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AI IN MANUFACTURING

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Corresponding author:
Tõnis Raamets
tonis.raamets@taltech.ee

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Virtual factory model development for AI-driven optimization in manufacturing

Tõnis Raamets, Kristo Karjust, Aigar Hermaste and Karolin Kelpman

Department of Mechanical and Industrial Engineering, Tallinn University of Technology, Ehitajate tee 5, 19180 Tallinn, Estonia

ABSTRACT

This paper examines the development of a virtual factory model to optimize overall equipment effectiveness (OEE) in a planned manufacturing facility. Using digital simulations based on a wood manufacturing setup, AI-driven models can be applied to analyze specific OEE metrics, allowing for targeted identification of production bottlenecks and efficiency improvements. The virtual factory enabled scenario testing for the proposed facility, providing actionable insights without impacting current operations. The preliminary results indicate that AI integration within a virtual factory can significantly enhance planning and decision-making for future production investments.

Introduction

Enhancing competitiveness and efficiency in manufacturing processes is a key priority in modern industry [1]. The optimization of production workflows through advanced technologies such as artificial intelligence (AI) and virtual factories offers innovative solutions for addressing bottlenecks and improving overall operational performance [2]. This study focuses on analyzing and optimizing the production processes of a wood manufacturing company by employing a virtual factory model augmented with AI-based tools [3]. In this study, the virtual factory evaluates a new manufacturing facility layout and production flows at the early design stage. Unlike previous studies that broadly explore AI applications in manufacturing [4], this research explicitly applies AI-driven clustering for real-time overall equipment effectiveness (OEE) optimization in wood manufacturing. The novelty of this approach lies in proactively integrating AI clustering techniques to detect and mitigate bottlenecks in a virtual factory environment. This allows manufacturers to simulate and refine production strategies before implementation, ensuring data-driven improvements in efficiency and cost reduction. The research investigates the production process of wooden window frames and doors, encompassing computer numerical control (CNC)-based machining and assembly tasks, material impregnation, and painting workflows. The primary challenges include balancing production flows, optimizing equipment utilization, and enhancing quality control. Using the Siemens Tecnomatix Plant Simulation (STPS) platform, the production flows of the new facility were modeled, and the optimal allocation of workstations and production resources was assessed [5]. The findings demonstrate that the virtual factory model, combined with the AI-driven analysis, is an effective tool for optimizing manufacturing processes.

Proposed approach for production process optimization and analysis

Optimizing production processes in wood manufacturing has become a critical requirement for ensuring competitiveness, operational efficiency, and adaptability to evolving demands. In the wood manufacturing industry, unique challenges arise due to the complexity of workflows, resource dependencies, and variability in product specifications. Addressing these challenges requires a systematic approach that combines cutting-edge tools and data-driven strategies. This study proposes a multifaceted methodology to tackle inefficiencies and enhance productivity within the wood manufacturing company's operations. The proposed approach consists of three key components: (1) virtual factory modeling, (2) real-time data collection, and (3) AI-based analysis. STPS was used to create a digital twin of a wood manufacturing facility, including CNC machining, material handling, and finishing workflows. The model was built using real-world production data provided by the company. We applied k-means clustering ($k = 5$, determined using the elbow method) to OEE data collected over three months to analyze production inefficiencies. The clustering algorithm segmented inefficiencies into meaningful categories, identifying underperforming workstations and recurring bottlenecks. The cluster validity was assessed based on the stability of identified workstation groups and their correlation with real production inefficiencies observed in the factory. As part of the AI-driven analysis, we identified the five worst-performing (bottleneck) workstations and the five best-performing workstations based on the OEE metrics. These insights were visualized to highlight key areas for process optimization and efficiency improvements. The identified bottleneck workstations exhibited higher idle times and lower throughput, whereas the best-performing workstations demonstrated stable efficiency with minimal downtime. The proposed framework builds upon prior research into the integration of virtual factory environments with autonomous systems for production logistics optimization [6]. Unlike previous approaches, this study focuses specifically on AI-assisted decision-making within a virtual factory environment in the wood manufacturing sector. The combination of real-time monitoring and AI-driven clustering analysis enables manufacturers to preemptively adjust workflows, enhancing production efficiency and flexibility.

