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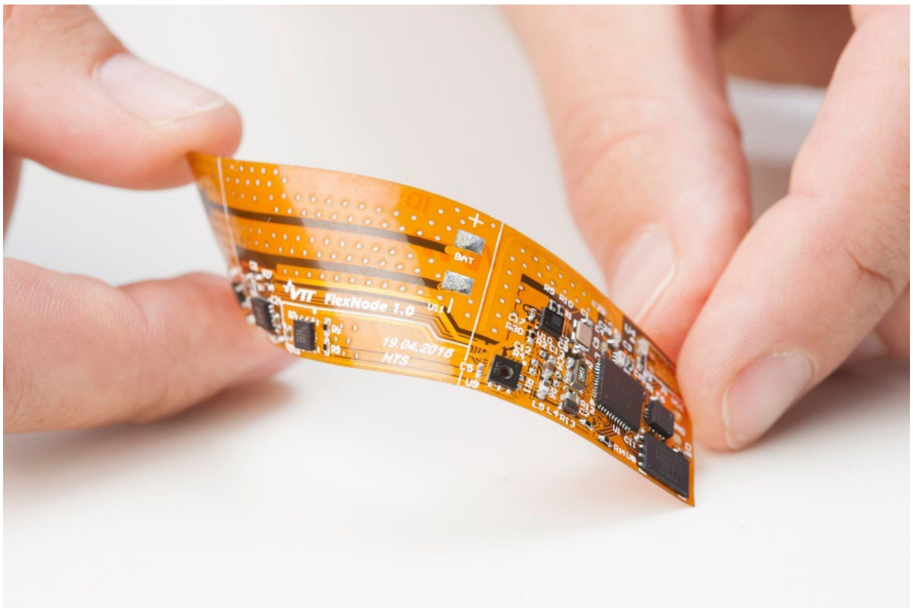

Circular Product Value Through AI Services in Discreet Remanufacturing and Paper Machine Process

Authors: Marko Jurvansuu, Atte Kinnula, Kimi Haapalainen, Elena Vildjiounaite, Selen Pehlivan Tort, Arttu Lämsä, Marko Jurmu, Harri Kiiskinen, Jussi Virkajärvi, Jarmo Vuorinen, Eveliina Jutila

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beyond the obvious

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Summary

Current industrial value chains are not designed for R-cycles, data and AI services in mind. Regulations (DPP, DGA) drive towards sharing product data which creates an opportunity to unlock new data driven value in R-cycles. However, it is not clear what is the new value that AI services could bring in concrete industrial use cases.

GG_CAI project was established to identify potential AI services, data sources and new value for chosen R-cycles. The approach was based on creating a minimum viable R-cycles and locating value adding AI services on the product lifecycle within that R-cycle. After careful considerations, and from 9-availabe R-strategies, two were chosen for which project targeted creating new solutions. First one is remanufacturing in discreet manufacturing and the second, refurbishment of paper making process. The latter was made in collaboration with VTT Jyväskylä pilot paper machine researchers.

The main outcomes of the project were a) Minimum Viable Closed-Loop in Remanufacturing with identified IPR possibilities for VTT AI research, b) AI service for paper machine process stability monitoring and c) Visual Language model implementation on steel part defect detection. Knowledge created in the project, provided input both to research strategy of BA5610 Human-centric AI team as well as for future research project proposals. In addition, a software notification was made on the develop AI paper process stability model.

Confidentiality	Public

Oulu 16.3.2026

Written by	**Reviewed by**
Marko Jurvansuu Principal Scientist	Heli Helaakoski Research Manager, BA56 Cognitive Industry

VTT's contact address

Kaitoväylä 1, 90570 Oulu, Finland

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Date:	16 March 2026
Signature:	DocuSigned by: FC4C3270428F48E...
Name:	Heli Helaakoski
Title:	Research Manager, BA56 Cognitive Industry, VTT

Preface

Authors like to thank VTT for funding and project steering group for their valuable contributions in project guidance that made this work possible.

Oulu, March 2026

Contents

1. Introduction

Circular economy is gaining traction in EU through regulatory updates and funding for the twin transition. Particularly approaches that combine data collection, governance, and analytics (AI) to extend product lifetime through R-cycles appear feasible, driven primarily by Digital Product Passport (DPP) standardization.

AI approaches for product lifecycle optimization are not new, and Industry 4.0 approaches in systematic data collection have further boosted this trend. Notably, predictive maintenance concepts couple together machine health information with availability of spare parts and maintenance personnel to optimize maintenance times.

Focusing on R-cycles opens new opportunities beyond predictive maintenance and includes the ecosystem viewpoint through data sharing and governance. Besides product lifetime extensions, new features and customer value can be introduced through AI services. Finally, sustainability data and information from product field use can not only be used for reporting, but also to operative decision-making within product stakeholders, facilitating sustainable work processes and practices around the product.

The challenge is that current industrial value chains are not designed for R-cycles, data and AI services in mind. It is also not clear what is the new value that AI services could bring in concrete industrial use cases.

2. Goal

One year research project targeted for 1-2 concrete AI service PoCs, where a chosen R-cycle is in focus for a real industry product and where AI could provided added value. A minimum viable R-cycle was to be made, which would help identifying potential R-cycles and value creation opportunities.

The impact of this work is in identifying and building new AI-related IPR in the context of circular economy, while increasing customer value through extended product lifecycles and additional digital services. The IPR goals included an invention report, software notification and journal publication. In addition, the knowledge created in the project could be used in Business Finland and EU project preparations that would continue the results to higher maturity level and creating impact for the industry.

3. Description

Project defined first most potential R-cycles and industry cases that would open up a possibilities to develop new IPR.

In Figure 1, is show Kirchherr 9-R framework [1] that describes 9 different R-strategies for circular economy. Project team needed to choose 1-2 strategies where to focus on as the project duration was one year, which limits the depth and breadth of contents. The decision criteria was based on choosing one R-cycle where is existing business that has high potential for scaling up with AI, and other one where rethinking of current business is needed.

