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Artificial Intelligence for wet-end optmization



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ABSTRACT

Over the past few years there has been an explosion in unstructured data across industry driven by affordable sensing technologies and adoption of analytical instrumentation. This sudden increase in data has resulted in industries spending significant amounts of time collecting, organizing and analysing content and very little time driving value with the data.

The paper industry is no exception. The application of deep learning to this data can uncover hidden insights leading to unprecedented value creation. Deep learning is the application of Artificial Intelligence/machine learning algorithms to data sets to deduce insights and relationships which drive process and business intelligence.

Many variables impact wet end chemistry and operations – temperature, pressure, pH, alkalinity, dissolved ions, suspended material, conductivity, colloidal charge, dissolved and entrained gases, hardness, furnish source and quality, filler quantity and quality, just to name a few. These have a significant impact on product quality, yield, equipment uptime and ultimately how well the mill does. Mechanical and operational variables also have a significant bearing on quality and productivity. How these factors interact with each other and impact critical to quality parameters is the elixir of paper making. AI/Machine learning is an aptly suited tool that can make achieving this elixir a practical goal for paper makers.

Through the use of machine learning algorithms, the authors have been able to achieve optimum productivity and quality in the wet-end across various grades and machine configurations. The overall results were observable and quantifiable improvement in FPR (first pass retention) and FPAR (first pass ash retention) and reduction is deposition problems in the paper machine.

MANUFACTURING INDUSTRY LAGS BEHIND IN DIGITAL TRANSFORMATION

Over the past few years there has been an explosion in unstructured data across industry driven by affordable sensing technologies and adoption of analytical instrumentation. This sudden increase in data has resulted in industries spending significant amounts of time collecting, organizing and analysing content and very little time driving value with the data.

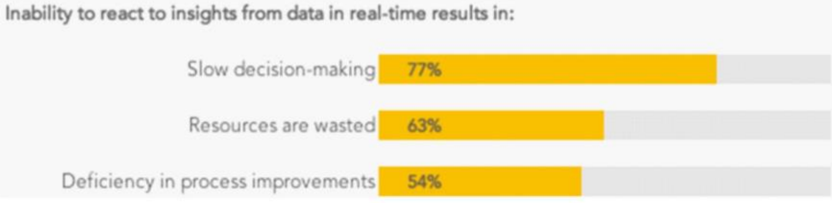
The manufacturing industry which includes everything from pulp & paper, metals and mining, food & beverage, power generation to automobile are no exception. As remote sensors, connected devices, and software capture a drove of data on the process and asset performance, plant managers are struggling to make sense of what all the data is saying and how to use it to improve performance. This issue is amplified by the increasing costs of energy, materials and labor making efficiency paramount. We wanted to examine the issue more closely and uncover the root of the problem on why data is seldom translating in to intelligence, as well as explore solutions on how industries can better utilize the data they are already collecting. To get this perspective, we surveyed >250 mid-level professionals across medium to large plants from anarray of industries to find out if and how they were collecting data, are they seeing value from this data, what in their opinion were risks of not leveraging this data, and what they thought was the missing link to optimize the return in on this data. (Methodology: In January 2018, a consultant was engaged to survey >250 plants in various industries. This survey was completed online and responses were random, voluntary and completely anonymous.)

Summary of responses:

- Nearly all (98%) of respondents said their companies use spreadsheets or other manual data entry documents
    - The top four areas of data collection –quality, material cost, labor time and operational parameters
- 76% of respondents said in order to take immediate action based on the data collected, software that analyze data in real-time or near real-time were needed

Problems and Reasons :

Despite the importance of this data, outdated processes like spreadsheets or standalone solutions were very common



in most organizations, often creating inconsistent and unreliable data, hidden cost of data capture and storage, even imperilling regulatory compliance. Additionally, these processes can get in the way of turning data into useful information. Manual data collection processes can also leave large segments of the manufacturing process siloed, inhibiting companies from seeing the complete picture. This leads to a number of issues, including mistrust in the data because manual processes are error-prone and may not reflect the most up-to-date information needed to make informed decisions.

- Fewer than6% of survey respondents said they take action on their data insights in an automated fashion
    - 61% said it was because some of their processes are automated, but most are manual.
    - 37% said that it was due to a lack of trust in the accuracy of data.

