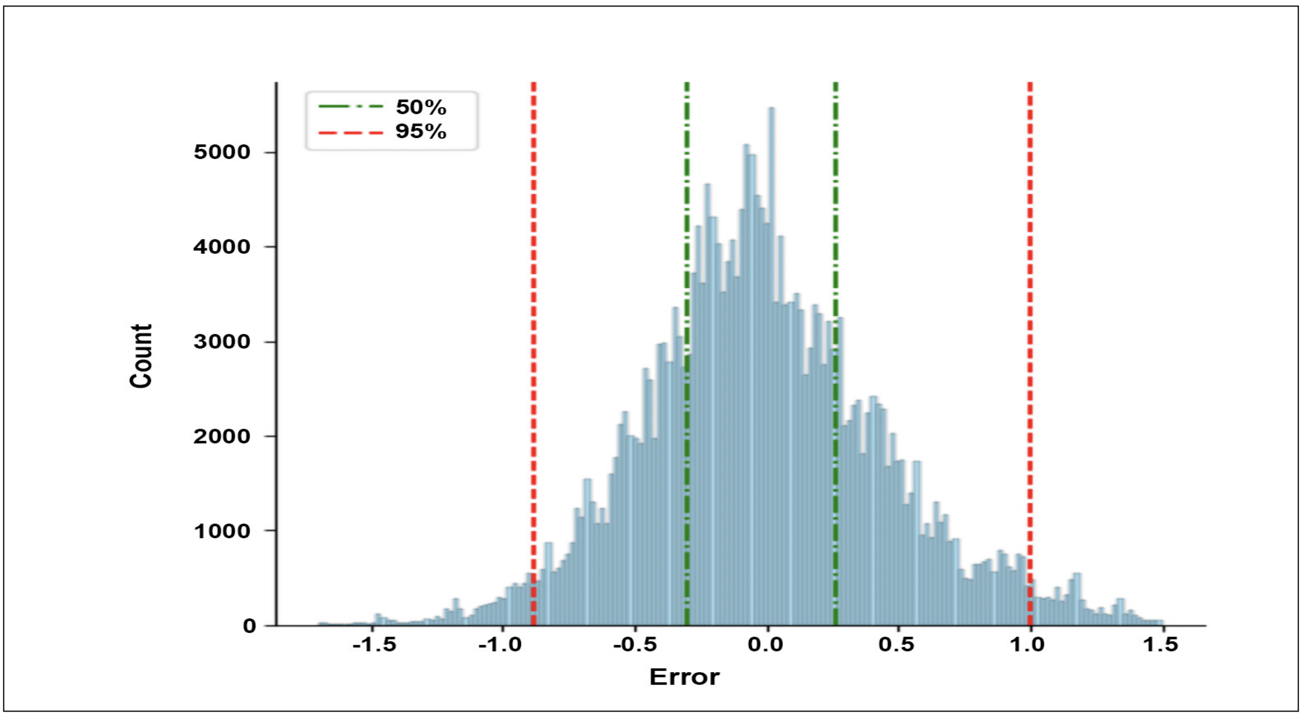
METHODOLOGY

AI determination of wet-strength resin dosage

As mentioned earlier, this paper centers on the predictive control of final product properties by utilizing real-time processes and quality parameters from data historian software. Different grades of paper have varied properties depending on meeting the end-user requirements. Their strength properties, including water resistance, grease resistance, and others, vary. An essential parameter in this context is WTS, which indicates the force that paper can withstand after exposure to moisture. This particular property holds critical importance, especially in the production of specialty-grade paper, where maintaining properties per the required specifications is crucial to the production process, as they are needed to perform well at the final conversion process.

A 90-day data transfer and analysis study was conducted at a specialty paper manufacturing facility. More than 20 different grades with a basis weight ranging from 50–120 g/m² were produced on a machine with a production capacity that ranges from 65 to 70 metric tons/day and a machine speed of 330 m/min. The filler content varied within the 20%–40% range. The primary objective of this program was to achieve a considerable reduction in chemical dosage and to significantly reduce the standard deviation in the wet tensile strength measured in the lab.