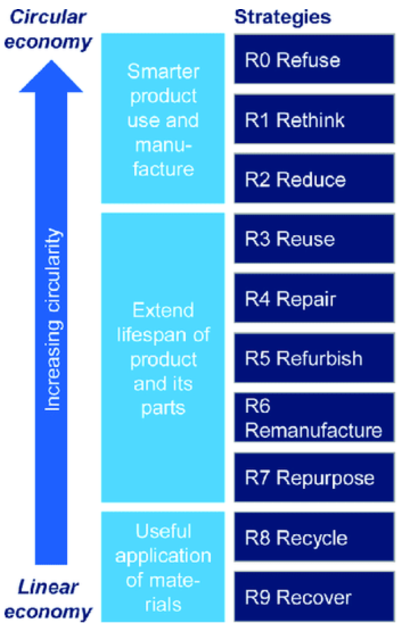

Figure 1. R-cycles in Circular Economy.

After careful examination through literature review, patent landscaping, presentations in industry networks such as SIX Smart Manufacturing and workshops around the R-framework, the project focuses were set to:

- Remanufacturing in discreet manufacturing
- Rethinking/Reducing in paper making processes

The focus areas were also influenced by potential impact to Finnish industry. In remanufacturing there are good amount of companies in Finland that manufacture and then remanufacture their products such as Ponsse, Nokia, Konecranes and Sandvik. In pulp and paper, the Finnish industry has been scaling down in recent years, and thus new approaches are needed. Such opportunity was identified from dry foam pilot paper process developed at VTT Jyväskylä that aims to reduce water and energy consumption.

In the following chapters, the main findings are presented for both focuses.

4. Methods

Project used several research methods, starting from literature review to actual AI software implementation and user verification. Patent landscapes were made to identify where other players are active and where would be potential white gaps with new IPR opportunities.

In addition to typical research methods, a new one was developed called “Minimum Viable R-Cycle” as depicted in Figure 2. The idea here is that after choosing R-cycle to examination, one would define what are the value chain partners and their value creation processes on that R-cycle. This would be followed by literature review to determine current state-of-the-art. Literature review provides understanding of the processes and challenges that value chain has when implementing that R-cycle. Patent landscape helps to identify where the new IPR value can reside and is there a freedom to operate. All this information finally meets up in a visualisation, where only most potential value creation opportunities are identified.

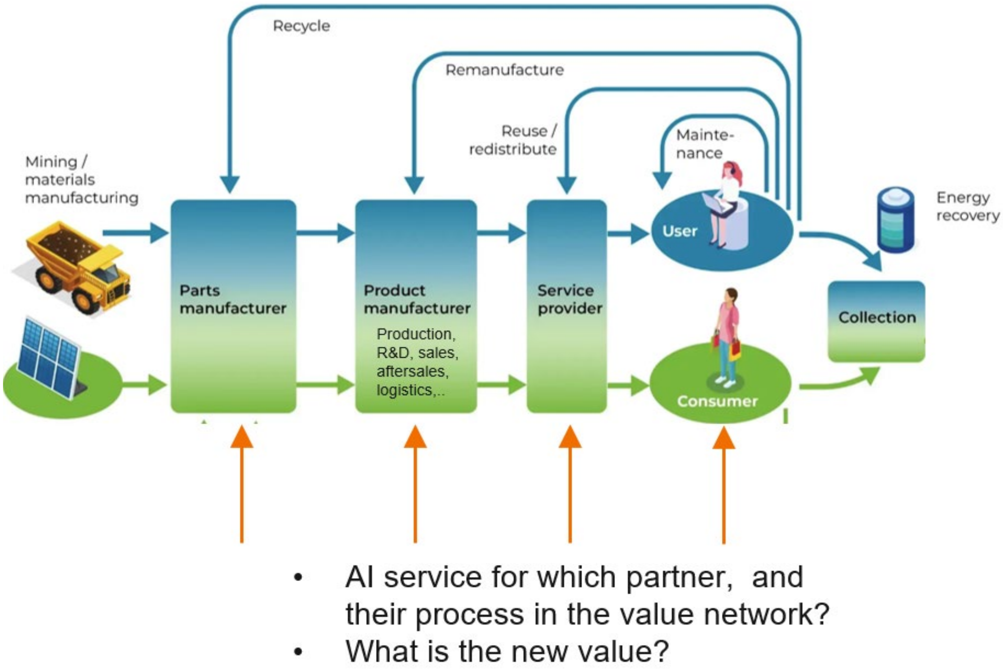

Figure 2. Goals for creating a minimum viable R-cycle. Picture modified from [2].

Project created full minimum viable R-cycle visualisation for remanufacturing case, and a partial one for paper process including only patent search results.

5. Remanufacturing of discreet products

5.1 Definition of remanufacturing

Remanufacturing is one of the R-cycle processes, a sustainable manufacturing approach to recover the value of end-of-life (EoL) products. It is the only R-cycle activity that can recover the quality of the products in as good or better than new in terms of appearance, reliability, performance and warranty [3] [4] [5] [6]. The geometric shape, materials, and the added value embedded in the original product is usually preserved [7] and the product is brought back to “as new” / “like-new” condition and to original performance, matching the original OEM specifications. Furthermore, accumulated information from the product faults / revisions / etc. and new technological advances can be leveraged to bring an older product up to the latest standard through remanufacturing, improving it with features or characteristics that are present in newer products. The remanufactured product can also be provided with warranty for a newly manufactured product

Products are reprocessed through an industrial process in a facility, as opposed to being repaired on the field. There are exceptions still, as on-site remanufacturing is used in rare cases where operation cannot be stopped for service. Remanufacturing process can be carried out by can Original Equipment Manufacturers (OEMs) for their own products, or it can be a business for an independent remanufacturer [7], who may provide service to OEMs, or have a mix of products they can remanufacture on their own e.g. for consumer markets.