Continuing with legacy processes puts manufacturing companies at an existential risk. Speed of process improvements, innovation and decision making will continue to be slow. Also, waste will continue. In order to cleanse data and take immediate action on data, surveyed respondents identified the following areas to take them to future state:

The survey enables one to conclude that data acquisition, storage and analysis to eventually drive intelligence to impact process and business metrics positively is a an area that manufacturing industry needs to make strides in. Also there is a strong desire among managers to move their factories toward digital transformation. This paper explores the matter in a more detail and a high impact use case of machine learning in paper making.

TYPES OF DATA

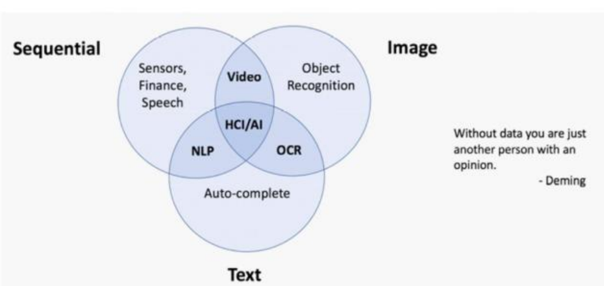


***Figure 1.** Types of Data*

In paper making, data is split into two main groups – sequential data and batch data. Sequential or time series data is time-stamped data of mechanical, operational and chemical parameters. Batch data is data used to trace raw material, additives and finished product through the shop floor and trace it all the way from vendors to customers. Sequential data is generally housed in the DCS or SCADA and batch data is stored in ERP systems. In some cases video data is also used to analyse product quality, identify defects or anomalies. Video can also be used for characterization of wood chips or logs. These are normally specialized stand-alone systems manned by dedicated operators or analysts.

In paper making, two areas of high impact from applying machine learning algorithms to time-series data is in the pulp mill and the wet end of paper making. Time-series data may originate from sensors and other machines in real-time or through time-stamped samples analysed in the lab. This offline data is as important as the online data.

IoT (internet of things) technology enables the real-time transfer of time-series data to the cloud where it can be stored and analysed. Figure 2 below represents the transformation of sensor data from the physical state in to binary representation for processing. Applying machine learning algorithms to this binary data results in insights which can be applied again to the physical world. In our case, it is sensor data for process parameters which is sent to the cloud through an internet gateway (edge computer which will interface hundreds of sensors to the cloud), analysed in the cloud using machine learning and relayed back to the edge to intervene in the process, for example, changing the flow rate of chemical dosing pumps.

***Figure 2.** Data transformation from physical to virtual and back to physical*

There are multiple techniques which can be used to analyse time-series data including moving-average, auto regressive, auto regressive moving average, hidden Markov, recurrent neural networks and deep neural networks or a combination. The deep neural network works best for paper making systems where the system is continually evolving and the current state may or may not have a dependency on the previous state(s). The model is trained through a method called back propagation through time. Pre-processing of data is a way to remove outliers to make the data more consistent to improve the model. In our case, we observed that pre-processing did not improve the accuracy of the model. The observation was that imposing assumptions on the model, did not improve accuracy. This further proves the true use case of artificial intelligence.

SOLID LIQUID SEPARATION

Papermaking is a large scale solid-water separation process, with the pulp slurry filtering over a moving wire. The process starts with a diluted pulp slurry including many components of varying chemistry and morphology.Successful papermaking is dependent on a good understanding of how to keep these different components within the solid phase which is formed on the wire, simultaneously removing large quantities of water. In the wet end, DAF/Poseidon for retaining valuable fines/ fillers and for reducing fresh water use and in the ETP for final treatment of effluent water, efficient solid-liquid separation is key. Specialty chemical additives are used in all of these stages of solid-liquid separation.

THE WET END

The machine wet end's primary goal is around two primary concepts – retention and drainage to achieve the desired productivity and quality.Chemical retention and drainage aids are applied to the furnish to increase the efficiency of the papermaking operation and to improve the quality of the finished sheet. Retention and drainage programs can provide significant cost and operating advantages for all grades of paper including paper, paperboard and tissue manufacturers. Without an effective retention program, large quantities of furnish components, mainly, fines and fillers could pass through the wire during initial sheet formation leading to low retention values. Low retention contributes to inefficient use of expensive furnish components. When filler and other additives are not sufficiently retained, the expected sheet properties are not met andthese unretained components can create machine deposits problems. A good retention program can also ensure better formation - more uniform distribution of fillers in the sheet and reduced sheet two-sidedness, improved opacity, reduced machine deposits, reduced wet-end breaks, holes and spots in the sheet due to high levels of fillers, fines and colloidal materials circulating on the wet-end of paper machine.

