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Empowering Productivity and Quality in AI Era

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Abstract:

In the modern era of artificial intelligence (AI), analytical models have become essential tools for enhancing productivity and quality across various industries. This paper delves into the significant role these models play, particularly in the pulp to paper optimization process within the paper industry. By leveraging advanced data analytics and AI-driven solutions, the industry can achieve remarkable improvements in efficiency, cost-effectiveness, and product quality.

The paper will explore the methodologies and technologies employed in optimizing the pulp to paper process, from raw material selection to the final paper product. It will highlight how AI and machine learning algorithms can monitor and control various stages of production, leading to reduced energy consumption, minimized waste, and enhanced environmental sustainability. Case studies and best practices will be presented to demonstrate the tangible benefits and transformative impact of these analytical models.

Through this exploration, the paper aims to provide insights into how the integration of AI-driven analytics can empower the paper industry to meet the challenges of a competitive market, drive innovation, and achieve sustainable growth.

The paper industry is undergoing a significant transformation through the optimization of the pulp-to-paper process, driven by advancements in analytical models and AI technologies. This optimization aims to enhance efficiency, reduce waste, and improve the quality of the final product. By leveraging data analytics, machine learning, and process automation, manufacturers can monitor and control various stages of production, from raw material selection to the final paper output.

The integration of AI-driven solutions enables real-time data analysis and predictive maintenance, ensuring that machinery operates at optimal performance levels. This leads to reduced downtime and maintenance costs, while also extending the lifespan of equipment. Additionally, advanced analytics help in identifying patterns and trends that can inform better decision-making, such as optimizing the mix of raw materials to achieve desired paper qualities and minimizing environmental impact.

Case studies from leading industry players demonstrate the substantial improvements in productivity and quality achieved through these technologies. For instance, the implementation of AI-driven process control systems has resulted in significant raw material savings, reduced chemical usage, and enhanced product consistency. These advancements not only contribute to cost savings but also support sustainability goals by reducing the carbon footprint of paper production.

This paper explores the methodologies and technologies employed in optimizing the pulp-to-paper process, highlighting best practices and successful implementations. The findings underscore the transformative impact of AI and analytical models in empowering the paper industry to meet the challenges of a competitive market, drive innovation, and achieve sustainable growth.

Keywords: *AI, Analytical models, Autonomous mills, Digital twins*

Introduction

Artificial intelligence (AI) is a central technology for enabling autonomy in a pulp and paper mill, as companies are aiming to increase the autonomy of their operations [1]. In a fully autonomous mill, production is at 100% control in all situations without manual intervention, the system monitors its own performance, and the system reacts to deviations automatically. Autonomous operations are pursued in a stage-wise manner, both when the degree of autonomy and process management and control layers are concerned (process technology, process optimization, mill-wide or value chain optimization, manufacturing optimization) [2]. However, the role of humans is still important, and it will evolve towards orchestrating and supervising operations, empowered by tools for monitoring, understanding, controlling, and optimizing the mill. Important value drivers for autonomous operations include:

- Improve sustainability along more optimized processes and reduced raw material consumption.
- Reduce fixed costs by centralizing control room operations and reducing the number of people.
- Improve safety along higher level of autonomy in field operations.
- Maximize asset performance and mill overall equipment efficiency (OEE) over the life cycle.
- Reduce the impact of ageing workforce and workforce scarcity through reducing the need for human intervention in highly complex and interactive processes.

AI solutions can be either analytical or generative. Analytical AI is used at specific tasks by fast and efficient data analysis without significant recollection of past outcomes. This makes it ideal for the rule-based decision-making and analysis in real-time scenarios. Generative AI focuses on creating new content and insights by synthesizing past and present data to make decisions. Generative AI models get better over time, making them more adaptable and strategic, by default. Examples of applications that leverage analytical AI are advanced soft sensors and real-time process optimizers. Examples of generative AI are complex engineering task assistants and field engineer virtual support systems.

While applying AI, we must ensure fairness, privacy, and security. Responsible AI principles include:

- Traceability: Plan how AI is trained, what information it has access to, and study the code libraries.
- Transparency: Define guidelines for how AI-generated is used and labeled, and who is accountable.
- Oversight: Make regular audits and assess the actions of AI.
- Governance: Continuously follow the development of the field, and review and update guidelines.
- Security: Set adequate safeguards and mitigate potential cyber threats and vulnerabilities.