The remanufacturing process consists of a set of operational activities. The exact list of activities varies in the literature, both regarding the number of activities and the terminology used for them. Typical activities listed include disassembly, inspection, cleaning, reprocessing (also called reworking, refurbishing, reconditioning, or even maintenance – essentially fixing the repairable parts and replacing those that cannot be fixed and possibly upgrading the product with newer features or technology), reassembly, and testing. Inventory or storage is sometimes included [8] and some authors include the acquisition of the used product or a part of it (collectively called 'core') [9], [10] or redistribution / reuse, while others [11], [7] see these as a part of processes outside the remanufacturing itself. The remanufacturing process can be further divided into two segments – Observation and disposition [11] (also called Inspection and testing [5]), where the core is processed for evaluation to decide whether or not it should be remanufactured, and Remanufacturing, where the core and/or its parts are then processed for future use [11]. The activities in these segments are sequential [11], with feedback loops, bypass loops, and exit points along the way [11] [9]. The actual order and mix of activities that each remanufactured core goes through depends on the characteristics of the returned product.

Remanufacturing is supported by two other processes – recovery [5] (also called collection [4]) that acts as a supply chain for the remanufacturing by acquiring and delivering used products, and redistribution (e.g., [7]), which is the process of distributing remanufactured products, e.g., back to the customers as a replacement, or via the market as a second-hand product (e.g., [5]), closing the *Remanufacturing R-Loop*. In literature this is also referred to as *remanufacturing system* [7], a *closed-loop supply chain* [11] [12], or a *closed product life-cycle system* [8].

We chose to use term Remanufacturing R-loop as remanufacturing system does not convey the idea of a cycle, a closed-loop supply chain can include other R-processes, and closed product life-cycle system involves maintenance.

According to [8], influential stakeholders in such systems are product designers, manufacturers, buyers/users, maintenance/service/repair providers, recyclers, and the remanufacturing operation itself. In addition, one can consider sales channels a stakeholder as well. The system in turn operates in a particular industry context – including the geographical location / coverage – which also has an influence on the system operation through legislation/regulations, customers, and relevant technology and how it evolves [8]. The system operation itself, the influential stakeholders, and the industry context bring in both enablers and challenges to the remanufacturing operation within the system [8]. The remanufacturer, in turn, carries out decisions on strategic, tactical, and operational levels, to manage its operations as part of the system [6] [9].

5.2 Remanufacturing R-loop

For our study we define the key processes and the sub-processes in the Remanufacturing R-Loop (Figure 3) as follows.

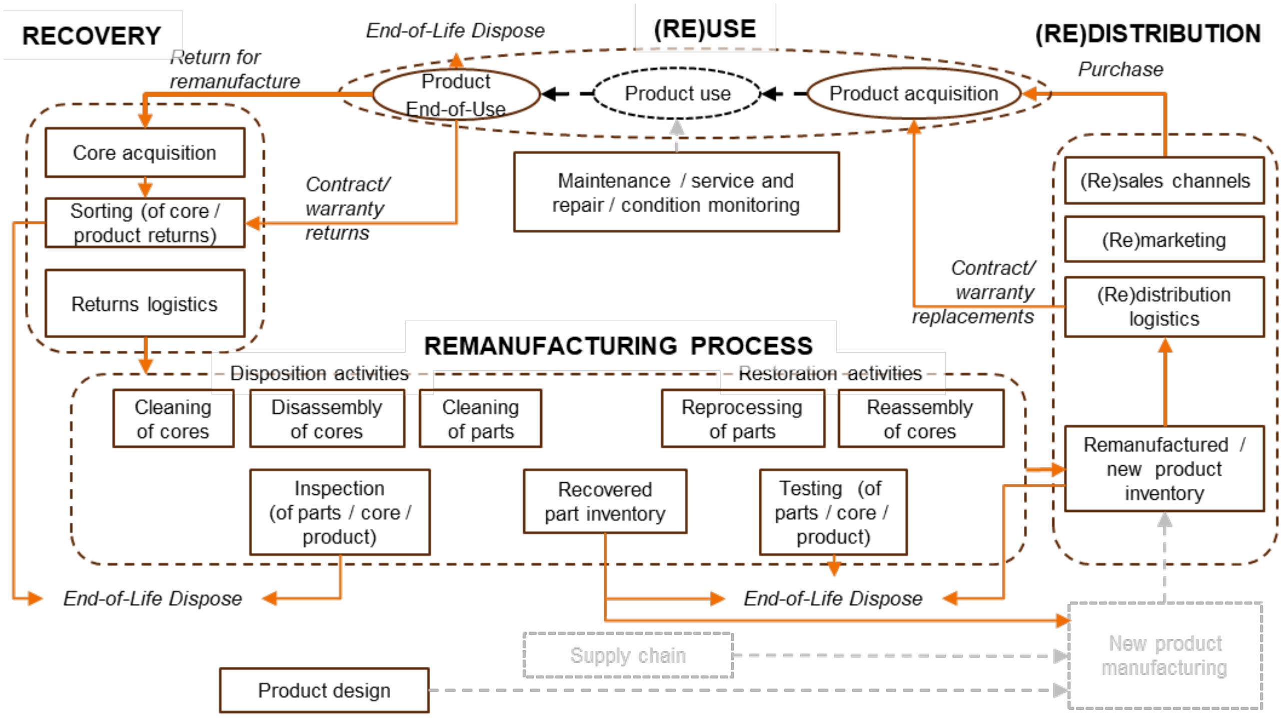

Figure 3. Remanufacturing R-loop.

The **(Re)use process** is about product's user's activities (denoted with ovals rather than rectangles), where the user acquires a product (either new or remanufactured) from a sales channel, uses the product, possibly supported by maintenance activities, and finally decides that the product or a part of it (here collectively called 'core') is at the end of its use.