Single-pass filler retention is typically much lower than single pass retention for total solids. Smaller filler components like calcium carbonate (0.2 – 5.0 μm), clay (0.3 – 2.0 μm) and titanium dioxide (0.1 – 1.0 μm) are more difficult to retain compared to larger components in the papermaking furnish like fiber(1,200 μm to3,500 μm). The size of opening of the forming wire ensures that retention of larger components will be close to 100%. This is not the case for fiber fines and fillers which may experience retention as low as 1% without the addition of retention aids.

Chemical mechanism of adsorption is critical to the retention of smaller particles. Adsorption is based on the attachment of the smallerfiller particles to larger furnish components that are more effectively retained within the solid phase during sheet forming. The relationship between particle size and retention on chemical and mechanical mechanisms is well illustrated on the Figure 3.

Specialty chemical partnersoptimize the retention and drainage program to maximize benefits and minimize impact on formation. They also develop protocols for monitoring wet-end conditions,build corrective actions to eliminate sources of variability and develop wet end control strategies that makes most sense from the point of increasing efficiency and stabilizing quality. Analysis of data to explain performance changes is also performed by these partners and to provide insights on how to better operate the retention program and assist papermaker with major grade changes.

Wet-end chemistry is the chemical interactions that occur in the water/fiber/additives stock from which paper is made. Wet-end conditions must be carefully controlled to obtain proper and stable formation, drainage, strength, sizing, etc. Many chemical variables on the wet end of the paper machine influence the process, but the primary factors affecting wet-end operations can be grouped into four main categories.

- pH
- Dissolved and suspended materials
- Charge - surface and colloidal
- Chemical additives

The best level of retention is determined by considering a) quality – too high retention may negatively impact formation, opacity, strength and machine runnability; too low retention may increase recirculation of certain furnish components resulting in undesirable deposition and related sheet defects and breaks, b) cost of fiber and filler losses caused by lower retention andc) cost of retention aids.

A "typical" material balance around the wet end of a paper machine is shown in Figure 4 to illustrate calculations of FPR and FPAR values.

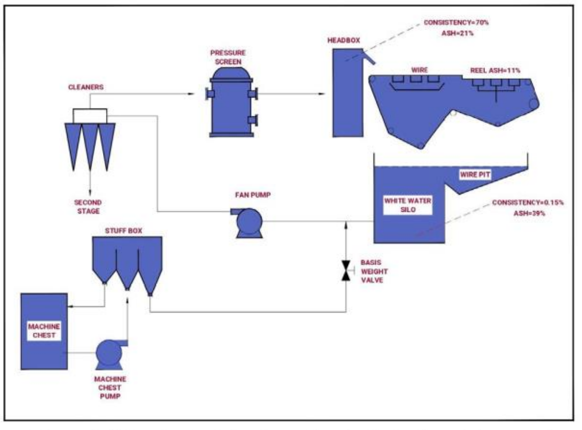


Figure 4. *Wet-end material balance showing typical consistency and ashvalues illustrating retention*

FPR (first-pass retention) and FPAR (first-pass ash retention) are the two most critical metrics to express retention in papermaking.pH, alkalinity, dissolved ions, suspended material, conductivity, colloidal charge, dissolved and entrained gases, hardness, furnish source and quality, filler quantity and quality, etc., all impact FPR and FPAR (See Figure 5).

ARTIFICIAL INTELLIGENCE

Automated real-time data cleansing: The first application of machine learning is to automatically analyse and clear out "bad data". Bad data could be anything from sensor error to electromagnetic noise to anomalies which need not be analysed. With the exception of laborious analysis of the data by an analyst, the best way to cleanse time-series data is a an unsupervised machine learning algorithm. The very definition of "bad data" is rewritten in real-time by this type of algorithm, resulting in >99.9% data cleansing accuracy. This is impossible to achieve at this rate of efficiency with any other tool, especially manually.

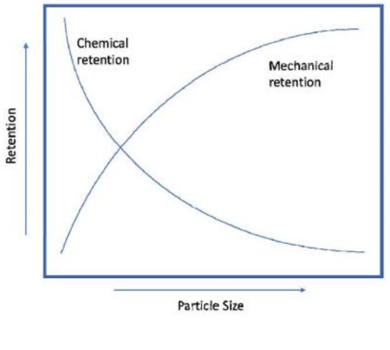


Figure 3. *Chemical and Mechanical retention for varying particle size*

Data on one to even three dimensions may be easy to learn from by using legacy tools by human experts. Machine learning algorithms on the other hand can learn in many more dimensions, even hundreds or thousands. These algorithms can look at high dimension data and recognize patterns and make predictions which humans cannot even come close to. This is very useful in papermaking as multiple variables interact at different unit operations and learning from this data can help predict and control productivity and quality better than ever before. Empowering these algorithms to use these models and automatically control input variable makes the use case for machine learning very powerful.