Figure 1 illustrates a systematic approach to optimizing production processes in the wood manufacturing industry. It highlights three key components: virtual factory, which enables the simulation and analysis of workflows; real-time data collection, which gathers operational data from the manufacturing floor; and AI-based analysis, which processes data to identify bottlenecks, predict inefficiencies, and provide actionable insights. Inputs such as machine specifications, workflow details, and production goals feed into the system, while outputs include optimized workflows, balanced resources, and improved quality control. These elements create a scalable and cost-efficient framework for addressing inefficiencies and enhancing productivity.

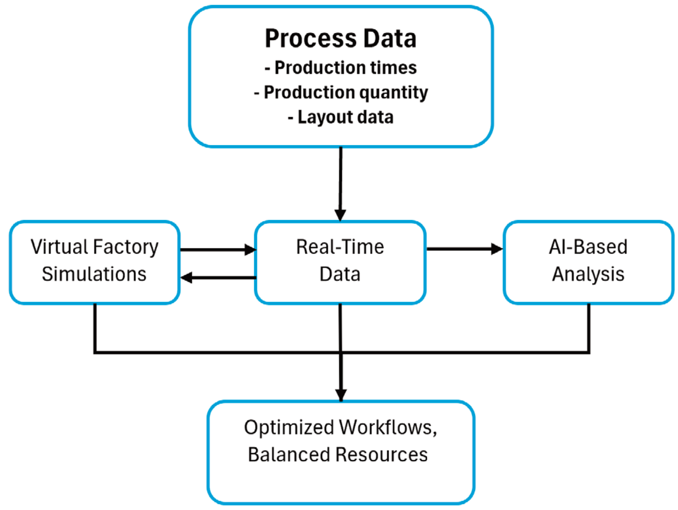

Fig. 1. Proposed framework for production process optimization.

Integration of the virtual factory environments (case study)

Virtual factories, developed like digital twins, are digital representations of physical manufacturing systems that enable detailed modeling, simulation, and optimization of production processes without disrupting real-world operations. These environments allow manufacturers to analyze workflows, machine interactions, material handling, and human resource allocation within the production line, facilitating informed decision-making and process improvements [7]. In this study, a comprehensive virtual factory model was developed for a wood manufacturing company. This tool enables the creation of a digital twin that replicates the physical production environment, allowing for a detailed analysis and testing of workflows without interfering with actual operations. The virtual factory model integrates essential production processes, including CNC machining, assembly, material handling, and finishing workflows. Key inputs, such as machine specifications, cycle times, and production targets, were provided by the company and integrated into the model to accurately replicate real-world conditions. Through this virtual representation, various production scenarios were simulated to predict potential inefficiencies, identify bottlenecks, and assess the impact of proposed changes on system performance. For instance, layout adjustments and transport flow optimization scenarios were tested to improve throughput and reduce idle time. Such applications of virtual factories enable manufacturers to experiment with process designs, resource allocations, and operational strategies without the risks and costs of physical trials. The effectiveness of virtual factories in manufacturing optimization has been extensively demonstrated in recent studies. Digital twin systems have been shown to enhance production efficiency by enabling real-time monitoring and predictive analytics, leading to significant reductions in downtime and improved resource utilization [8]. Additionally, virtual factory models have proven effective in streamlining workflows and optimizing resource allocation, resulting in lower operational costs and higher throughput [9].

Figure 2 presents the virtual factory model created for the wood manufacturing company using the STPS software. The layout depicts the production flow, encompassing CNC machining, assembly, material handling, and finishing workflows. Accompanying the model is a "Resource Statistics" chart, which provides insights into key performance indicators (KPI) such as resource utilization, working times, idle times, and bottlenecks across various stations. This virtual factory model facilitated the simulation of production scenarios, including layout optimization and transport flow improvements, identifying inefficiencies, and the development of actionable strategies to enhance overall throughput and reduce idle time.

