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Application of AI-based Approach in Paper Making Process

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Abstract:

This paper explores AI's role in revolutionizing the pulp and paper industry, explicitly predicting Wet Tensile Strength (WT) for specialty-grade papers. A 90-day study achieved a 15% chemical dosage reduction and an 80% decrease in Wet Tensile standard deviation. The real-time dosage prediction led to optimizing the Wet Strength Resin consumption and improved process stability. 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 consistent product quality within the dynamic landscape of papermaking. The approach used for wet-strength optimization has been used to optimize other aspects of pulp, paper and packaging production.

Keywords: *artificial intelligence, machine learning, process control, standard deviation, wet tensile strength, chemical dosing, product quality and consistency, papermaking.*

Introduction

The pulp and paper industry has a rich history spanning over a century. The initial processes were designed based on the assumption of abundant resources and limited technological advancements. However, as time has progressed, both the availability of resources and the technological landscape have undergone significant transformation. With growing economic pressures and sustainability concerns, industries worldwide, including pulp, paper, and packaging, are re-evaluating traditional practices to improve efficiency and reduce resource consumption.

In today's competitive landscape, reducing energy, water, and raw material consumption is no longer just an option but a necessity. The increasing market competition, price fluctuations, and heightened environmental consciousness have compelled industries to find innovative ways to optimize operations. As a major consumer of energy and water, the pulp and paper industry is actively seeking new strategies to enhance efficiency, maximize output, and minimize waste.

One of the most promising advancements in this pursuit is the integration of cutting-edge technology. The industry is progressively embracing automation, alternative raw materials, and continuous process innovations. Among these technological advancements, artificial intelligence (AI) and machine learning (ML) have emerged as key drivers of Industry 4.0[1]. AI harnesses the vast amounts of data generated by manufacturing processes, unlocking insights that were previously difficult to interpret. By leveraging AI-powered analytics, mills can optimize production, reduce operational costs, enhance product quality, and improve supply chain efficiencies.

The adoption of AI is no longer just an advantage—it is becoming a critical enabler for sustainable and cost-effective manufacturing. As the industry continues to evolve, embracing digital transformation will be fundamental to staying ahead in an increasingly resource-conscious and competitive world [2].

AI AND PAPERMAKING

Papermaking is a process of juggling between large number of variables that impact the paper machine's efficiency and the product's final quality. Whenever there is a variation, the challenge is to identify the cause and devise strategies to prevent such deviations in the future. One must analyze vast data sets to be able to conclude.

Traditionally, most of this data was collected via lab 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 is not enough to control the complex papermaking process [3].

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 [4].

The papermaking process involves numerous variables that constantly fluctuate, making it a dynamic rather than a theoretically ideal process. Merely optimizing each variable within a defined range without considering the intricate interrelationships may prove ineffective [5]. Unlike statistical analysis tools that rely on predefined assumptions and models, artificial intelligence (AI) utilizes advanced algorithms, specifically machine learning and deep learning, to autonomously discern patterns and relationships within high-dimensional, unstructured datasets. This capability is crucial for capturing complex, non-linear relationships inherent in papermaking. Real-time analysis of these dynamic processes, accounting for variations in raw material qualities such as recycled paper and water, yields optimal results. AI models, adaptable and capable of learning from new information, provide a dynamic and evolving solution. The automation features of AI streamline the analysis process, reducing the need for manual intervention and expediting decision-making.

METHODOLOGY:

AI controlled Wet-Strength Resin addition

This paper centers on the predictive control of final product properties by utilizing real-time processes and quality parameters from Data Historian. Wet Tensile Strength, indicates the force paper can withstand after exposure to moisture - a critical property for specialty grades.

A 90-day study was conducted at a specialty paper manufacturing facility. More than 20 different grades with a basis weight ranging from 40 - 100 g/m2 were produced on a machine with a production capacity that ranges from 80 to 90 tons per day and a machine speed of 325 – 375 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.

Haber's eLIXA® Mt. Fuji was leveraged to achieve the objective. eLIXA® Mt. Fuji acted as a platform to bring together process and quality parameters from across the plant and analyze in real time. A custom ML model was built to predict the required WSR dosage.

The chemical dosing was then 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 for a six month period was systematically gathered. The data collected was from various sources, such as machine process parameters and lab 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

Multivariate data analysis was conducted 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. It can significantly improve model performance by making key patterns in the data more accessible to the algorithm. Say, one need not look at both load and energy power of the refiner. They could be combined and looked at together giving better insights to the model. To select from the features which showed multicollinearity, mutual information score was calculated with respect to the target, and features influencing the target were selected. Additionally, the collinearity identified in the data set was removed. The primary key influencing variables were sheet ash, pH, grammage, WSR dosage, etc.

Grades were also grouped together to create a larger data set for model building. The grades which are rarely run may not generate sufficient data to create models independently but can be grouped with grades that run over larger period. 20 grades were grouped into 4 different groups, helping in the model building process.

The data set 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 Wet Tensile Strength and to develop models predicting the same.

Model evaluation

Different models are developed via Support Vector Regression (SVR), K-nearest Neighbors (KNN), Linear regression, etc. These are then tested on a testing dataset and assessed using metrics such as R-square and Root Mean Square Error (RMSE) values. This evaluation aimed to identify the model that exhibited the closest correlation with the Wet Tensile strength values obtained through lab 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

Lab vs. Predicted Wet Tensile Strength

The first step in evaluating the effectiveness of the model is to assess its accuracy in predicting wet tensile strength. The confidence in the model's predictive capabilities is established by analyzing its R-square (R^2) value, which serves as a key statistical indicator of the correlation between the predicted and actual wet tensile strength values. In this case, the model achieves an impressive R^2 value of 0.94, indicating a strong alignment between predicted and observed results.

