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Transformative Impact of AI-Integrated Filtrate Turbidity Testing in Pulp and Paper Manufacturing

Dr. Claudy D'Costa
Head - Sensor R&D Division
Haber

Abstract:

Conservation and sustainable use of resources – fibre, water, and energy is a major focus of many industries and especially the pulp and paper industry. An important parameter and also very useful for ensuring sustainable resource management is the measurement of filtrate turbidity at various stages of papermaking. Filtrate turbidity stands as a vital parameter in ensuring operational excellence, and final product quality. This paper explores an artificial intelligence (AI) enabled technique where filtrate turbidity measurement is used as a surrogate for determining the charge demand and thereby optimising chemical additives usage. For eliminating human error in the determination of filtrate turbidity, a fully automated filtrate turbidity tester (FTT) that complements the integration of the AI unit is furnished in brief. AI enables multi modal analysis in real time and the capacity to handle a large amount of data. Details and results of a case study exploring the correlation of filtrate turbidity with charge demand and thereafter the use cases in retention and drainage control, and strength properties optimisation is also discussed. From our study using machine learning (ML) techniques, we could find a good correlation between filtrate turbidity and charge demand in papermaking systems where the anionic trash was high, mainly deinked pulp, mechanical pulp, and virgin pulp with chemical carry over. This correlation was used to train our AI/ML model to predict coagulant dosage from filtrate turbidity.

Keywords: *Filtrate turbidity tester (FTT), Coagulation, Charge demand, WSR optimization, Artificial intelligence (AI)*

Introduction

AI in pulp and paper will drive rapid transformation of the industry enabling long term sustainability and profitability. Data to enable models will be key to AI's impact on the industry. Real-time process data using advanced sensing technologies will play key role toward this. Measuring the filtrate turbidity of process water holds significant importance in order to ensure the quality of water in the papermaking process. It serves as a crucial parameter for assessing the clarity and purity of process water, which is integral to various stages of papermaking. Within the complex milieu of pulp and paper manufacturing, where water is extensively utilised for tasks ranging from pulp dilution to paper formation, maintaining optimal turbidity levels is paramount.

Within the realm of process optimization, filtrate turbidity testing plays a pivotal role in evaluating the papermaking system performance with respect to chemical additive usage. By quantifying filtrate turbidity levels, operators can assess the effectiveness of the additives used for retention and drainage, and for strength improvement. These filtrate turbidity measurements enable fine-tuning of chemical additives based on process parameters to achieve optimal efficiency, and ensure consistent product quality.

Challenges of Manual Filtrate Turbidity Testing in the Pulp and Paper Industry:

In the pulp and paper industry, filtrate turbidity testing is critical in maintaining process efficiency and product quality. However, traditional manual methods present significant challenges, which are as follows:

1. **Delayed Response and Operational Inefficiency:** Traditional manual sampling and laboratory analysis introduce significant delays, preventing real-time adjustments to turbidity fluctuations. This results in extended periods of suboptimal process performance or off-spec product output, reducing overall operational efficiency.
2. **Intermittent Data and Process Variability:** Without continuous monitoring, turbidity data is collected

at discrete intervals, potentially missing transient events and short-term fluctuations. Continuous monitoring systems are necessary to capture these fluctuations and provide a comprehensive understanding of process performance [3].

3. **Inconsistency in data:** Filter paper even from the same manufacturer that is used for filtration has variability in pore diameter which leads to poor repeatability. A lack of universally accepted standard procedures add to the inconsistencies in data and prevent data comparison. Variability in sample agitation, filtration speed, and handling techniques leads to inconsistent filtrate turbidity measurements [4].
4. **Increased Operational Costs:** Manual filtrate turbidity testing necessitates dedicated personnel, specialised equipment, and laboratory resources, driving up operational costs. Delays and inaccuracies in testing also contribute to increased waste, rework, and associated expenses.
5. **Suboptimal Chemical Utilisation:** Accurate, real-time filtrate turbidity data is essential for optimising the dosages of process chemicals such as coagulants and flocculants. Without it, chemical usage may be inefficient, leading to higher costs, process upset, and potential environmental impacts.

The lack of continuous, real-time data hinders detailed process analyses, innovation, and the ability to test and refine new process configurations, limiting technological advancement and process improvement initiatives. Towards addressing these concerns, we have developed a fully automated AI-ML enabled filtrate turbidity tester (FTT).