The eLIXA proprietary technology from Haber (Pune, MH, India) was applied to facilitate this objective. With specialized sensors, data across several parameters was collected in real time and analyzed using in-house-built proprietary ML algorithms. The chemical dosing was then



1. Agreement between the model predicted and laboratory value of wet tensile strength.

	Target WTS (N/15 mm)	Mean	Standard Deviation	CpK
Figure 2a — Baseline (past one year)	8.5	8.28	0.46	1.54
Figure 2b — Autonomous control	8.5	8.49	0.12	4.04

I. Comparison of results for the selected grade of paper (60 g/m^2) before and after introducing artificial intelligence (AI) control. A significant increase in the process capabilities index (CpK) without impact on expected wet tensile strength (WTS) was observed.

controlled automatically to intervene and take proactive action. As a result, the variability from the target wet tensile was significantly minimized, with optimum chemical dosage, leading to better quality output at minimal cost.

Data extraction and cleaning

Data for 100+ process parameters over a six-month period was systematically gathered. The data came from various sources, such as machine process parameters and laboratory data via historians and sensors.

Subsequently, a data cleaning process was done to eliminate inconsistencies and errors. This involves removing duplications, identifying and excluding unwanted outliers, and thoroughly checking for missing data. Following the data cleaning phase, the data set was split into training and testing data subsets to enable model building.

Multivariate analysis and model building

Having ensured quality data was present, a comprehensive analysis was conducted. Multivariate data analysis was performed to understand the correlation among these variables. The goal was to pinpoint the significant drivers among the extensive list of 100+ variables influencing the wet tensile strength. After several iterations, we could identify 14–17 variables as key influencers. Feature engineering was undertaken with the help of subject matter experts and correlation analysis, which takes raw data and transforms it into features usable for predictive model construction. Additionally, the collinearity identified in the data set was removed. The primary key influencing variables were sheet ash, pH, grammage, WSR dosage, etc. The dataset was split into training and testing data subsets to enable model building. The significant variables were then subjected to further regression analysis to identify a relation with WTS and to develop models predicting the wet tensile property.

Model evaluation

Different models were developed via support vector regression (SVR), K-nearest neighbors (KNN), linear regression, etc. These were then tested on a testing dataset and assessed using metrics such as coefficient of determination (R^2) and root mean square error (RMSE) values. This evaluation aimed to identify the model that exhibited the closest correlation with the WTS values obtained through laboratory testing. In other words, the model that best explains the relationship between the variables and wet tensile value was selected.

After evaluating and finalizing the wet tensile prediction models, a WSR dosage prediction algorithm was developed for real-time dosage predictions across all grades. This algorithm predicts the accurate WSR consumption required to achieve the target wet tensile, considering the real-time variations in the machine process parameters. Models were then deployed and integrated with deployment codes.

RESULTS

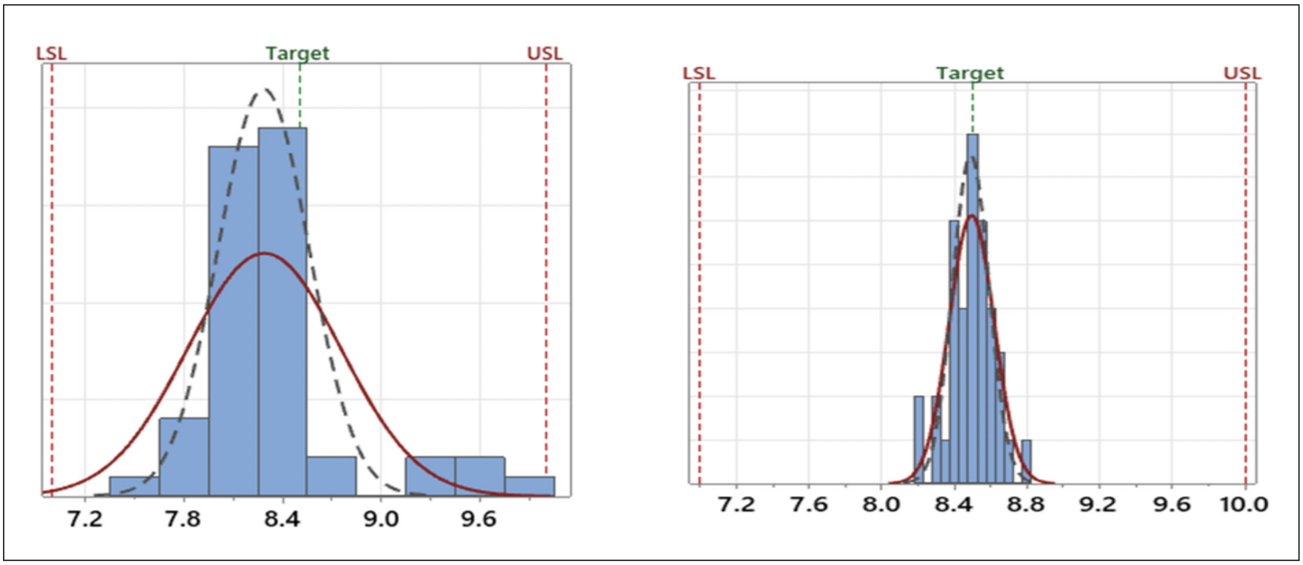
Laboratory vs. predicted wet tensile strength