This paper highlights examples on how AI-powered monitoring and control solutions are prevalent in the pulp and paper industry. Emphasis is placed on process optimization, and a pulp mill case study on mill-wide optimization by Valmet is presented. Valmet has strategically integrated AI into its operations to drive innovation and efficiency through both analytical and generative AI. By leveraging AI, Valmet enhances its operational capabilities and strengthens its competitive position in the global market, enabling it to better serve a diverse and international customer base. In the realm of analytical AI, Valmet utilizes advanced analytics to extract valuable insights from large process datasets. This includes statistical analysis, data mining, mathematical modeling, and machine learning to understand trends and relationships within the data, thereby enhancing process optimization and improving end quality. Generative AI allows to enhance efficiency, reduce costs, and improve productivity of operations by helping e.g. field service engineers and technical support teams to diagnose and resolve issues, suggest troubleshooting steps, and provide technical documentation to customers, while decreasing lead times. Automated report generation is another application area of generative AI (service and performance reports, RFP responses, compliance documentation, etc.), reducing manual workload and ensuring reporting consistency.

This paper is structured as follows. Section 2 gives examples of the role of analytical models in process area monitoring and optimization. Section 3 presents the mill-wide optimization case example. Section 4 contains the conclusions of the paper.

MATERIALS AND METHODS

AI-driven Data Integration and Optimization of Process Areas

Improved operation at pulp and paper process areas can be gained through more efficient utilization of collected process data, and through active optimization of process area key performance indicators (KPI) through advanced process control (APC). In addition, advanced process analyzers are used for providing reliable data for these solutions. The integration of wet-end, runnability, and sheet quality data with machine direction (MD) optimizer can be highlighted here as an example of improved data utilization. Wet end stability of the machine is a mirror to the runnability and the quality of the end product. Alone, grams per square meter (gsm) and other properties can't give much info about what is actually causing quality defects. Variations in the retention loop can result in sheet breaks, as well as variations in quality parameters like gsm, moisture, and holes. MD optimizer can integrate the data from the retention sensors, web monitoring sensors and the web inspection systems in a single report (Figure 1). This quality map enhances the decision-making capabilities of the process supervisor and results in less breaks and quality rejects.

Figure 1. Integrated Quality Map from MD optimizer.

For process area APC control, benefits have been documented during multiple years of pulp and paper implementations, with some examples for pulp in Table 1 [3] and in the works of several authors [4-6]. APC solutions leverage analytical models as internal controller models, for feedforward compensation, as soft sensors to generate missing process data, for calculating control-relevant data like constraints or KPIs, for custom heuristics, etc. The role of analytical models in AI powered process area optimization solutions is thus to embed the inherent process knowledge and dynamics of the target system into the control problem.

Table 1. Examples of average benefits from pulp mill optimizer implementations.

	Reported benefit			
Process	**Production**	**Quality**	**Energy**	**Other utilities**
Washing	+2-4% production through debottlenecking		+2-5% evaporation steam savings	–5-15% washing loss, chemical savings
Bleaching	+3% bleaching capacity	–20-40% final brightness variability		–7-15% chemical use
Evaporation	higher evaporation capacity	+30-60% black liquor stability	–3-8% steam consumption	–20-50% concentrator washing
Recovery boiler	+2-6% liquor throughput	+30-60% green liquor stability	+1-4% steam production	
Lime kiln	+4-10% CaO production	–20-40% residual carbonate variability	–4-8% energy consumption	

While the purpose of APC optimizers is to make the individual process areas work optimally and while their optimized KPIs also contribute to the overall mill performance, interactions between process areas generate bottlenecks for production and quality, as a whole. Coordination of the individually optimized process areas and prediction of the future mill balance are essential for pushing the total production towards higher-level KPIs. Mill-wide optimization is presented in the next subsection as an analytical solution for this purpose.