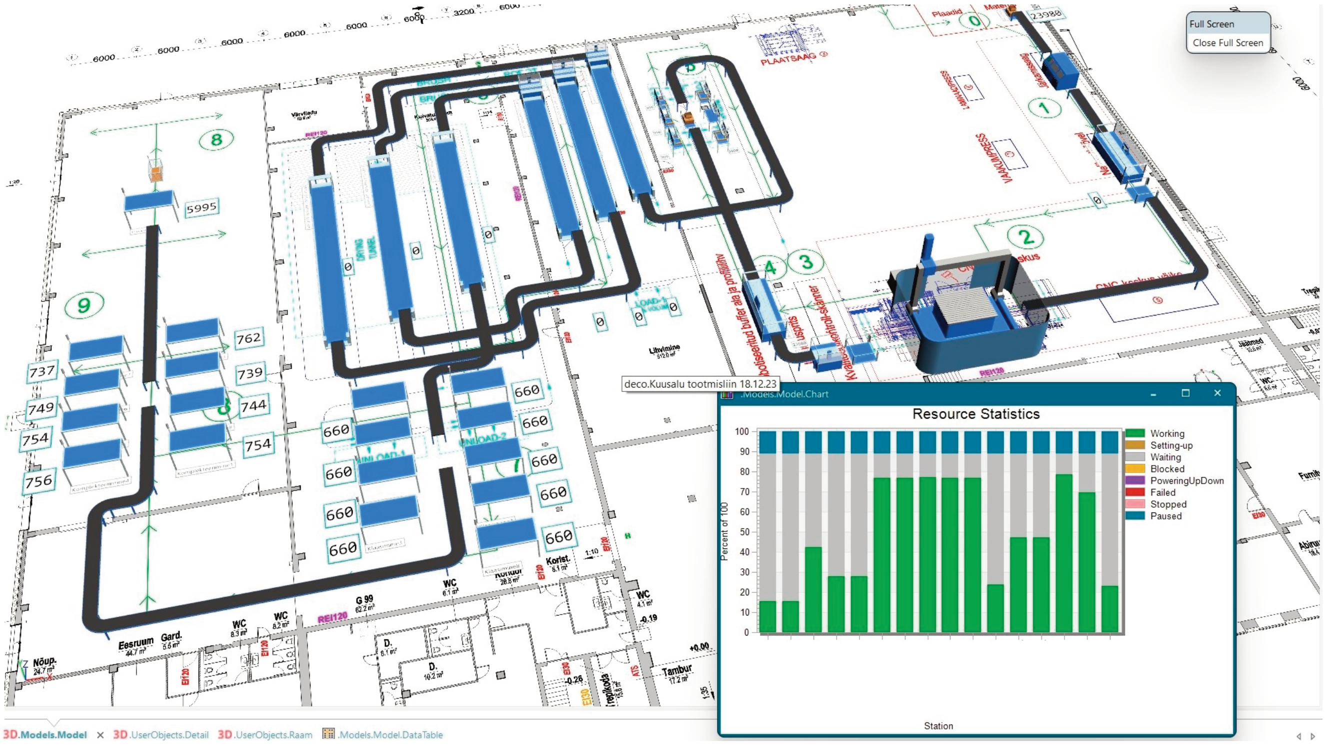

Fig. 2. Virtual factory model developed using STPS.

Real-time data collection for enhanced accuracy

Real-time data collection, enabled by manufacturing execution systems (MES), provides critical metrics such as machine availability, cycle times, resource utilization, and defect rates. These metrics are integrated into the virtual factory model to ensure that it remains an accurate and dynamic representation of the physical production environment. Continuous monitoring supports effective simulations and data-driven workflow optimization [10]. MES with real-time data collection capabilities ensure operational transparency, enabling real-time adjustments to workflows and enhancing production efficiency. Integration with digital twin technology has been shown to improve OEE through enhanced scheduling accuracy and predictive maintenance [11]. This capability is essential in dynamic manufacturing environments, where agility and responsiveness are critical for adapting to fluctuating production demands. The DIMUSA MES interface, as shown in Fig. 3, visualizes critical production metrics for specific machines, such as a crosscut saw and a four-sided planer. These dashboards display KPIs [12,13], including availability, performance, quality, and OEE. The system tracks real-time working hours, short stops, long stops, and off times, providing a clear overview of machine performance and utilization.

This visualization enables factory operators to monitor production in real-time, identify inefficiencies, and make immediate adjustments to workflows. By integrating this data into the virtual factory model, decision-makers can enhance process accuracy and efficiency. Real-time data collection aligns with Industry 4.0 principles, facilitating automation, connectivity, and the use of advanced analytics. These systems enable factories to transition seamlessly between production scenarios, reducing downtime and improving resource allocation.

