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Digitalization in Action: AI/ML Driven Decision Support in Pulp & Paper

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Abstract:

In today's fast-paced industrial landscape, pulp and paper mills face mounting pressure to boost productivity and quality while building a foundation for future digital initiatives. Yet, striking the balance between quick operational wins and long-term scalability can be challenging. This paper will showcase real-world examples of how mills are leveraging digitalization to achieve immediate, measurable improvements, such as proactive anomaly detection, reduced downtime, optimized energy usage, and while setting the stage for more ambitious initiatives in AI and machine learning.

Keywords: *Partial Least Square (PLS), ETL Process (Extract, Transform, Load), Model Predictive Controls*

Introduction

In the realm of process and manufacturing industries, comprehensive digital and data management solutions play a pivotal role in developing AI/ML based solutions. These solutions often begin as Process Information Management Systems (PIMS) & develop in the various AI/ML Based closed loop controls. Eventually, they empower engineers, operators, and plant managers by providing real-time access to critical data. The goal? Faster troubleshooting and informed decision-making capabilities.

Amid the buzzwords of IT/OT convergence, organizations seek answers: How can they enable data-driven decision-making across their enterprise? The answer lies in connecting all production data seamlessly. Leveraging existing tools while strategically adding new ones drives change without disrupting operations. AI/ML, PIMS, data historians, and analytics platforms—all part of this ecosystem—ensure that accurate, actionable data reaches the right people at the right time. So, whether it's a pulp and paper mill, an oil refinery, or a chemical plant, the quest for efficiency and problem-solving persists, guided by the principles of gradual, strategic IT/OT convergence.

Stages in AI v/s Process (Human) Collaboration

The progression of AI being Assisted to Autonomous Intelligence is not linear. Organizations may utilize AI tools at different stages depending on the specific task or application shown in Figure 1. Ethical considerations are crucial at every stage of AI-human collaboration and understanding the strengths and limitations of both humans and AI is essential for successful collaboration. By fostering a collaborative environment between humans and AI, leaders can unlock new levels of productivity and innovation.

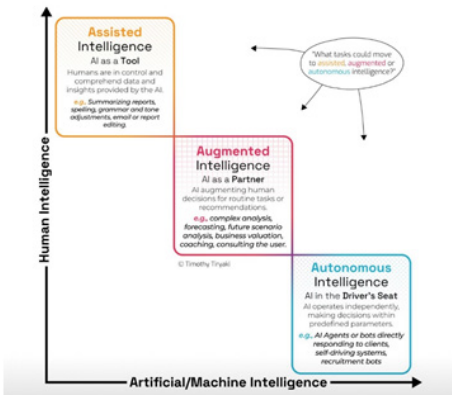


Figure 1. Stages in AI V/s Human Collaboration

Stage 1 : Assisted Intelligence (AI as a Tool)

In this initial stage, AI acts as a supportive tool, enhancing human capabilities. Humans remain in complete control, utilizing AI to augment their existing skills and knowledge. Think of it as a powerful calculator or a highly efficient research assistant. Examples include AI-powered spell checkers, grammar correction tools, and software that summarizes lengthy reports.

Stage 2: Augmented Intelligence (AI as a Partner)

As the relationship evolves, we enter the realm of Augmented Intelligence, where AI becomes a more active collaborator. AI now goes beyond simply

providing information; it offers valuable insights and recommendations to guide human decision-making. This partnership allows humans to tackle more complex tasks, such as analysing large datasets, forecasting future trends, and developing strategic plans. The human retains the ultimate decision-making authority, but the AI significantly enhances their ability to make informed choices.

Stage 3: Autonomous Intelligence (AI in the Driver's Seat)

The final stage, Autonomous Intelligence, represents a significant shift in the human-AI dynamic. In this scenario, AI operates independently within predefined parameters, making decisions and taking actions without direct human intervention. This is where we see the emergence of self-driving cars, AI-powered robots performing complex surgeries, and AI systems managing entire supply chains. While human oversight is still essential, the AI takes on a more significant role in executing tasks and achieving desired outcomes.

This Paper showcase more actionable use cases in each stage of AI Human Interaction in Pulp and Paper operations using the various data driven AI tools like dataPARC, Control SUITE and MACS.