Increased Autonomy through Mill-Wide Optimization

Mill-Wide Optimization (MWO) is a real-time advisory solution for optimizing an entire pulp and paper mill, either as "planning" applications for providing future process area targets, or as "tracking" applications for tracing the upstream or downstream impact of process operations and disturbances. The solution is based on the mathematical optimization of a flowsheet model of the mill (high-level digital twin). The flowsheet unit modules contain the relevant input–output relationships for the optimization problem, identified based on historical or design data of the mill. Pulp and liquor components and properties are tracked throughout the flowsheet. The process equations, objectives, constraints, and discrete future events like production stops together form the optimization problem, which is solved on an equation-oriented basis [9]. Mathematical optimization is a key technology in the field of AI [7-8], as it leverages the inherent knowledge embedded in analytical process and performance models in a systematic way. Solving a properly defined optimization problem guarantees that the best possible process area targets and trajectories are obtained based on the desired KPIs, up-to-date process data, and formal mathematical theory. In comparison, optimality can typically not be similarly guaranteed for pure machine learning (ML) solutions.

The mill-wide optimization problem is configured and periodically solved alongside the mill (Figure 2) in a dedicated MWO online platform. The model equations are continuously adapted based on process data from the distributed control system (DCS) of the mill, and each optimization cycle is started from the current mill state. In addition, "what if" scenarios can be optimized in a separate planning mode. The user interface mainly consists of a compact flowsheet view of the mill, which enables the user to adjust current and future production limitations and view the optimized production target trajectories and bottlenecks.

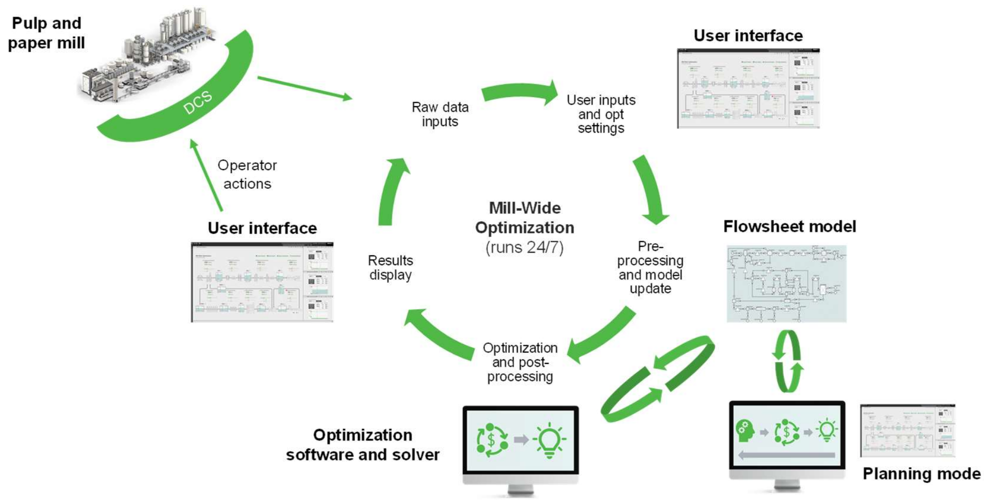

Figure 2. Simplified cycle of the real-time mill-wide optimization solution.

For each optimization cycle, the mill personnel review the MWO results, and accepted targets can be implemented as process area setpoints. As a result, mill operators, engineers, and management can base daily production decisions on the online balance and forecast of the mill, highlighting the importance of analytical process models for informed decision-making. The mill-wide model also ensures that operating decisions are coordinated towards higher-level KPIs. The interaction between the mill staff and the MWO solution as an open-loop advisory system ensures the practical relevance of the optimization results.

RESULTS AND DISCUSSION

MWO Case Study Setup and Audit

MWO was implemented as mill-wide production planning for a market kraft pulp mill in the case study. The purpose was to optimize current and future production rate targets for eleven process areas to maximize pulp production at the digester. Secondary objectives were defined for tracking inventories towards their setpoints and avoiding excessive production rate changes. The case study concerned the basic production planning setup that focuses on pulp, liquor, and lime inventory management for pushing production on a mass and volume basis, although this setup can also be modified e.g. with a steam and power model layer.