AI-based analysis for data-driven optimization

AI plays a pivotal role in the proposed methodology by analyzing the collected data and generating actionable insights. By leveraging AI-driven clustering techniques, production inefficiencies can be identified more effectively, allowing manufacturers to address systemic bottlenecks before they escalate into major disruptions. This study applied clustering methods to OEE metrics to identify patterns and segment production data into meaningful groups. K-means clustering (k = 5, determined using the elbow method) was selected as the primary approach due to its efficiency in handling large industrial datasets and its ability to create clearly defined clusters based on similarity measures. K-means clustering was chosen over other machine learning approaches, such as hierarchical clustering or Gaussian mixture models, due to its efficiency, scalability, and adaptability to manufacturing environments. The time complexities of the k-means clustering, hierarchical clustering and Gaussian mixture models are given in Table 1 [14].

It can be observed from Table 1 that in the case of large dataset capacity, the time complexity of the k-means clustering is substantially lower than that of hierarchical clustering. The Gaussian mixture models complexity is higher due to covariance computations. Unlike deep learning methods, k-means provides interpretable cluster assignments, enabling engineers to quickly identify underperforming machines or processes. Since OEE metrics fluctuate based on production schedules, k-means effectively groups machines by performance trends, making it easier to track changes over time and

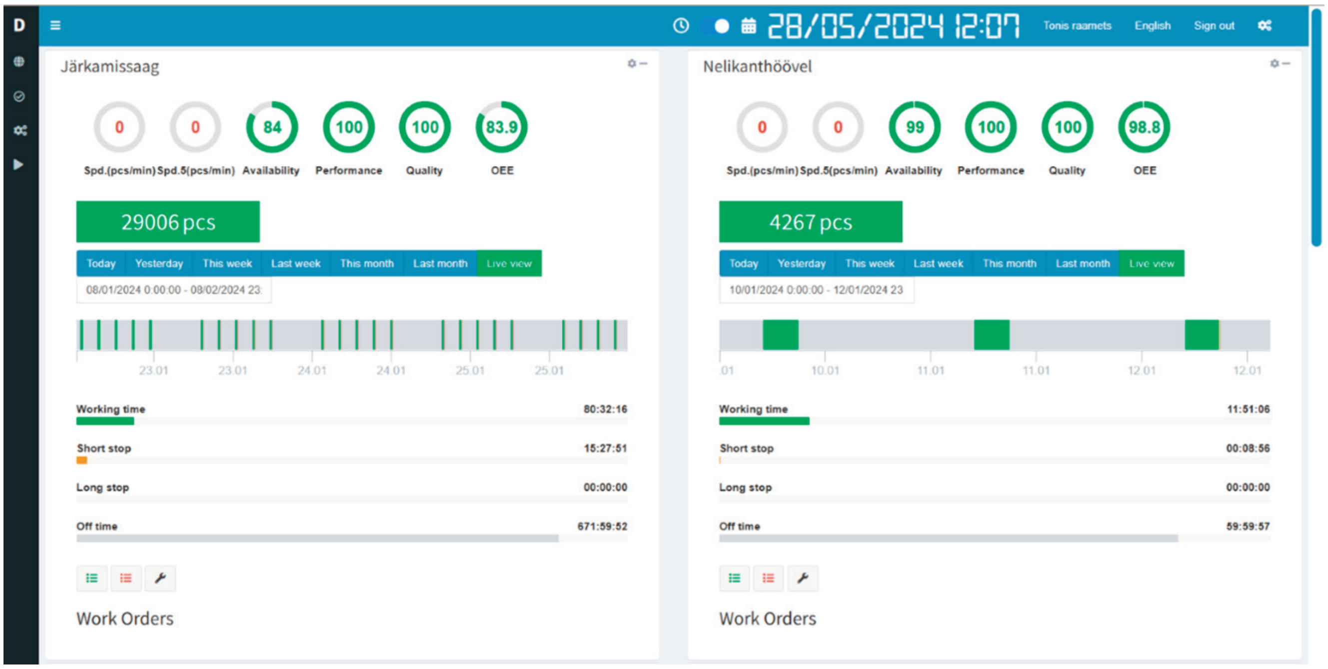

Fig. 3. DIMUSA system interface for real-time data collection.