Artificial Intelligence for Process Optimization:

The pulp and paper industry continually pursues innovative solutions to boost process efficiency and product quality. AI plays a pivotal role in this quest, offering insights that range from simple energy conservation practices, such as turning off idle equipment, to complex tasks like detecting leaks, inefficiencies, and potential breakdowns. AI's prowess lies in its capacity to gather, analyse, and predict outcomes from vast datasets, identifying bottlenecks and proactively addressing them [5]. Real-time data collection and analysis, made possible by online sensors, allow for precise control over variables, essential for competitiveness in this industry.

The rise of Industry 4.0 has ushered in a new era of AI integration, enabling real-time adjustments based on data insights, thereby enhancing efficiency and meeting industry demands. For instance, AI facilitates predictive maintenance, minimising downtime and optimising inventory management through accurate forecasting, preventing both overstocking and shortages. ML models further refine processes by leveraging extensive datasets, boosting operational efficiency and energy optimization.

This integration of AI and ML technologies into pulp and paper equipment not only optimises resource utilisation but also addresses a myriad of operational challenges. The notable improvements underscore the potential for wider industry adoption of AI-driven turbidity testing equipment, promising enhanced efficiency and sustainability.

The AI-integrated, Automated FTT:

Many instruments used in the paper industry rely on the sample filtrate (supernatant) since measuring the sample from head-box or white-water is difficult due to presence of particles. The particles might interfere directly with the measurement or at times make the post cleaning of the equipment for the next measurement cycle difficult. Usually the filtrate is obtained through a manual filtration, before carrying out say a charge demand measurement. The manual filtration can be a gravitational method that uses filter papers readily available to the industry. Such filtration methods are subjective to the operator, the type and make of filter paper used, involve labour intensive procedures, often non comparable across different machines, lack standard methods, and are non-practical for continuous monitoring.

The need for an automated filtration unit, that solves many of the problems mentioned above, is evident. Here we discuss the design and development of a real time filtrate analysis unit that can deliver quick batches of filtrate from input samples ranging from consistencies around 0.05% to 5% [3]. The idea was to create a filtrate generating unit that can be plugged into any stage of the paper making process and continuously obtain consistent levels of filtration. We integrated a turbidity/TSS sensor to the filtrate unit to receive continuous turbidity data that is relayed to the AI/ML-based engine. As a matter of fact, sensors measuring different parameters can be plugged into the flow cell to cater to the individual needs of the industry.

The FTT unit (Figure 1) has an automated sampling system controlled by various values and a filtration unit containing a metal filter mesh. This metal filter mesh is the key component in ensuring the repeatability of the filtrate turbidity measurement. The metal mesh, usually made of SS304, has uniform pore sizes and is reusable. The pore size of the filter mesh can be selected according to the application and once optimised by comparing with a standard filter paper like a Whatman filter paper, the unit will provide consistent results thereafter without the need for repeated calibration. There is a wash cycle after each measurement cycle to ensure that the pores in the mesh are kept clog-free. The entire system is designed to withstand mild acid wash in case such a requirement arises.

The sample that needs to be filtered is delivered to the filtration unit where gravity or vacuum assisted filtration can be carried out. The filtrate is then passed into a flow cell that contains a turbidity sensor that continuously transmits the relevant values. The whole system is automatically controlled using a Programmable Logic Controller (PLC) and completes the sample to filtrate cycle in less than 10 minutes. Simple schematic of the system is shown in the figure (Figure 1) below.

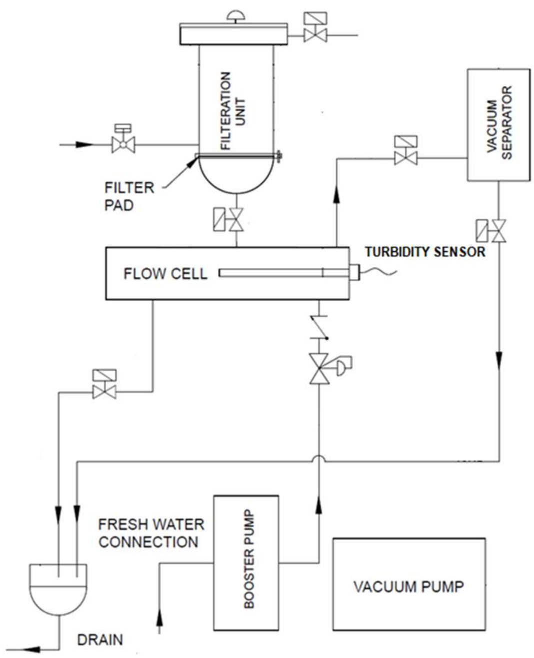

Figure 1: Schematic of the automated AI-ML enabled FTT

FTT proves to be a powerful tool since it eliminates many of the inconsistencies from manual filtering and their limitations thereof. The consistent filtration ensured repeatability and also enabled us to find correlations with other relevant parameters of the system. One of such case studies is mentioned in the coming sections.