In the **Recovery process**, Core acquisition is about the activities and strategies to acquire the used products from the end users, Sorting is about grading of the acquired / returned core to decide if it has potential for remanufacturing, or should it be moved to other R-cycles, or to disposal. The Returns logistics is about the physical and organisational infrastructure that collects and moves the returned cores to the remanufacturing facilities. These sub-processes operate in different dimensions, e.g. Core acquisition takes place within the Returns logistics infrastructure, but is not part of the latter as a process. Furthermore, Sorting can take place also in the remanufacturing facility, rather than in the field, but in this process schema it is still considered to be part of Recovery process.

In the **Remanufacturing Process**, the four disposition sub-processes can be combined in different ways, and can also be iterative, depending on product or even on an individual case. Inspection of cores or parts is similar to sorting in Recovery process, but focuses on more detailed analysis of the condition, to decide if the core or part is to be disposed (e.g. to another R-cycle) or if there is enough value for further reuse or processing, and what kind of restoration processing is needed. Cleaning of cores and parts, and Disassembly of cores into parts is done to facilitate inspection or further processing. The restoration activities are about returning the item back into required condition for a new lifecycle and include three sub-processes focusing on processing the materials, and a supporting sub-process for inventory management. Reprocessing sub-process carries out the actual restorative activities, e.g. repairing or replacing damaged parts. Reassembly assembles things into a returnable core, or a re-sellable product. We include upgrading into this step. Testing of parts, the core, or product is a step to ensure that the quality requirements for re-sale are met, either through an actual test, an inspection, or otherwise determining the quality of the remanufactured item. Items failing this step may be put into another remanufacturing iteration, dismantling to parts for reuse with other cases, or disposal. The Inventory management of parts supports the remanufacturing activities by providing needed parts, including those for upgrades, but can also move items to disposal if their usefulness is coming to an end.

The **(Re)distribution process** makes the products available for customer's acquisition. Here we make allowance that the business may move both new and remanufactured products through this process, i.e. the sub-processes are similar in principle, although may differ in practice. The sub-processes include Product inventory that supplies the Sales channels through Distribution logistics, and a Marketing activity to drive sales. The Product inventory may also move products to disposal if the product is e.g. being discontinued.

New **Product design** and manufacturing with supply chain are not as such a part of the Remanufacturing R-Loop, but product design does have an impact on remanufacturability, hence it is included here as a meaningful sub-process. While the **(Re)use** process is part of the Remanufacturing R-loop, it is more a customer side operation and the focus of this paper is on the remanufacturer's operations. For this reason, we have decided to keep **(Re)use** out of scope and only touch on the Product acquisition and Product end-of-use sub-processes from it, as they interface with **(Re)distribution** and **Recovery** processes.

5.3 AI in remanufacturing

AI applications in discreet remanufacturing are still rare, but typically include predictive maintenance, quality control, supply chain optimization, and demand forecasting. These applications help manufacturers improve efficiency, accuracy, and productivity across various operations.

A scientific survey of use of AI in (vehicle or machinery) remanufacturing was conducted. Analysis over 797 articles, selected from recent literature surveys on use of AI in vehicle or machinery remanufacturing[1], and over 134 patents from a patent search by a VTT patent organisation.

From these, 309 articles and 47 patents were judged to be in the final set, arranged to 4 decision-making levels: PROCESS, OPERATIONAL, TACTICAL, and STRATEGIC level articles/patents. From latter 3, the results are less structured and thus their categorisation was more challenging, hence they give only a rough view to how AI is used on these higher decision levels. Some articles identified more than one AI use case, hence the number of items is greater than the number of articles.

From these tables, value creation opportunities were identified based on two criteria: 1) amount of publications which shows that there is demanding unsolved challenges are and 2) number of patents, that show industrial relevance and help to identify potential customers and freedom to operate for new IPR.

[1] Search keywords: literature review, artificial intelligence, AI, machine learning, forecasting, remanufacturing, discrete manufacturing, vehicle, machinery, work machine, construction machine, etc.