The assurance of the accuracy of the predicted wet tensile strength is validated by the R^2 value of 0.94. The proximity of this value to 1 signifies a high level of accuracy in the model. Additionally, in **Fig. 1**, the model demonstrates a notable consistency, with 95% of the variation between the laboratory WTS and predicted WTS falling within the range of -1 to 1. This tight correlation indicates the reliability and precision of the model in replicating the laboratory-derived wet tensile strength values.

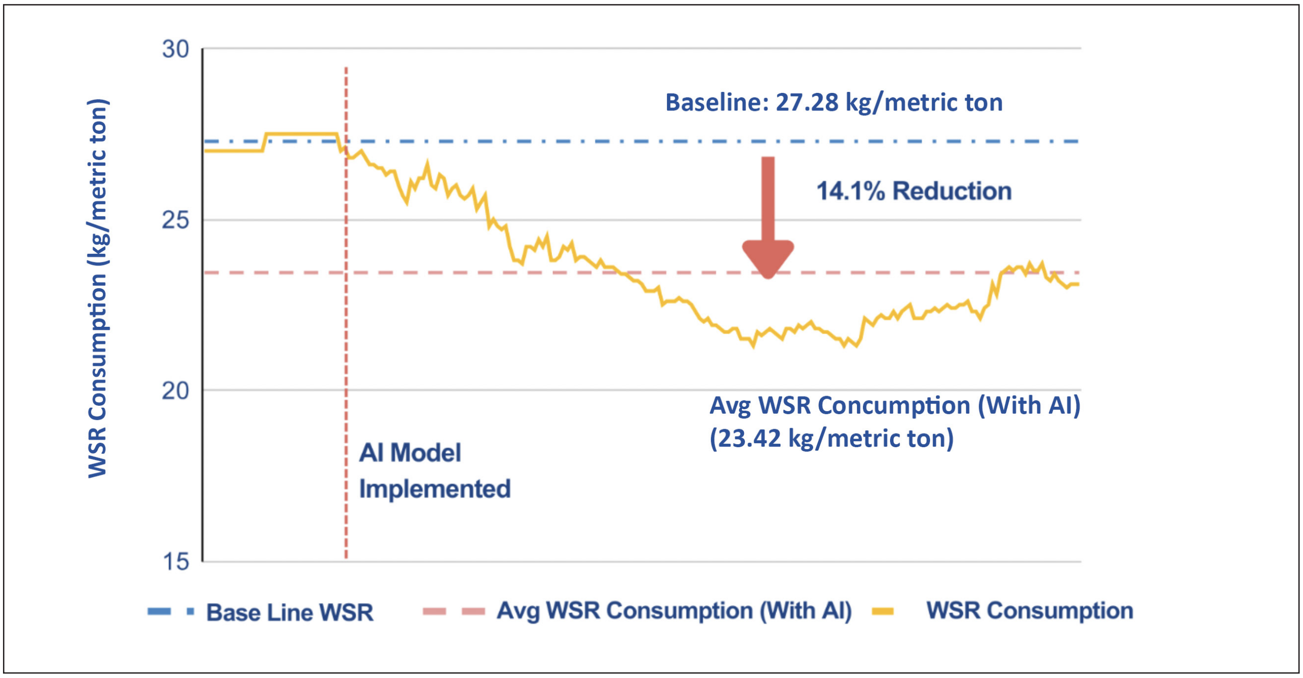
Product quality

Table I compares the baseline data for Grade 1 with the basis weight of 60 g/m^2 collected over one year before our project and after the process was optimized with the AI approach. Grade 1 had a maximum production run on the machine during the AI model implementation. This product's target WTS is 8.5 N/15 mm. As per historical data averaged over the past year, the baseline WTS is 8.28 N/15 mm, accompanied by a standard deviation of 0.46 N/15 mm. The introduction of real-time dosage prediction reduced the standard deviation, now measured at 0.12 N/15 mm. In other words, the standard deviation was reduced by 73%. This improvement is essential in enhancing product quality and minimizing variations in the final output.