Assisted Intelligence: Mill-Wide Data Integration for real time ETL Process (Extract, Transform and Load)

Unifying Production & Process Data for Real-time Intelligence helps to gain actionable insights into production processes, we must first consolidate data from diverse sources. This includes historical process data from historians, real-time information from DCS/PLC systems, production planning details from ERP systems, and quality control results from LIMS. A critical step is integrating this data into a centralized repository like a data warehouse or data lake. To achieve this, we implement ETL processes to extract data from each source, transform it into a consistent format, and load it into the repository. API integrations streamline this process by enabling real-time data extraction directly from sources. With a unified data foundation, we develop interactive dashboards using powerful & user-friendly tools like dataPARC. These dashboards display key performance indicators (KPIs) such as Overall Equipment Effectiveness (OEE), yield, and inventory levels.

Use Case 1: Real-time Charts and Graphs provide dynamic visualizations of production trends, downtime analysis, and quality correlations. Interactive Maps visualize production locations, material flows, and equipment distribution presented in Figure 2. Drill-down capabilities empower users to explore data in detail, focusing on specific time periods, production lines, or equipment.

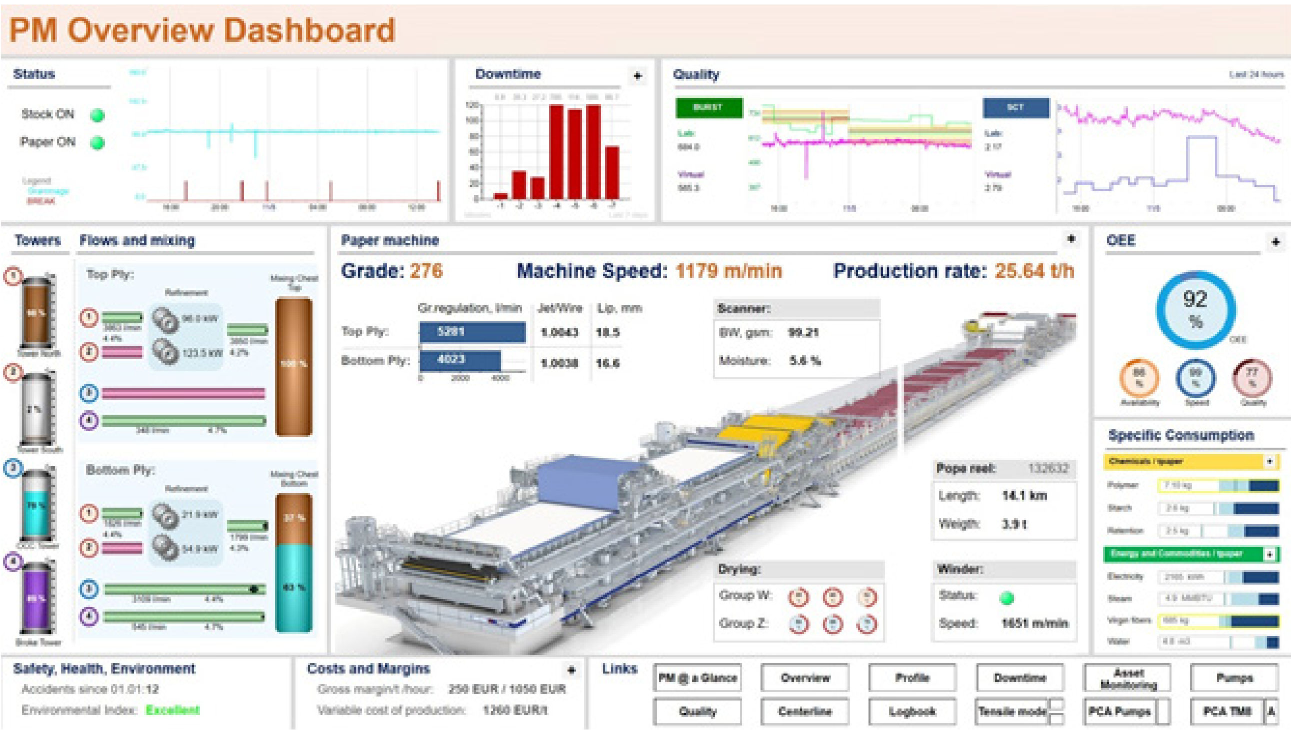
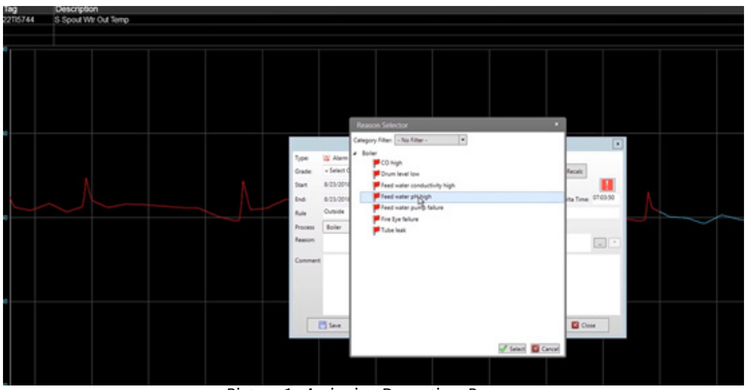
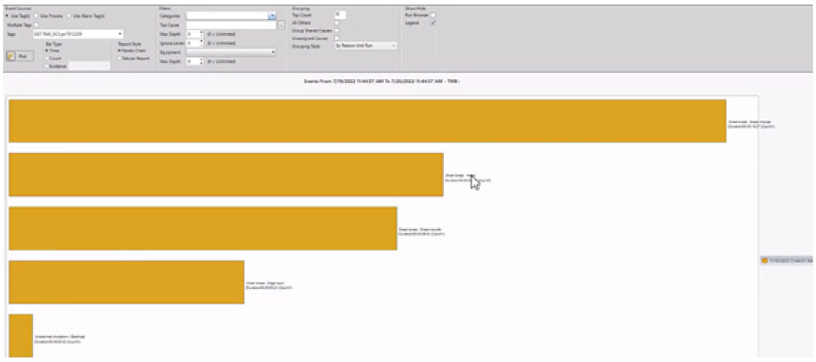