Case Study:

Filtrate Turbidity and Charge Demand

The initial study was to test our hypothesis regarding the possibility of establishing a correlation between the filtrate turbidity and the charge demand.

The FTT unit was deployed at a customer site to test out our hypothesis and conduct the correlation studies. More than 100 days of data was collected and analysed.

Experiments and Methods:

Headbox samples were collected from different paper machines (PM) to check for the soluble charge demand (SCD), particulate charge demand (PCD), and total charge demand (TCD). The filtrate from our FTT unit was collected and a charge detector was used for charge measurement. The FTT mesh size selected for the study was 45μm.

Table 1 shows the correlation values that were obtained using a machine learning model that segregated the data grade-wise. We see a strong correlation of data in Grade B and C, but poor correlation for Grade A. The model selects the best correlation coefficient that can be used for creating the correlation. Values in the range of 0-30% are discarded, 30-70% is kept as a secondary parameter and values more than 70% are used for further analysis.

The equation used for finding the correlation coefficient is as given below

$$y = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2(y_i - \bar{y})^2}}$$

Table 1: The correlation (coefficient) results are given below

Grade	PM - 1			PM - 2		
	TCD	SCD	PCD	TCD	SCD	PCD
A	15%	4%	13%	22%	23%	7%
B	-	84%	-	-	15%	83%
C	26%	72%	-	-	-	79%

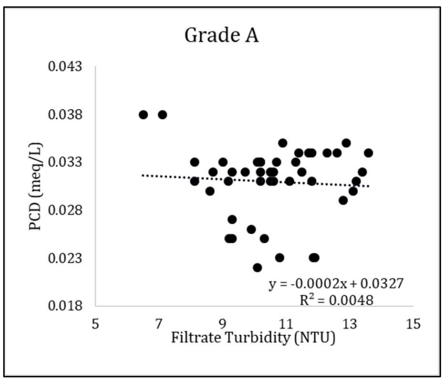

Figure 2: PCD vs FT

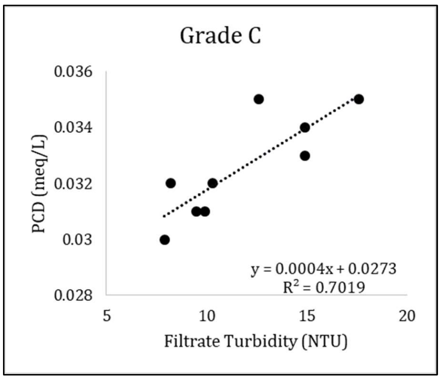

Figure 3: PCD vs FT

Table 2 shows the strong correlation observed for the broke sample. Such a high correlation provides us with a strong model to use the filtrate turbidity values as a surrogate for charge demand as discussed in the previous sections.

Table 2: The correlation data from coated broke treatment

Type	PM		
	TCD	SCD	PCD
Broke	86.20%	87.94%	76.06%

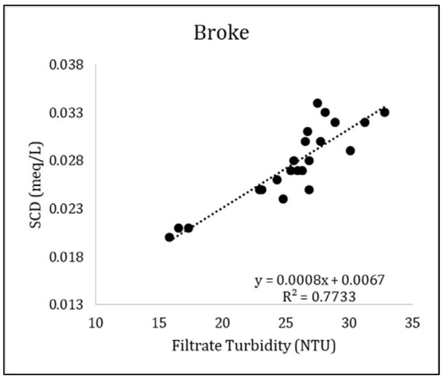

Figure 4: SCD vs FT

After establishing the correlation, we move on to the possibilities of using the data to check the applicability in chemical dosage control. The model is built using the best correlation parameter and a set of training data depending on the paper machine. Since the charge demand for each system is unique, the model is fed with grade wise historical data. Once the charge demand and filtrate turbidity correlation coefficient is extracted, it is used with a linear fit or a polynomial fit depending on the data. Once the model is established, it can give an estimate of the PCD or SCD from the filtrate turbidity data.