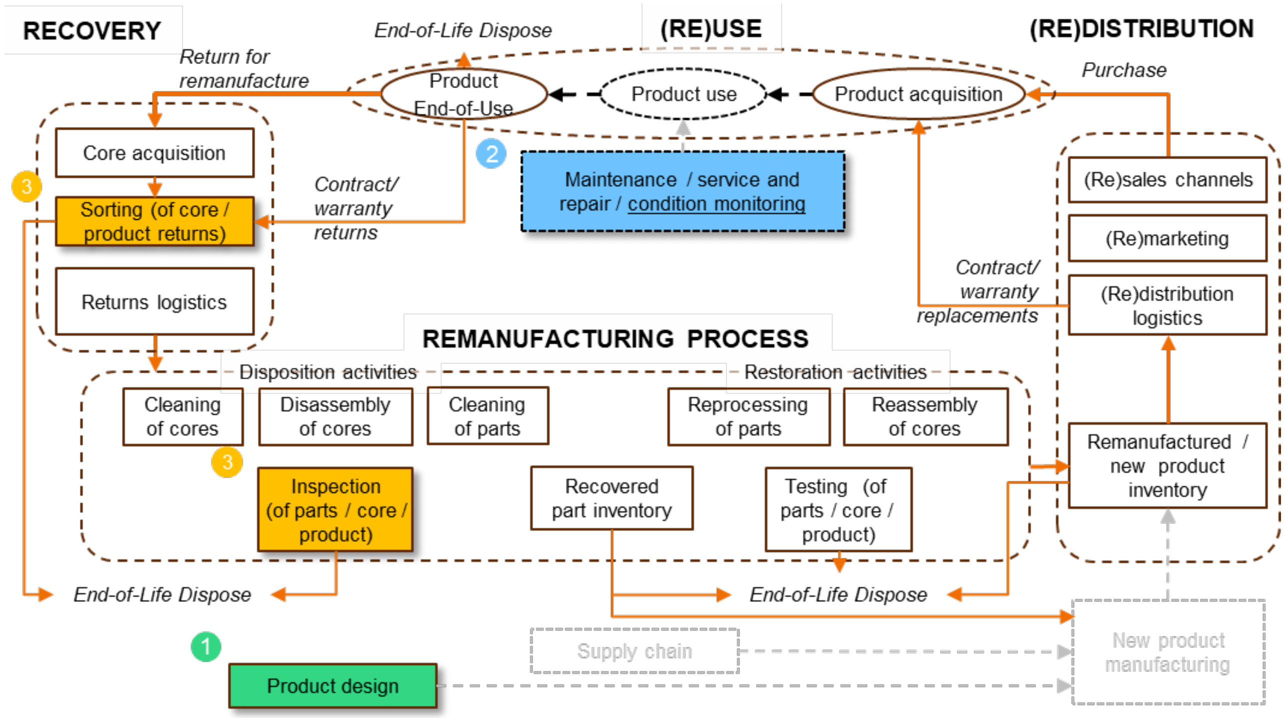

Figure 4. Minimum Viable Remanufacturing R-loop with potential AI value creation opportunities (coloured).

Tables were evaluated in a workshop, where value creation opportunities for AI services in were identified. As a result, the most potential ones are (coloured and numbered circles in Figure 4), in order of importance for impact: (1) Design, (2) Supply-Demand condition and (3) Inspection. These three topics are discussed in the next chapter related to their IPR potential for Cognitive Research area and current AI development therein.

5.4 IPR Potential

(1) AI in PRODUCT DESIGN

The main opportunity was found to be AI-guided Design (1) for Maintenance and Remanufacturing. It brings value by enabling and enhancing remanufacturing business in the first place, contributing to EU goals on sustainability. Impact: Design dictates how easy or difficult the product is to maintain and remanufacture. Any decisions taken at this stage are critical for the profitability potential of remanufacturing operation.

Challenges: Design for remanufacturing (and maintainability) can conflict with other objectives (e.g. unit cost minimisation). Design for remanufacturability is still fairly new paradigm and related design knowledge is not widely spread.

Solution: An agentic system that can capture and store knowledge (from prior documents, but also from new learnings) and equipped with a model that can analyse and evaluate conflicting objectives can significantly help in designing products that are easier to maintain and can be remanufactured.

No patents for found for that specific (AI in remanufacturing design) challenge, but several articles exist.

(2) AI for solving SUPPLY-DEMAND and CONDITION variability

The flow of core returns is the “supply chain” for remanufacturing. Like any manufacturing operation, the supply must be reliable and ideally optimised. An unstable / unreliable supply can undermine profitability of the operation, if e.g. there is no supply when there is market demand, or can incur excess costs if buffers (inventory) have to be used to counter unreliability. This creates two problems, customers cannot be promised in advance that they will get remanufactured parts when they need and second, OEM cannot reserve remanufacturing capacity, resources and spare parts in advance, which creates additional costs and delays in delivery. Maintenance keeps the system operational for longer, contributing to sustainability.

Challenges: A key problem in remanufacturing is that core returns are unpredictable and vary highly regarding the quality (condition), the quantity, and the timing. Purchasing or acquiring the cores is a cost, and their profitability varies not only due to their condition, but also according to market demand.

Solution: Analytical model to prompt the user when the core should be maintained (is cost-effective to service on the field), and when it should be sent to be remanufactured (has enough value left).

Prior research / patent status for maintenance was not studied in GG_CAI, but one patent(*) from remanufacturing patent search is related to this field.

(3) AI in SORTING and INSPECTION

Disposition decision dictates whether the core is processed further – a wrong decision will either waste an opportunity (core that could be remanufactured) or incur a loss (core that turned out to be un-remanufacturable)

Challenges: High variation in condition due to different usage patterns / conditions, age / wear, etc. makes sorting / inspection a challenging task. Experienced people do better decisions, but learning is slow and transfer of knowledge is difficult.

Solution: A Visual Language Model (VLM) trained for inspection, and possibly use of multiple inspection technologies (data fusion: visual, multispectral, ultrasound, etc.) has good potential to automate the entire process, or at minimum highlight the findings to user, who can then make more educated decision.

Prior research in this area included 11 related patents and 12 scientific articles. 4 patents were on generic descriptions of inspection-disposition process, 4 are specific to inspection methods used (Images, 3D, ultrasound, magnetic), 3 are product-specific, none of which use VLMs. It can be expected, that rapidly advancing capability of VLMs can bring new research area and commercial implementations in upcoming years.

5.5 Use of Visual Language Model in inspection purposes

Computer vision is used in various stages of remanufacturing such as sorting, disassembly and inspection. Here we focus on visual inspection for defect detection of detecting and classification, which is challenging due to diverse defect types and their low occurrence. Inspection is critical part of remanufacturing process, as it is labour intensive and it defines the next steps for the part in question. For example, decision whether the part is susceptible to remanufacturing and from that, after disassembly to detect what parts need to be replaced, welded or otherwise manipulated. All these decisions affect heavily on the total cost of the remanufacturing. The target is thus to automate as much as possible of the inspection as well as provide more detailed information of the part condition for the human operator where full automation is not possible.

In addition, there exists documented and publicly available data set for benchmarking such models. MVTec anomaly detection dataset [13] containing 5354 high-resolution color images of different object and texture categories. It contains normal, i.e., defect-free images intended for training and images with anomalies intended for testing. The anomalies manifest themselves in the form of over 70 different types of defects such as scratches, dents, contaminations, and various structural changes.