Figure 2. Paper Machine Interactive Dashboard



Picture 1 : Assigning Down time Reason

Use case 2: Proactive Downtime Management is integrated into the dashboard. By integrating with DCS/PLC alarms, we automate the logging of downtime events, capturing crucial information like timestamp, duration, equipment ID, and operator notes. Root Cause Analysis, aided by techniques like Pareto charts, helps identify the most frequent causes of downtime. This analysis supports the creation of insightful reports for shift reviews, maintenance planning, and continuous improvement initiatives, enabling proactive measures to minimize downtime.



Picture 2 : Pareto charting downtime for period of time

Alarm Causes Pareto for
Plant
Events From: 8/22/2018 11:24:00 AM To 8/23/2018 11:24:00
AM

Start	End	Duration	Alarm Desc.	Equipment	Comment
VAN.Sample.PM1.QualityIndex					
8/23/2018 3:16:00 AM	8/23/2018 4:31:00 AM	01:15:00			Pat spilled something
	Total Duration	01:15:00			
VAN.BLR.243_SS_674					
8/23/2018 10:27:00 AM	8/23/2018 10:29:00 AM	00:02:00			Issue with feed water
	Total Duration	00:02:00			
VAN.PHD.02PM2Down					
8/22/2018 1:07:14 PM	8/22/2018 1:30:14 PM	00:23:00			not my fault
	Total Duration	00:23:00			
VAN.PHD.02PM2Down					
8/23/2018 8:32:13 AM	8/23/2018 8:40:14 AM	00:08:01			not my fault
	Total Duration	00:08:01			

Picture 3 : Auto Generated Report for the selected Time period

The benefits from Mill-Wide Data Integration for real time ETL Process (Extract, Transform and Load) are substantial:

- Real-time insights empower proactive responses to production challenges.
- Data-driven decisions. Eliminates silos and enables strategic decision-making.
- Reduced downtime through proactive maintenance and root cause analysis.

Augmented Intelligence: Anomaly Detection & Deviation Detection using Partial Least Square Models

Predictive models are extremely useful in monitoring and optimizing manufacturing processes. Predictive modelling in manufacturing, when combined with an alarm system, can be used to alert changes in processes or equipment performance and prevent downtime or quality issues before they occur. PLS stands for "Partial Least Squares". It's a linear model commonly used in predictive analytics.

PLS models are developed by modelling or simulating one unknown system parameter (y) from another set of known system parameters (x's). In manufacturing, for example, if you have an instrument that is sometimes unreliable, but you have a span of time in which it was very reliable, it is possible to simulate, or model, that parameter from other system parameters. So, when it moves into an unreliable state, you have a model that will approximate, or simulate, what that instrument should be reading, were it functioning normally.

PLS Formula: **y = m1x1 + m2x2 + … + mnxn + b**

In this formula, the single (y) is approximated from the (x's) by multiplying each by a coefficient and adding an intercept at the end.