From the historical data, the AI-ML system starts learning about the characteristics and starts categorising the responses as required. The prediction of the required dosages are calculated after considering the current data and also the history of the papermaking system. The critical difference when compared to a Proportional-Integral-Derivative Controller (PID) control of a typical Distributed Control System (DCS) is that, although such a controller keeps the value within the Lower Acceptance Control Limit (LAL) and Upper Acceptance Control Limit (UAL) the fluctuation between the limits are not effectively reduced, the AI system practically limits the dosage depending on the current values and historical data. The deeper understanding of the particular system helps in reducing the variation bandwidth and keeps the system within the 90% set point instead of continuous fluctuation. In the rare event of a huge variation, the model flags it as a system failure and needs to be addressed separately. Another major advantage is the ability of the AI-ML system to cater to multiple parameters before taking the control decision, like say pH in certain cases.

Results of AI-ML driven testing:

1. In Coagulant dosage in cases where anionic trash is present

Coagulant is used for charge neutralisation to maximise the overall retention of the fibre, fines, and filler in a papermaking system [6]. As we have established a model that can use the filtrate turbidity value in place of charge analysis values, it will help in optimising the dosage of coagulant and improving the overall performance, retention, and productivity of the system in a continuous manner without relying on charge analysis data. The FTT could be installed typically before the addition of coagulants.

From the filtrate turbidity value and historical chemical dosage value, the model classifies filter turbidity values and chemical dosages to different clusters. Thereafter the new chemical dosage value is predicted depending on the cluster where the values fall. Figure 5 shows such a cluster where the filtrate turbidity and coagulant dosages are mapped. We used K-means clustering to predict the dosages.

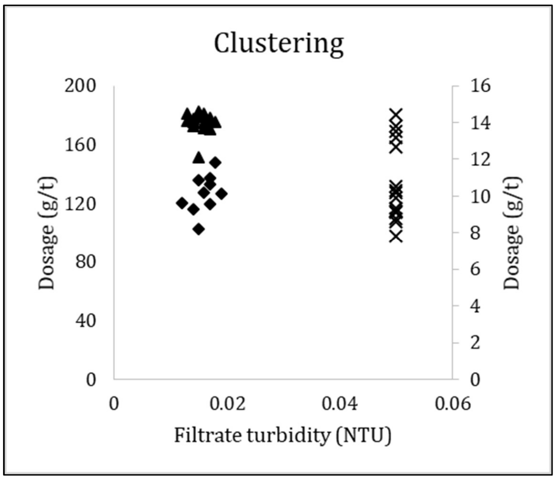

Figure 5: Clustering done by the ML model

2. In WSR optimisation to achieve target wet strength

In the next case we consider the control of Wet Strength Resin (WSR). We have taken the case of papermaking systems that use recycled furnish like deinked pulp. Here anionic trash poses a challenge that needed to be addressed using the AI-ML model. The model considers a two tier approach where first the anionic trash is neutralised without compromising on the pH value before WSR comes in contact, thereby ensuring that the cationicity of WSR is not consumed inefficiently and predicting the optimal dosage of WSR. We can use coagulant in lieu of WSR as anionic trash controller thereby reducing the WSR demand, which is significant owing to the cost of wet-end chemicals (which can even go up to 20% of world pulp and paper producers' total raw material expenditures) [7]. Here also we use filtrate turbidity as an indicator to predict charge and control the chemical dosage.

The estimated correlation coefficient for the filtrate turbidity values to SCD was 74.32%. The data was fed into a ML model and here we used support vector regression (SVR) to predict the coagulant dosage value. The final dosages fell within the acceptable limit.

Conclusion:

With the advent of AI in industries, we are seeking solutions to many problems that were thought to be difficult to solve. In addition to that, AI also enables us to go beyond what is humanly possible, track across multiple parameters, and make smart decisions in real time. By training the AI model we can incorporate all the variables that are interlinked so as to run the process at peak performance. As demonstrated in this paper, we could use turbidity measurement as a surrogate for a more expensive or complicated charge measurement set-up. This was made possible by combining automation of the filtrate generation process, running linear regression and finally using an AI model to predict the ionic demand.

Abbreviations:

- AI: Artificial Intelligence
- ML: Machine Learning
- FTT: Filtrate Turbidity Tester
- TSS: Total Suspended Solids
- PLC: Programmable Logic Controller
- PM: Paper Machine
- SCD: Soluble Charge Demand
- PCD: Particulate Charge Demand
- TCD: Total Charge Demand
- PID: Proportional – Integral – Derivative Controller
- DCS: Distributed Control System
- LAL: Lower Acceptance Control Limit
- UAL: Upper Acceptance Control Limit
- WSR: Wet Strength Resin
- SVR: Support Vector Regression

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