Table 1. Comparison of time complexities

Time complexity	K-means clustering	Hierarchical clustering	Gaussian mixture models
	$O(n * k * d)$	$O(n^2 \log(n))$ – optimized	$O(n * K * d)$
Meaning of parameters	n – number of data points, k – number of clusters, d – number of dimensions	n – number of data points	n – number of data points, k – number of Gaussian components, d – number of dimensions

implement data-driven optimizations. The proposed approach enables a deeper understanding of the factors affecting availability, performance, and quality within the manufacturing process. By applying clustering algorithms to OEE metrics, specific production bottlenecks and inefficiencies were identified. These insights were used to optimize resource allocation, balance workflows across the production line, and implement targeted predictive maintenance strategies, reducing downtime and improving overall system performance. The clustering-based analysis has proven effective in manufacturing, offering precise optimization strategies that enhance production efficiency and resource utilization [15]. By incorporating these methods, this approach ensures a proactive and data-driven framework for optimizing manufacturing operations.

Figure 4 presents the results of the clustering analysis applied to the OEE metrics, visualized as a scatter plot. The x-axis represents availability (%), while the y-axis represents performance (%). Each point in the plot represents an individual workstation, and different colors indicate the cluster to which each workstation belongs based on its operational characteristics. The clustering analysis effectively groups workstations according to their efficiency levels, revealing patterns across the production environment. Workstations located in the lower-left quadrant exhibit both low availability and low performance, identifying them as critical bottlenecks that require intervention. In contrast, workstations in the upper-right quadrant maintain high availability and high performance, serving as benchmarks for optimal efficiency. This visualization provides a clear overview of production imbalances, helping manufacturers pinpoint underperforming workstations and analyze the causes of their underperformance. Workstations within the lowest-performing clusters often suffer from frequent downtime, suboptimal scheduling, or inefficient resource utilization. By leveraging these insights, targeted actions such as redistributing workloads, adjusting production schedules, or implementing predictive maintenance strategies can be taken to enhance efficiency. The ability to visually segment workstations based on OEE data ensures that production optimizations are data-driven rather than reactive. This approach allows for proactive decision-making, leading to more balanced workloads, minimized downtime, and improved overall production performance.

A scalable and cost-efficient framework

The key advantages of the proposed methodology are its scalability and cost efficiency. Unlike traditional trial-and-error approaches, which require significant time and resources, this integrated framework minimizes risks and provides immediate feedback on the feasibility of proposed changes. It is particularly well suited for dynamic manufacturing environments, where adaptability and responsiveness are crucial.