Use Case 1: Simulating flow from valve position, power, or delta pressure (dP). In this particular case had a condensate tank in which the flow kept reading zero on their real-time production trend, even though they knew their pump was pumping condensate. Using dataPARC' s predictive modelling tools, we looked at the historical data and found periods of time when there was a flow reading, and they modelled the flow based on the pump amps during those same periods.

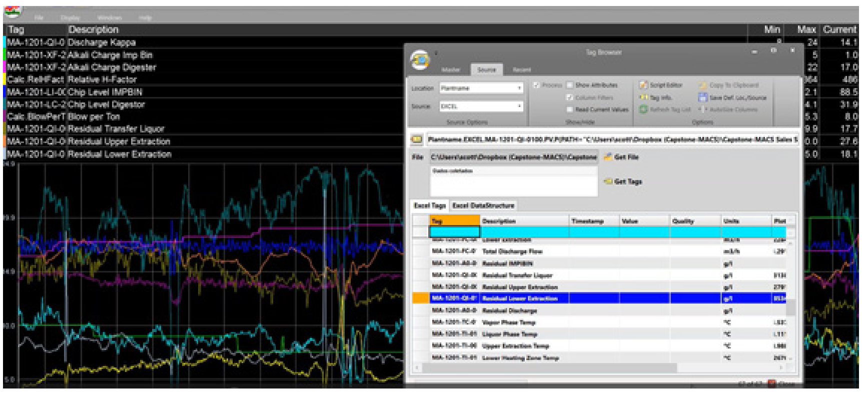
So, when the flow itself got so low that the flow meter wouldn't register it, they still had a model of flow based on pump amps, because the pump was still pumping and registering pump amps.

Use Case 2: Producing discrete Laboratory test results modelled from a set of continuous process measurements. This example, there is a Digester Kappa results test every four to six hours in the LAB. But to know the probable Kappa Value between those tests ,a PLS models is generated using variables around Digester like Alkali flow, Steam Flow, Temperature, Levels , etc. Using dataPARC PLS tool a model of those discrete test results are generated and used for continuous monitoring and corrections.

How to build a PLS Model

We'll use the example we discussed where we simulate Digester Kappa using Alkali Flow, Residuals Alkali, Temperature, Level etc.

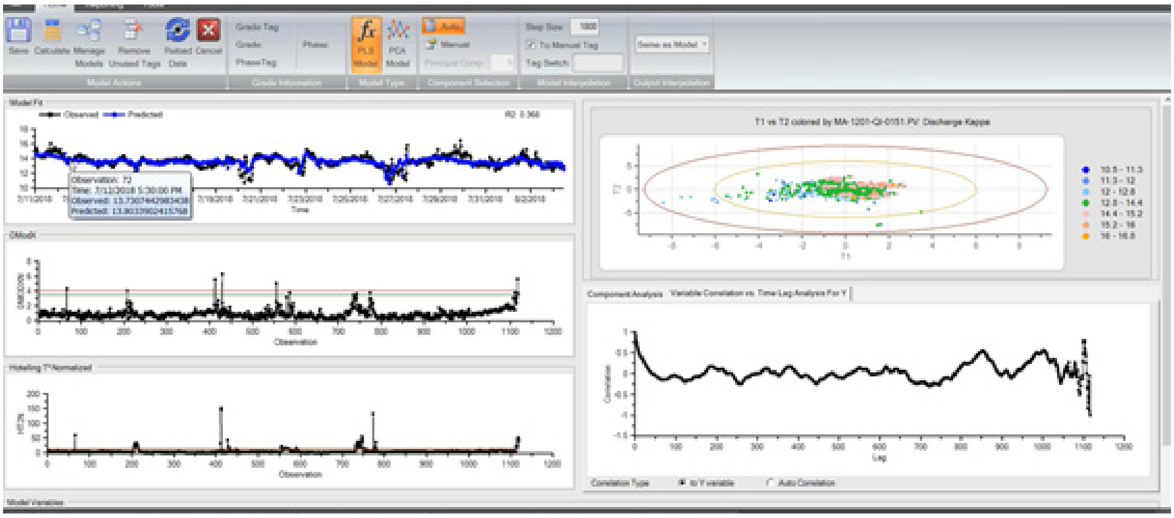
Step 1 : Identify Variables: Using dataPARC, we build these models from trends. Here we have a trend showing various variables around Digester (Picture 4). This data is being pulled from our data historian software.