An R^2 value close to 1 signifies a high level of predictive reliability, demonstrating that the model effectively captures the underlying relationships between variables influencing wet tensile strength. The closer this value is to 1, the more precise the model's predictions are, as it accounts for the majority of variations within the dataset. This high accuracy ensures that the model can be confidently used for process optimization, enabling better control over wet tensile strength and minimizing deviations in the papermaking process.

Additionally, in Fig 1, the model demonstrates a notable consistency, with 95% of the variation between the lab wet tensile strength and predicted wet tensile strength falling within the range of -1 to 1. This tight correlation indicates the reliability and precision of the model in replicating the lab-derived wet tensile strength values.

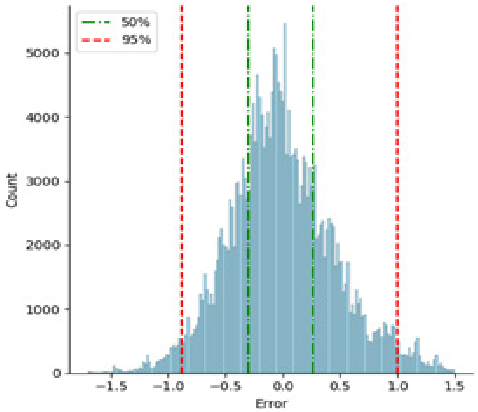


Fig 1: Agreement between the model predicted and lab value of wet tensile strength.

Product Quality

Table 1 provides a comparative analysis of the baseline data for Grade 1 with a basis weight of 45 g/m², collected over a one-year period before the implementation of AI-driven process optimization and after the integration of AI into the manufacturing process. Grade 1 was selected for evaluation as it experienced the maximum production run on the machine during the AI model implementation, providing a robust dataset for comparison and validation.

For this specific product, the target Wet Tensile Strength (WT) was set at **10.5 N/15mm**. Analyzing the historical data from the preceding year, the baseline Wet Tensile Strength averaged **10.28 N/15mm**, with a standard deviation of **0.46 N/15mm**. This level of variation suggested inconsistencies in achieving the desired wet tensile strength, leading to potential fluctuations in product quality.

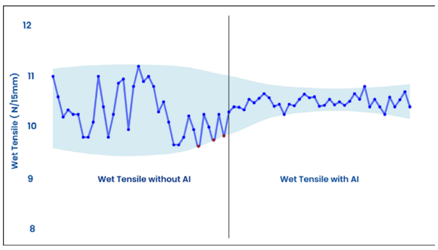
Following the deployment of real-time AI-driven dosage prediction, significant improvements were observed in process stability and output consistency. The standard deviation of wet tensile strength was reduced to **0.12 N/15mm**, marking an impressive **73% reduction in variability** (as illustrated in Fig. 2). This enhancement was primarily achieved by **dynamically adjusting the wet strength resin dosage in real time, rather than relying on a fixed set point for chemical dosing.**

By continuously analyzing process parameters and predicting wet tensile strength in real time, the AI model ensured that the target wet tensile value was consistently met. This not only improved the overall **product quality and uniformity but also minimized wastage, optimized chemical usage, and enhanced operational efficiency.** The ability to reduce variability while maintaining target specifications underscores the value of AI in driving precision and reliability in paper manufacturing processes.

Table 1: Baseline data for Grade 1

	Target WT (N/15mm)	Mean	Standard Deviation
Fig.2 (a) Baseline (past one year)	10.5	10.28	0.46
Fig.2 (b) Autonomous Control	10.5	10.49	0.12

Fig 2: Wet tensile before and after AI-optimization



WSR consumption

Wet Strength Resin consumption was predicted for various grades based on the targeted Wet Tensile Strength, the composition of paper grades, and the variations in machine parameters. During the preceding year, Grade 1 had an average WSR consumption of 27.28 kg/ton. However, through the AI model implementation phase, a reduction in average WSR consumption was observed, which dropped to 23.42 kg/ton while maintaining the wet strength. Real-time dosage control helps to reduce over dosing.

A key advantage of this AI-driven approach is its ability to **predict the resulting wet tensile strength before resin** is dosed, allowing operators to make informed dosing decisions. Traditionally, to mitigate the risk of falling below the required strength parameters, manufacturers often **maintained excess resin dosing as a safety buffer.** This practice not only led to **higher operational costs** but also introduced potential issues related to over-application, such as runnability concerns or residue buildup.

With AI-based predictions, the process is now **proactively adjusted** rather than reactively corrected, meaning resin dosage is applied **only as needed**, ensuring **both cost efficiency and product consistency.** This data-driven approach enables manufacturers to **confidently meet wet strength targets while simultaneously reducing chemical consumption, improving sustainability, and optimizing production economics.**

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

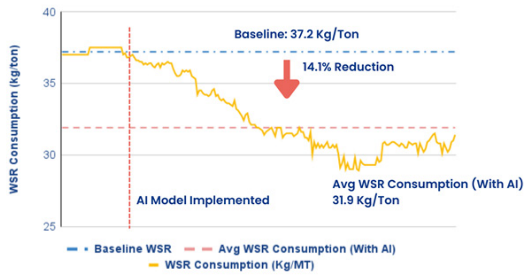


Fig. 3 WSR consumption before and after AI implementation

Conclusions:

In conclusion, this paper underscores the pivotal role of AI in revolutionizing the pulp and paper industry using an example of predicting and controlling Wet Tensile Strength in specialty-grade paper production. The results of the 90-day study illustrate the efficacy of AI in achieving a 15% reduction in chemical dosage and an 80% decrease in the standard deviation of Wet Tensile Strength. 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 was presented in this paper, 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.

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