The predicted optimization horizon was 72 hours, with an automatic optimization frequency of 30 minutes. The interactive user interface was implemented in the mill DCS environment, with a similar user experience to Figure 3. In addition to the optimized future trajectories and the current optimized targets, the "open-loop" levels of inventories were also shown on the main display, as well as the process area bottlenecks. These bottlenecks indicate where increasing the overall pulp production would require exceeding process area minimum or maximum limits.

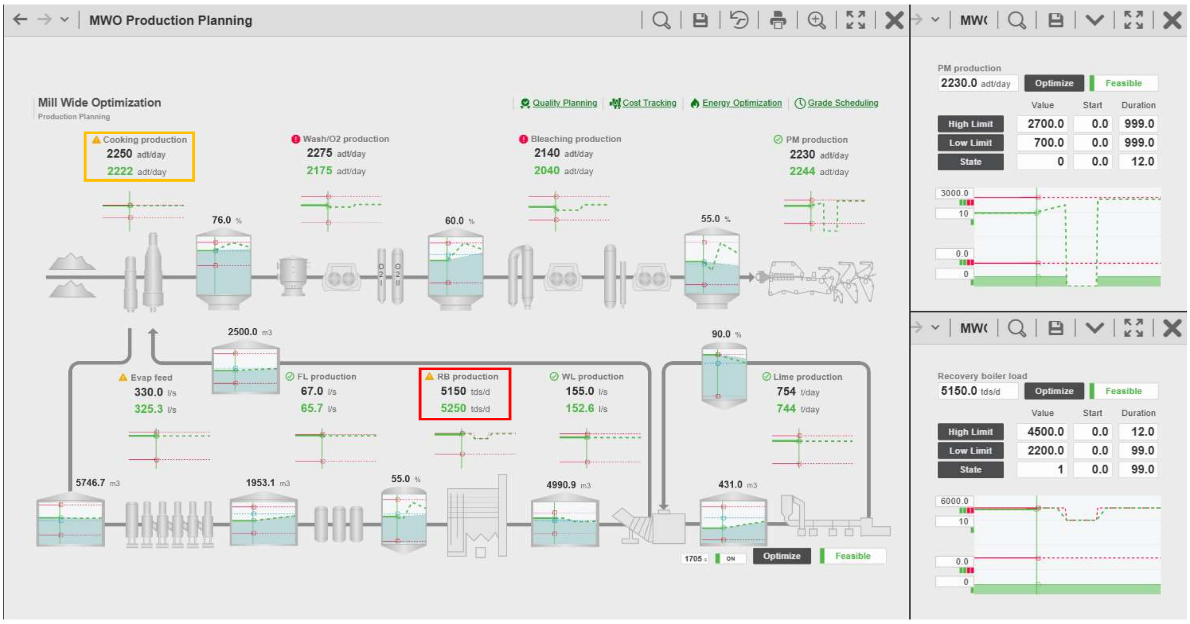

Figure 3. Production planning demo, showing optimized production rates (green values), optimized trajectories (dashed lines), and predicted open-loop levels (blue) for a 12h paper machine stop and related recovery boiler load reduction. Full and partial bottlenecks are shown with colored frames.

The MWO implementation started with a "re-optimize the past" audit to evaluate the overall production increase potential. This involved outlining the process flowsheet, collecting and preprocessing the mill data, defining the analytical model equations, identifying the model parameters, and configuring the optimization problem. This offline MWO solution was then simulated one optimization horizon at a time for one year of historical data, comparing the optimized production rates to the realized ones. The analysis resulted in a maximum improvement potential of 4.5%, as well as the bottleneck results in Table 2.

Table 2. Process area bottlenecks for optimal operation in the case study.

Process area	Cooking	Washing	Bleaching	Pulp Dryer	Evapo-rators	Recovery Boiler	Causti-cizing	Lime kiln
Bottleneck frequency	4.1%	1.5%	6.8%	0.6%	30.9%	11.1%	42.2%	2.4%

The real-time MWO solution was constructed from the offline application by refining the optimization configuration, models, and weight factors in the dedicated MWO platform. Great emphasis was also placed on creating a joint situational awareness through user interface design. The online commissioning was followed by an eight-month intensive monitoring period with the MWO active to realize the estimated production increase potential. This monitoring period was eventually succeeded by a continuous improvement and service program, focusing on maintaining high mill performance.