Picture 4: Trend of different pulping variables

Step 2: Establish Time Periods for Evaluation: Historian with an analytics tool helps to pull the data from different time period and time align various data from different data sources. This is the data we'll use to build our model. It is very important to evaluate a model against a time period that is not included in the dataset. To determine if the model is valid going forward. Because as time goes on, it will be using data that it never saw.

Step 3: Generate the Modelled Data: With AI Driven predictive modelling tools, building the model is as simple as adjusting some configuration settings and clicking "Create New PLS Model" (Picture 5). The model will be generated using the data from the tags in our trend we looked at previously. Of course, with more effort, this data can also be produced and managed in Excel as well.



Picture 5 :

Step 4: Evaluate the PLS Model : The first thing to do when we build a PLS model is clean up the data. Or at least look for opportunities to clean up the data.

T1 vs. T2

Look at the T1 vs. T2 graph (Figure 3). What we're looking for here is a single grouping of data points within the circles on the graph. A single "clump" of data points indicates we're looking at a single parameter, or operating regime. If it appeared we had two or more clusters of data points, it'd be a good indication we have multiple operating regimes represented in our model. In that case we'd want to go back and build distinct models to represent each regime.

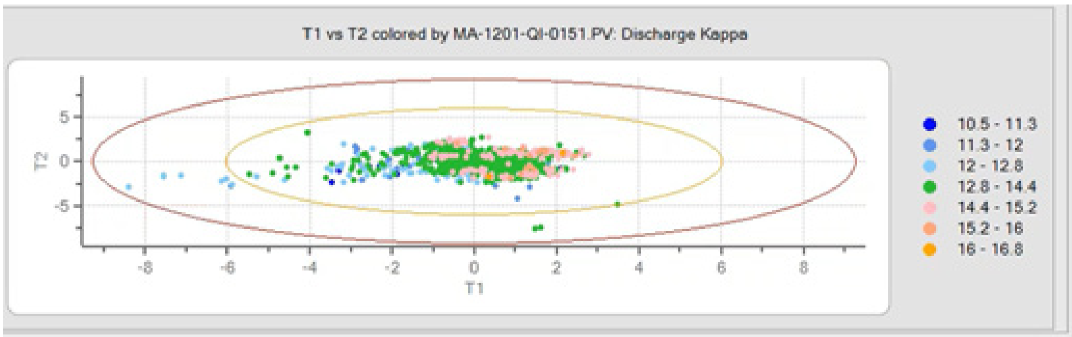


Figure 3. T1 vs. T2 graph representing bivariate data relation

Step 5 : Evaluate Y to Y

Using a common Y to Y plot (Figure 4), we can view the original Y and the predicted y plotted against each other. In this example they're very close together and you can see that the R-squared value is reasonably good, which we'd expect when we're modelling Digester Kappa. Check out that R-squared. 0.368.

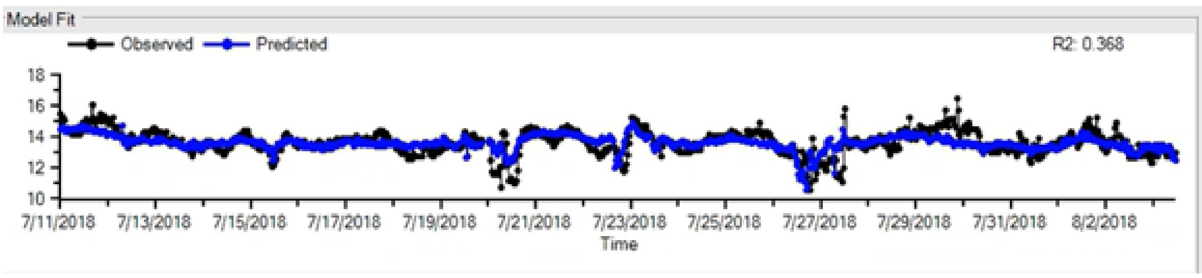


Figure 4. Y at time t vs. Y at time t-1 auto correlation plot

Step 6: Using PLS Model as a continuous data TAG

We can import the model we built from our source data and lay that over real data from that second time period to see how accurately it would have predicted the flow for that period of time. We used an 11-day period to create a model, and now, the predicted values of the Digester Kappa are nearly identical to the actual values from that time period as presented in Figure 5. Perfect!