Based on a state-of-the-art survey of computer vision models, we chose one of the recent approaches, MVREC [14], for experimentation in the project. It stands for a general few-shot defect classification framework proposed for industrial visual inspection. The study also introduces a new subset of the dataset based on MVTec for few-shot classification tasks. The MVTec-FS dataset is a refined version of the MVTec AD dataset, designed specifically for few-shot learning research. While current anomaly detection tasks primarily focus on defect localization, datasets tailored for defect type classification are rare. To address this gap, the MVTec AD dataset was reprocessed to create a benchmark suitable for few-shot defect classification task. Additionally, it can be also used for few-shot object detection and unified multimodal classification. Novelty in this approach lies as it offers more generalizable, data-efficient, and scalable defect classification for industrial applications by using the ALPHA-CLIP model as the backbone and augmented data samples. It uses a few-shot, multi-view region-context approach. In comparison, most of the prior work rely on fully supervised learning, AI based sorting, or spatial damage localization, and require large labeled datasets or task-specific pipelines.

Figure 5 shows examples of images in the MVTec dataset, including a defect-free image and two images containing anomalies. Anomalous regions are highlighted in close-up figures together with their pixel-precise ground truth labels.

We investigated the MVREC model and its implementation on the MVTec-FS dataset, reproducing the results using a V100 GPU in a PyTorch environment for training and testing[2]. We also explored large-scale models such as ALPHA-CLIP, which enhances the original CLIP architecture (CLIP is a model that learns to match images and text by encoding images with a Vision Transformer and text with a transformer into a shared feature space) with an auxiliary alpha channel and is fine-tuned on region–text pairs, and observed that they can achieve good performance even with simple data augmentation strategies and few samples for defect classification. We also replaced AlphaCLIP with DINO as the visual backbone, however, we observed relatively lower performance in a few experimental settings.

Few-shot learning is particularly important in industrial settings, as it allows models to adapt to new defect categories with minimal labeled data, which can be collected and annotated quickly from other parts or product lines. However, the images in the experimented dataset are cleaned and consist of cropped regions of interest, which makes detecting defects from a wider field of view more challenging and requires further processing to extract parts from objects.

[2] https://github.com/ShuaiLYU/MVREC/tree/main

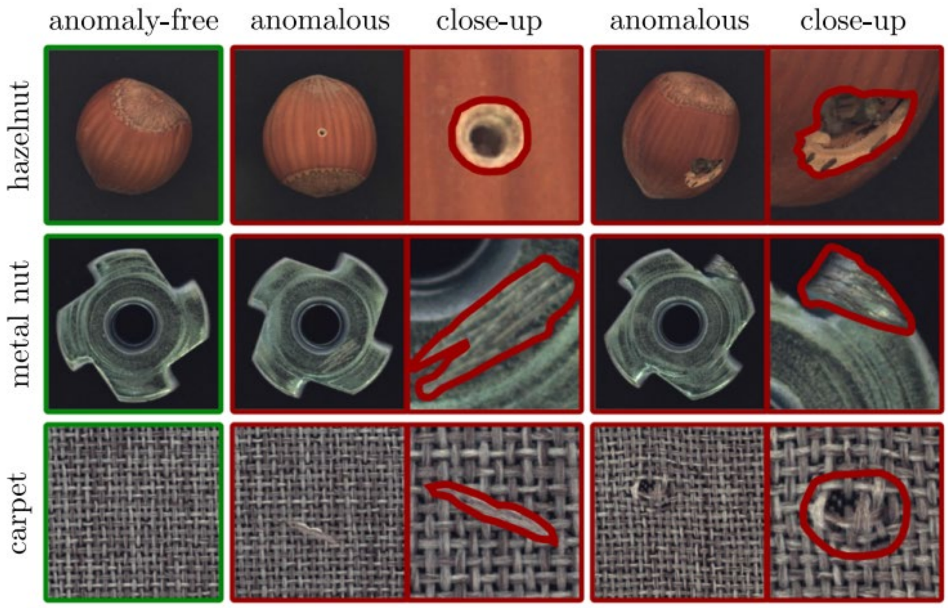

Figure 5. Example of images in MVTec dataset.

6. Rethinking of paper making process

This chapter provides an overview of the challenges and solutions in the paper-making industry, particularly focusing on the integration of machine learning and AI technologies to enhance processes and sustainability.

6.1 Introduction

The paper-making industry faces critical challenges in reducing energy and water consumption—two of the most resource-intensive aspects of the process. Drying and refining stages consume substantial energy, while traditional wet web formation requires large volumes of water, creating environmental and cost pressures. Addressing these issues is now a top priority for sustainability and competitiveness.

Active research and development is underway to tackle these challenges. Technologies such as foam-based web formation and dry forming based processes offer promising solutions, as they significantly reduce both water usage and energy demand. Foam-based systems replace water with stabilized foam, minimizing drying requirements, while dry forming processes eliminate water almost entirely, enabling faster production and lower thermal energy consumption.

Integrating these technologies with AI-driven automation positions the industry to achieve substantial reductions in resource use while maintaining high product quality. This approach is essential for meeting sustainability targets, complying with environmental regulations, and ensuring long-term profitability.

By applying AI-driven modelling and control, manufacturers can rapidly identify stable operating conditions for foam and dry forming systems, improving process reliability and efficiency. AI enables real-time parameter tuning, predictive quality control, and adaptive adjustments, reducing trial-and-error experimentation and shortening development cycles. We summarise patents about using machine learning methods at different stages paper-making process, present paper market and challenges in paper industry.

6.2 Paper Market

The global pulp and paper market is valued at approximately USD 362.41 billion in 2025, with projections reaching USD 1.27 trillion by 2033, growing at a CAGR of 1.8% [15]. Pulp and paper market can be split into:

- Virgin pulp and paper, made directly from wood, offering superior strength and quality. These products are extensively used in packaging, hygiene products, and premium printing applications.
- Recycled pulp and paper. It is usually used for packaging, newsprint, and towel products, reducing environmental impact and conserving resources.