MWO Real-Time Solution Observations

The monitoring period proved that MWO production planning has the potential to increase production and provide benefits to mill operations on a continuous basis. An average digester production increase of 5.2% was recorded, with similar increases for O2 delignification and bleaching

[9]. In addition, situations were recorded where further production increase would have been possible based on the mill balance, if not for momentary practical limitations. This was also reflected in the monthly bottleneck analysis [9]; otherwise bottlenecks largely corresponded to the results in Table 3.

The MWO solution helped the mill to evaluate the feasible digester production target, and having continuous access to an up-to-date mill balance contributed to an increased confidence to push cooking production targets [9]. MWO production planning also provided a tool for debottlenecking the process by testing the impact of individual process area limitations (Figure 4). Avoiding production losses through planning of upcoming process area stops and slowdowns, and reacting to unplanned process area disturbances, were seen as important functions of the tool.

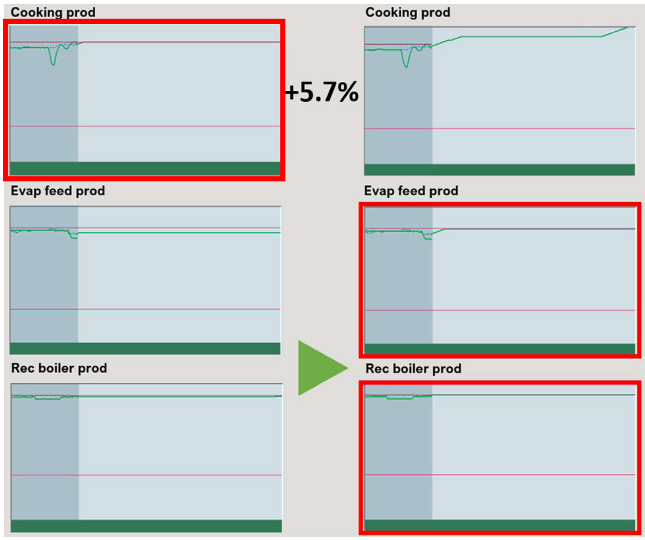

Figure 4. Debottlenecking investigation, where the cooking maximum limit was relaxed to discover the next bottlenecks (red frames) at the evaporator and recovery boiler, revealing a maximum improvement possibility of 5.7% in this case, if cooking was pushed beyond its maximum limit.

The monitoring period highlighted how MWO can help build collaboration between process areas, shifting decision-making from reactive and department-centric to proactive and mill-centric, especially for the coordination between the fiber line and the recovery line during production rate changes. The MWO solution also provided different shifts and operators with an ability to make decisions in a repeatable way based on process data and proven algorithms. This emphasizes the role of analytical model approaches in AI-based systems, as alternative technologies like ML would require large amounts of training data to ensure a similar degree of repeatability, and extrapolation outside the training data can be unreliable.

Conclusion

As the pulp and paper industry faces new challenges and opportunities, both individual process areas and overall mill production efficiency need to be optimized using AI-powered decision-making tools. Empowered by advanced solutions for monitoring, analysis, control, and optimization, mill roles will evolve towards orchestrating and supervising mill operations, and pushing production towards higher efficiencies, lower costs, and increased sustainability. Providing mill personnel with reliable, functional, and understandable solutions for running mill operations becomes especially important when the most experienced operators and engineers are retiring from the workforce, as optimizing the production has largely relied on their process knowledge and manual calculations in the past.

The advanced process control and mill-wide optimization case examples of this paper highlight the benefits of these technologies for pulp mills, as well as the role of analytical models in the AI era. Solutions like mill-wide optimization employ analytical models for optimizing mill performance in a transparent mathematical framework, providing a direct way to leverage embedded process knowledge for more informed decision-making. The impact of individual process and tuning parameters can be observed and adjusted more clearly than in a pure machine learning approach, and solution optimality is guaranteed. On the other hand, the optimization setup also needs to be configured carefully and maintained by the mill, and managing the tradeoff between many objectives can be challenging. Furthermore, generative AI is typically more suited for generating non-conventional and desirable suboptimal solutions than analytical AI approaches. As a result, the authors believe that analytical and generative AI together form a solid foundation for pursuing autonomous operations in the pulp and paper industry.

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