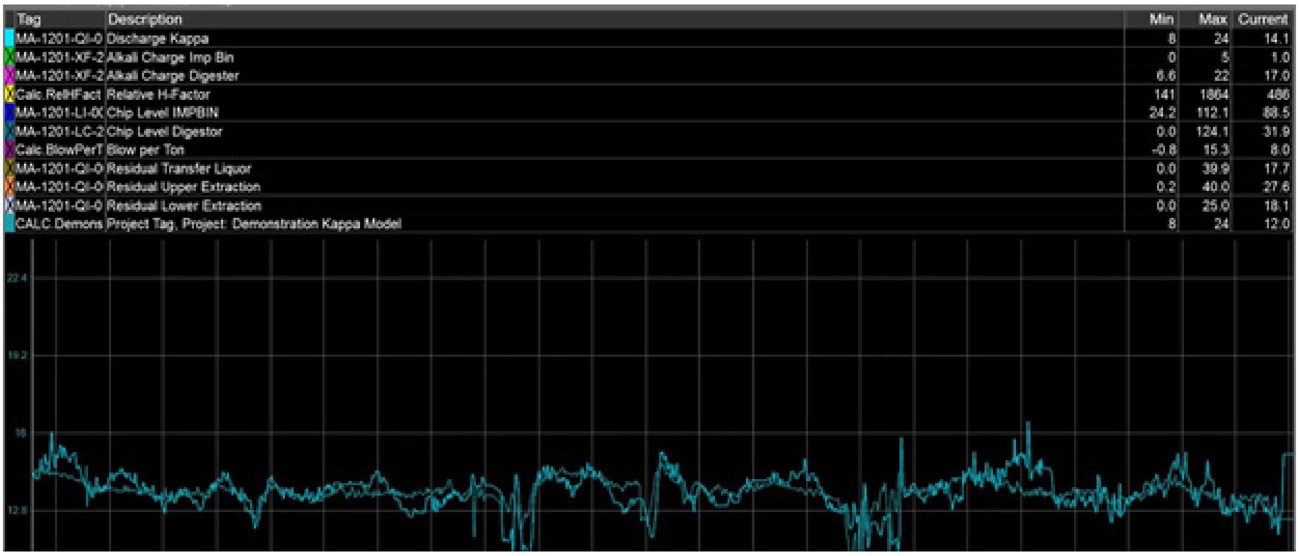


Figure 5. Prediction Test result over time periods

The benefits from using AI driven Partial Least Square Models are substantial like:

- Provide early warnings for potential quality or maintenance issues.
- Moves from reactive to proactive management by getting Important Measurement values .

Autonomous Intelligence: Model Predictive Advanced Process Controls

The pulp and paper industry is increasingly embracing Autonomous Intelligence, where AI systems operate independently within predefined parameters, making decisions and taking actions without direct human intervention. This stage represents a significant shift towards automation and optimization within the industry.

Advanced control comes into play from the level of basic control through that of process optimization. Instead of having the operators manually adjust control units for specific variables, advanced systems provide generalized models that automate regulatory and constraint control as well as process optimization. In regulatory control (Picture 6) single loop feedback improvements such as feedforward, cascade control can be used to supplement PID algorithms. Time delay compensation techniques can also be applied to compensate for long delays permitting tighter control. At the level of constraint control, multivariable techniques (Picture 7) can be used.

Advanced control technology is therefore a combination of:

- Advanced hardware (online sensors, pneumatic or electronic analog with digital systems, computer hardware and digital control units)
- Advanced control algorithms at regulatory, constrained and optimization levels.