Main trends:

- Traditional paper is giving way to e-paper: printing paper market (printed advertisements, books and magazines, packaging, brochures and catalogues, newspaper, etc.) is expected to grow at CAGR of 3% from 2025 to 2031 [16], while e-paper market (consumer electronics and enabling technologies, e.g., LCD) is expected to register a CAGR of 13.2% from 2025 to 2031 [17].
- Expanding e-commerce sector has significantly increased demand for packaging materials
- Green regulations: requires decrease use of plastic, decrease deforestation, decrease water consumption etc.

Green regulations are simultaneously a driving force and a restraining factor: on the one hand, they drive replacement of plastic packaging with paper packaging. On the other hand, they require to prevent deforestation and water crisis, therefore limiting availability of wood pulp and water – traditions materials for paper making. However, since the need in high quality paper decreases (the only exception is high-quality speciality papers, but it is a relatively small market segment), this situation allows to use more recycled materials and new materials (e.g., bamboo). Currently, recycled pulp and paper represent about a quarter of paper market.

Resource scarcity presents a significant challenge. Water scarcity can be addressed by using close water cycle, i.e., cleaning used water in the end of the process and using it again, which requires extensive technological upgrades and thus increases production costs. Electricity demand and carbon emissions can be also decreased by developing and applying new technologies, such as replacing water with foam, using AI to optimise processed etc., but it also requires investments in technological upgrades. In addition, economic instability and supply chain disruption due to geopolitical tensions (e.g., trade barriers) make acquisition of raw materials and chemicals more difficult.

Therefore paper-making market currently has lower profitability margin than earlier, and suffers from price volatility due to raw material, energy, and transport costs volatility and high interest rates. Paper market growth is driven by increasing demand for sustainable packaging, hygiene products, and specialty papers.

6.3 Paper making process

Paper making process can be simplified to series of processes as depicted in Figure 1. Each of these are shortly described.

Pulping is a process of turning raw materials into a fairly homogeneous mass. Input material is usually wood, although nowadays various other materials are being explored, e.g., leaves, old paper etc. Pulping can be purely mechanical, such as grinding, or can involve chemicals. After the pulping process, the fibres are washed and screened to remove any remaining impurities. The resulting pulp can then be used to make paper or further refined to improve its properties.

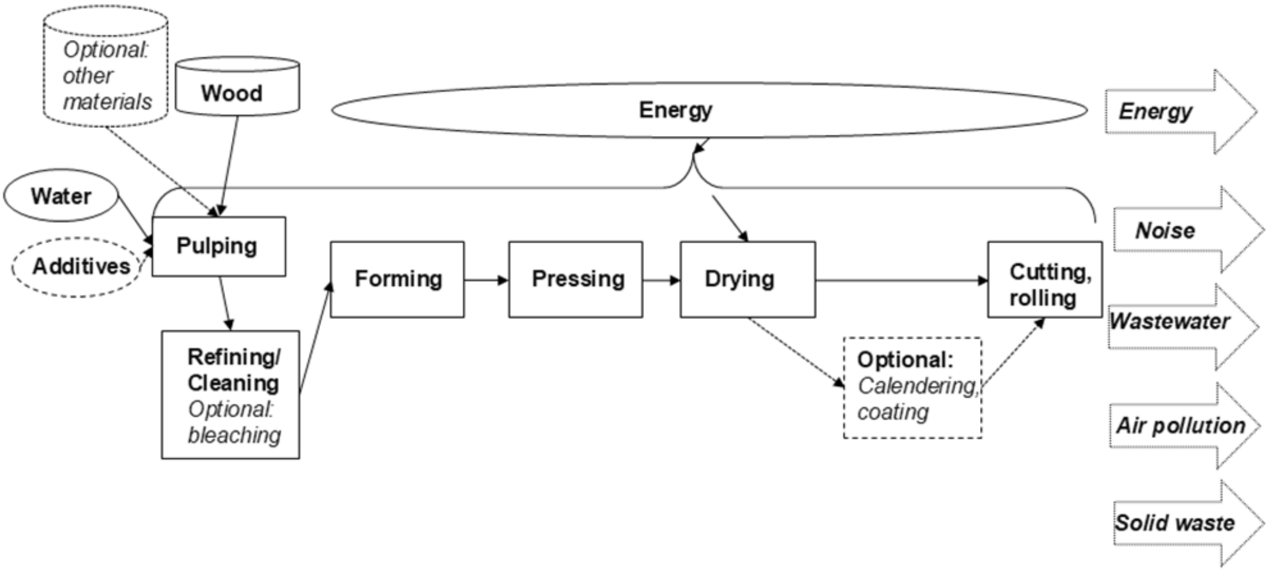

Figure 6. Paper making process.

Refining typically involves passing the pulp through a series of conical or cylindrical refiners, which use rotating discs or bars to pulp to further separate and refine the fibers to create a pulp with the desired properties for the specific paper product being produced. The refining process can be adjusted to control the degree of fiber separation and the resulting fiber characteristics, such as fiber length, strength, and flexibility. After refining, the pulp may go through additional cleaning and screening processes to remove any remaining impurities before being sent to the paper machine for further processing.

Bleaching (optional): used to improve the brightness and whiteness of the paper. Bleaching removes residual lignin and other impurities from the fibers, which can cause the paper to turn yellow over time. There are several methods of bleaching used in the paper industry, such as using chlorine, oxygen, peroxine or ozone. After bleaching, the pulp is washed and screened to remove any remaining chemicals or impurities. The resulting pulp can then be used to make paper or further refined to improve its properties. Many paper manufacturers have shifted towards using chlorine-free or totally chlorine-free (TCF) bleaching methods in order to minimize environmental impacts.

Often, pulp making is performed separately from other paper production steps: for example, VTT facilities in Jyväskylä get ready-for-use pulp from the plants, specialized in its production.