The process capability index (CpK) is a metric measuring process control by assessing its spread within specification limits. When assessing CpK, historical data for Grade 1 indicates a CpK of 1.54 (**Fig. 2a**). In contrast, during the autonomous control of WSR, a higher CpK of 4.04 was achieved (Fig. 2b). A higher CpK value signifies the production of fewer defective products. This shift indicates that



2. Process capability (a) before and (b) after implementing artificial intelligence (AI) optimization.



3. Results of the application of AI in optimizing the use of wet strength resin (WSR). The graph clearly illustrates the reduction of WSR from the baseline of 27.28 kg/metric ton to 23.42 kg/metric ton after 90 days of implementation of the AI model.

implementing the predictive model will significantly elevate the overall performance of the products manufactured on the machine.

Wet strength resin consumption

The WSR consumption was predicted for various grades based on the targeted WTS, the composition of paper grades, and the variations in machine parameters (**Fig. 3**). During the preceding year, Grade 1 had an average WSR consumption of 27.28 kg/metric ton. However, through the AI model implementation phase, a reduction in the average WSR consumption was observed, which dropped to 23.42 kg/metric ton while maintaining the desired target WTS of 8.5.

These results demonstrate the model's ability to optimize WSR consumption without compromising the essential quality parameters. Moreover, the results indicate a decrease in average consumption and a reduction in standard deviation, as previously discussed. This signifies enhanced consistency and predictability in the production process. Additionally, the calculated CpK values surpass the baselines provided by the customer, reflecting a higher level of process capability and adherence to quality standards. In summary, compared to the established benchmark data, the WSR automation program has resulted in a dual benefit of reducing WSR consumption and improving overall process reliability.

An added advantage of this model is that it is self-learning. It continuously learns from changes in the variables and their relationships and incorporates them into the prediction. This makes it a robust solution that adapts to process changes.

CONCLUSION

In conclusion, this paper underscores the pivotal role of AI in revolutionizing the pulp and paper industry using an example of predicting and controlling WTS in specialty-grade paper production. The results of the 90-day study illustrate the efficacy of eLIXA technology in achieving a 15% reduction in chemical dosage and an 80% decrease in the standard deviation of WTS. The real-time dosage prediction algorithm optimizes WSR consumption and enhances process reliability, as reflected in the improved CpK values.

As the pulp and paper industry continues its trajectory towards sustainability and efficiency, the integration of AI emerges as a transformative force, offering a potent toolset for proactive decision-making, cost savings, and improved product quality. Even though an example of wet strength optimization alone was presented in this paper, the eLIXA AI-driven technology can be used to optimize any chemical or mechanical operation on the paper machine, including (but not limited to) such applications as retention, drainage, dry strength, sizing, and refining. **TJ**

ABOUT THIS PAPER

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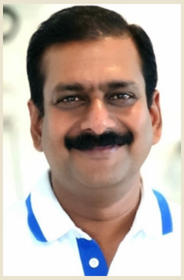
Artificial intelligence (AI) has emerged as a powerful tool capable of propelling the paper industry toward efficiency, sustainability, and innovation. This work illustrates how the use of AI process control allowed optimization of the use of wet-strength resins while improving the quality and consistency of the product quality.

In any AI implementation project, a crucial step is accessing data that is often deposited in several different databases and homogenizing it. The technology used in this paper accelerates this process.

In this project, it was very rewarding to see how much further improvement was possible with AI when working on a well-established existing application. With this technology, mills can lower the cost of chemicals and lessen time requirements from mill personnel. These are typical benefits that mills can expect when embarking on AI discussions.

If good data exists, the AI approach can optimize all aspects of pulp and paper production. We are now involved in many different areas of pulp and paper mills.



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