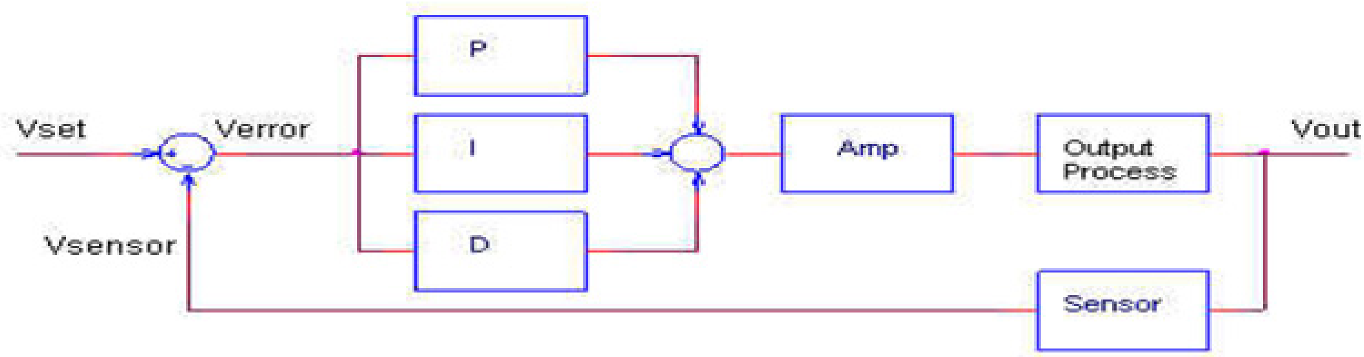


Figure 6: Regulatory control single loop feedback to supplement PID algorithms

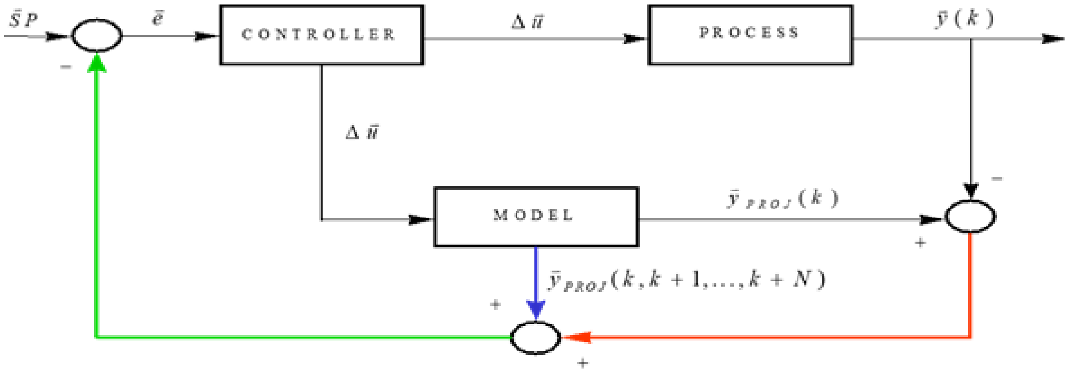


Figure 7: Multi-variable technique to control constraint

Use Case 1: Final Paper Ash Optimization. European 75000 tpa specialty paper machine produces grades with high demand of wet strength. This machine has big variation in ash level, especially when broke content is high. High peaks in ash level leads to wet strength loss and runnability issues. Therefore, customer must set big safety margin in fresh filler dosage which leads to high fiber cost. 30-hour trend in Figure 6 shows the magnitude of variation.

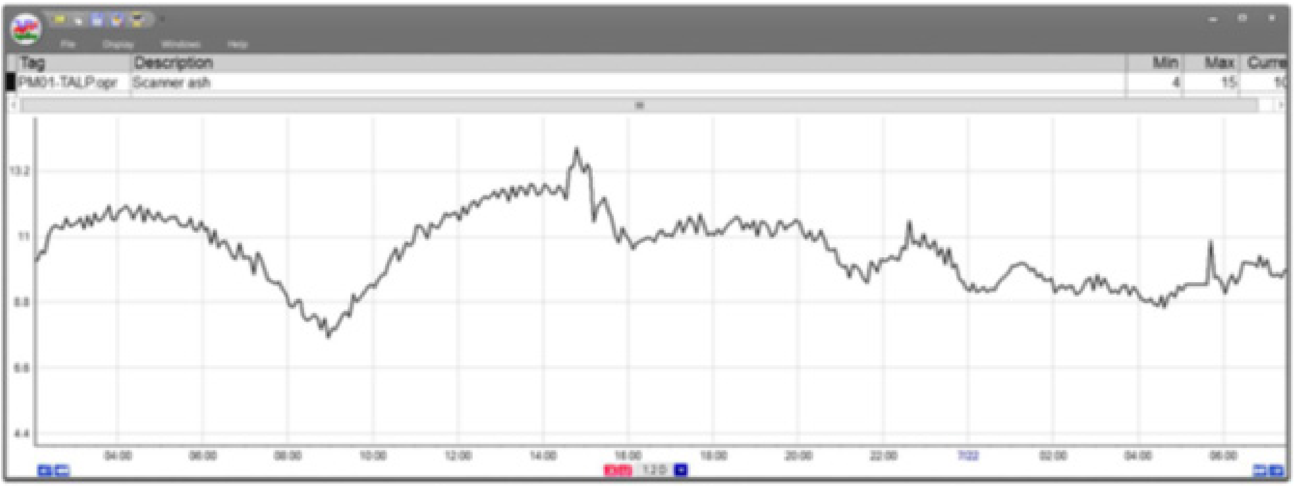


Figure 6. Scanner Ash Variability for 30 Hours

The Solution was to use AI based Model predictive Filler level optimization, which includes step by step approach such as Expert process review to find development areas, Evaluation of regulatory controls, Installation of Retention and Pulp Ash sensors to key locations, Multivariable Advanced Control Algorithm to stabilize sheet ash. Results are shown in Figure 7.