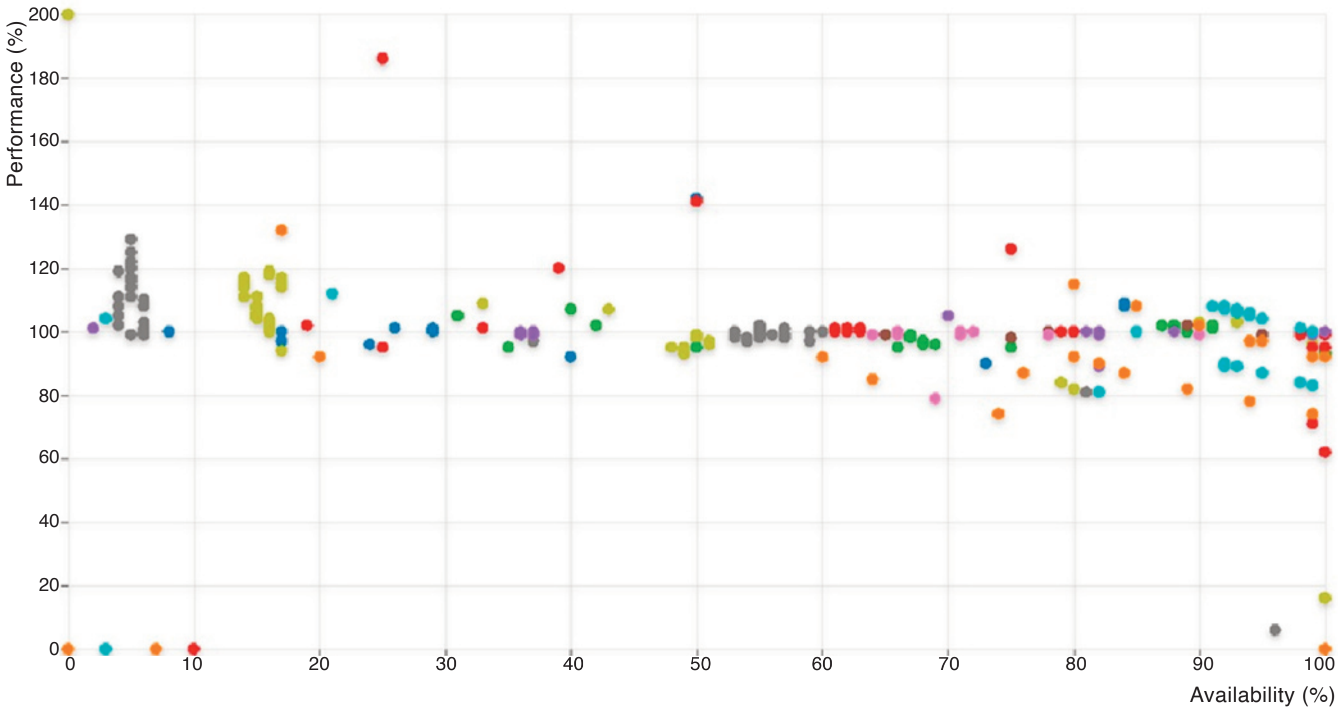

Fig. 4. Clustering analysis of OEE metrics (Dimusa MES).

By combining the predictive power of virtual factory models, the accuracy of real-time data collection, and the analytical depth of AI-based techniques, this methodology enables manufacturers to achieve continuous improvement and maintain a competitive edge in their industries.

Conclusion

The proposed approach presents a comprehensive framework for identifying inefficiencies and optimizing workflows in the wood manufacturing company. By combining advanced simulation tools, real-time monitoring systems, and AI-driven analysis, this methodology enables a deeper understanding of production processes and their performance. Simulation tools allow manufacturers to create a digital twin of the production environment, where different scenarios can be tested without disrupting actual operations. Real-time monitoring systems continuously collect production data, tracking machine availability, performance metrics, and potential bottlenecks. The AI-driven analysis processes this data, detecting patterns and inefficiencies that may not be immediately visible through traditional monitoring methods. By integrating these components, the proposed framework not only identifies operational weaknesses but also provides data-driven recommendations for improvements. This enables proactive decision-making, allowing managers to anticipate and address production challenges before they escalate. The result is a more efficient, resilient, and optimized manufacturing process, where resources are utilized effectively, workflows are balanced, and productivity is maximized.

Data availability statement

All data are available in the article.

Acknowledgments

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Virtuaaltehase mudeli arendamine tehisintellektil põhinevaks tootmise optimeerimiseks

Tõnis Raamets, Kristo Karjust, Aigar Hermaste ja Karolin Kelpman

Uuringus käsitletakse tehisintellektil põhineva analüüsi rakendamist virtuaaltehase mudeli arendamisel eesmärgiga optimeerida tootmisseadmete üldist tõhusust puidutööstusettevõttes. Uuringus kasutati Siemens Plant Simulationi tarkvara, et luua digitaalne kaksik, mis võimaldab tootmisvoogude simulatsiooni ja analüüsi. Lisaks koguti reaalajas andmeid tootmisjuhtimissüsteemi abil, et mudelit täpsustada ja pakkuda dünaamilist ülevaadet tootmisprotsessidest. Kogutud andmete analüüsimiseks rakendati klastrianalüüsi, mis võimaldas tuvastada kitsaskohti ja ressursikasutuse ebatõhusust. Simulatsioonide ja andmepõhiste soovituste põhjal optimeeriti tööjaamade paigutust ja ressursijaotust, mis parandas tootmisvoogude tasakaalu ja vähendas kitsaskohtade esinemist. Tulemused näitavad, et virtuaaltehase mudelite ja tehisintellekti integreerimine aitab tõsta tootmisvoogude tõhusust, vähendada seisakuid ja suurendada investeeringute planeerimise täpsust. Pakutud lähenemine toetab tänapäevase puidutööstuse vajadust paindlike, skaleeritavate ja kulutõhusate lahenduste järele, järgides Industry 5.0 põhimõtteid.