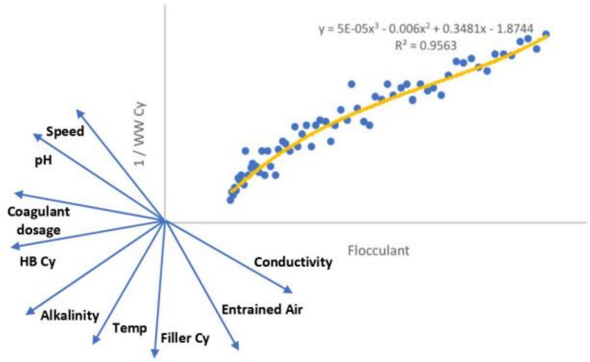


Figure 5. Multi parameter relationships in retention

In the graph above a third order polynomial equation is able to explain and predict whitewater consistency based on flocculant dosages. Inverse of whitewater consistency is plotted against flocculant dosages. This can be reasonably explained by a polynomial equation. In reality, there are many other variables that have an impact on this curve. To effectively analyse all of these variables and their interrelationships in real-time to predict and control the dosage of a chemical retention aid, a machine learning algorithm was used. As shown in figure 6 below a consistent whitewater consistency for the same headbox consistency was achieved with varying flocculant dosages by a machine learning model by analysing the interrelationships between all variables and also controlling coagulant and sizing dosages.

It was observed that the algorithm was able to detect with high level of accuracy (~100%) changes in grammage. Not only could the model detect grammage changes, it could also detect layer switches on the fly. A change in grammage is a shock to the equation, which is a step change. As seen in Figure 6for different grades, the relationship curves are significantly different. The machine learning algorithm can automatically detect change in grade even if the change is random and not in a recurring pattern. It was observed that when the grade repeats, it still follows the curve for a certain period of time,

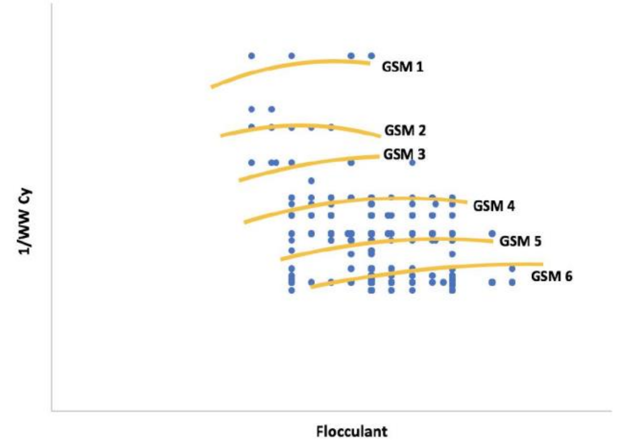


Figure 6. Relationship curves for different grades

approximately 90 days. Beyond the period the curves start to change for the same GSM. Hence, this necessitates the redevelopment of the curve as the older curves are no longer applicable even for the same GSM. This could be driven by subtle changes in furnish source or quality, of filler source or quality, or a combination, or some other unknown reason. Also, it can be observed that more steadywhitewater consistency is achieved by learning from all the other variables that have an impact on retention. The flocculant dosage required to achieve the target WW consistency is quite accurately forecasted by the model.

The same algorithm was applied to close looped systems where conductivity values in the water loop are greater than 5,000 micro Siemens. It was observed that retention aid (flocculant) effectiveness significantly diminished when conductivity increased beyond a threshold level and effectiveness was re-established if the conductivity decreased. The algorithm deduced that this threshold varied from system to system and also trended positively or negatively over time and this trending could be correlated with other variables changing in the system. These threshold values could then be used for timing the purging of the water loop to maintain retention performance and over longer periods of time achieving greater than 10% increase in retention values.

In a dynamic market, mills desire to have the flexibility to change thickness/GSM and vary the layers as per the market demand. Unfortunately, this comes at a cost of lower retention and performance. By using artificial intelligence, the mill can achieve target retention without compromising on cost or quality.