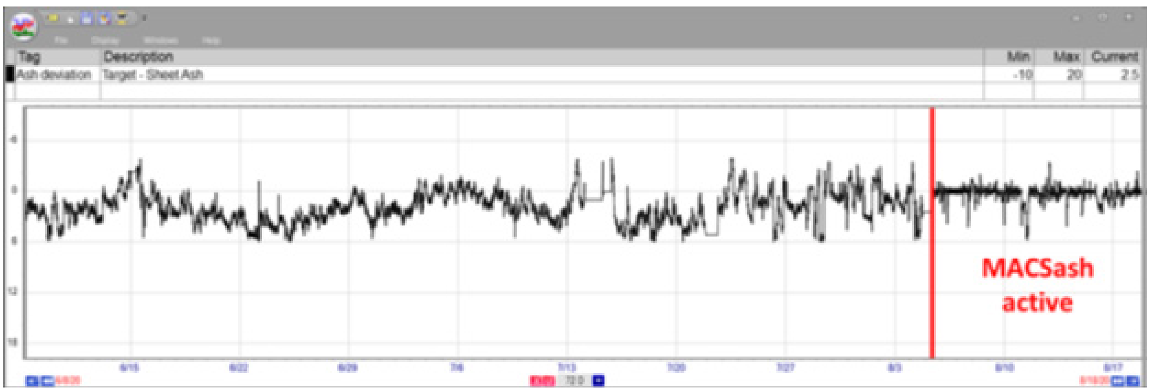
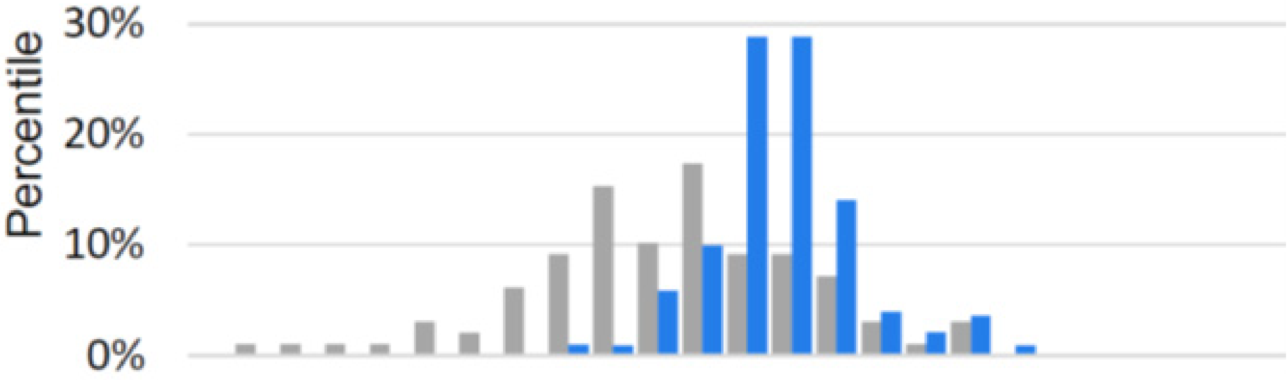


Figure 7. Control Result comparison – Before and After

The benefits from Model Predictive Advanced Process Controls are:

- Reduced variability enabled higher ash setpoint, while maintaining wet strength targets. More narrow distribution and increased ash level is shown in Picture 8.
- MACSash project led to average savings of 5,5 €/t
- Ash variation reduction by 80%
- Average sheet ash increased by 1 %



Picture 8: Sheet ash distribution before (grey) and after control (blue)

Conclusions:

In summary, the pursuit of efficiency, data-driven decision-making, and continuous digital transformation remains a driving force across industries. This relentless pursuit reflects the inherent resilience and adaptability of businesses in today's dynamic environment.

The convergence of human expertise and advanced AI technologies is crucial for navigating this evolving landscape. By embracing AI advancements early on, organizations can accelerate progress and gain a competitive edge. Rather than reinventing the wheel, leveraging existing AI tools and proven innovations provides a solid foundation for building upon. The synergy between established principles and cutting-edge AI solutions often yields remarkable outcomes, driving innovation and sustainable growth.

Conflict of interest: The authors declares no conflicts of interest.