Forming is transforming the pulp into a continuous sheet of paper on a paper machine. The pulp slurry is pumped onto a moving mesh screen or wire via so-called headbox. As the pulp travels along the screen, water is drained off, and the fibers begin to bond together to form a wet web of paper. The consistency and speed of the pulp flow are carefully controlled to ensure that the paper sheet has the desired properties, such as strength, smoothness, and thickness.

Pressing: the wet web of paper is squeezed between two or more rolls to remove more water and improve the paper's density and strength. The number of press sections and the pressure applied during pressing can vary depending on the desired properties of the final paper product. Pressing process removes the majority of the remaining water from the wet paper web, which can account for up to 50% of the paper's weight. As the paper web is squeezed between the rollers, the fibers are flattened and compacted, resulting in a denser and stronger paper product. The pressing stage helps to prepare the paper web for efficient drying.

Drying: the paper web is passing through a series of heated cylinders or other drying methods such as vacuum to remove the remaining water and bring the paper to its final moisture content. The drying process is carefully controlled to ensure that the paper is dried uniformly and without any damage to its structure or surface properties. Several sets of heated cylinders are usually arranged in a specific sequence to gradually reduce the moisture content of the paper web. As the paper web travels through the drying section, it is subjected to increasing temperatures and decreasing humidity levels, which cause the remaining water to evaporate. The drying process can affect the paper's strength, smoothness, and surface properties. Proper control of the drying temperature, humidity, and airflow is critical to ensure that the paper is dried uniformly and without any defects.

After drying the following optional post-processing steps can be performed: calendering, coating, and surface sizing. Their goal is to improve paper surface and to enhance paper for specific purposes.

6.4 Patent landscape on utilising AI in paper making processes

To understand AI and ML use in paper-making, we performed patent search using keywords such as “artificial intelligence” and “machine learning” and cooperative patent classification (CPC) code D21 to find patents which are related to the paper industry. It should be noted that the keywords “AI” was not used as it retrieved all patents that have the letters in any word. Classification D21 refers to paper-making, production of cellulose.

Altogether, 380 records in 91 simple families were found. The patents were explored (one from each family) and marked relevant or marginally relevant.

Search results demonstrate a clear upward trend in patent applications starting from 2015, with more significant growth from 2018 onwards. In typical year, there has been around 10 patent applications and about 3 granted patents. Record was at 2024 where 6 patents were granted. It is worth noting that the data for years 2023 and 2024 are still incomplete as patent applications are typically published 18 months after filing. Since patent examination can take several years, statistics are incomplete from 2020 onwards, but even incomplete statistics shows a notable increase in using AI in paper-making.

The top 30 owners of the largest patent portfolios are presented in Figure 7. Horizontal line presents the number of simple patent families and the simple legal status: which patents are active, pending or no longer active. Siemens AG stands out with 15 patents, though most of them are inactive. Several other organisations, such as Voith Patent GmbH, ABB (Schweiz) AG, and Zhejiang University of Technology, hold smaller but more active portfolios, suggesting ongoing innovation. The presence of pending and active patents across many players indicates that while some technologies may be maturing, new developments are still emerging in the field.

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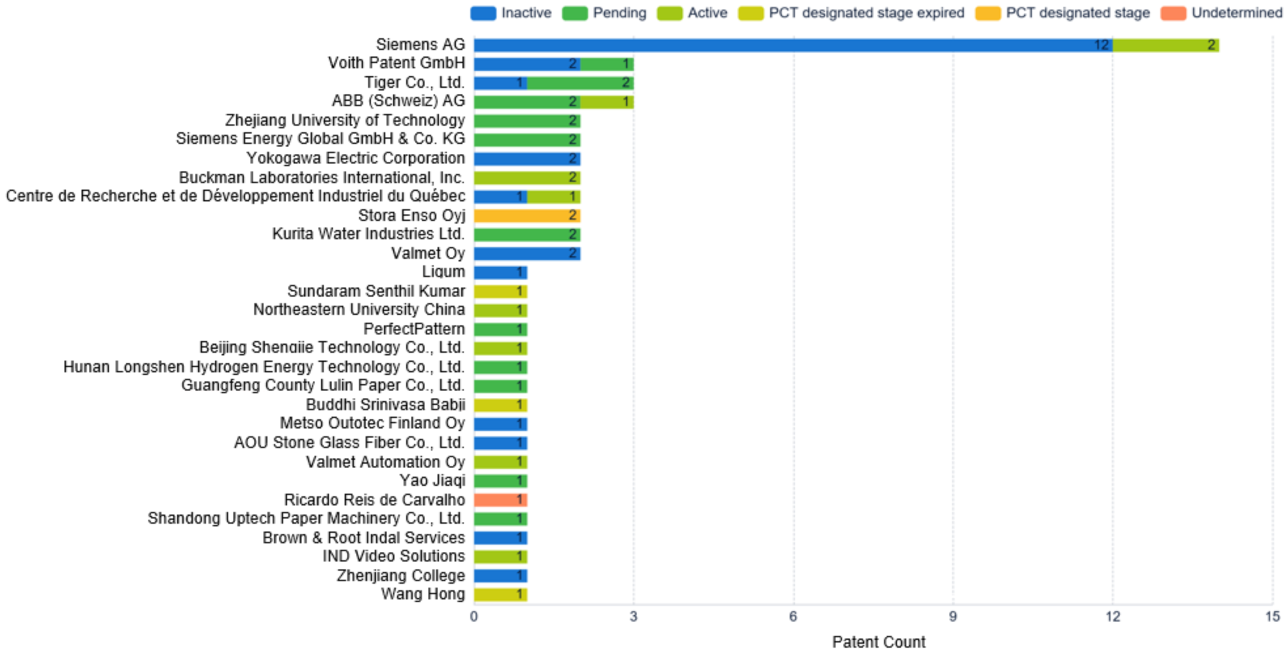

Figure 7. Top 30 owners of largest patent portfolios (AI in paper making).

Based on patent analysis, AI or other machine learning methods (e.g., optimisation) are used on all stages of paper-making process, see Figure 8.

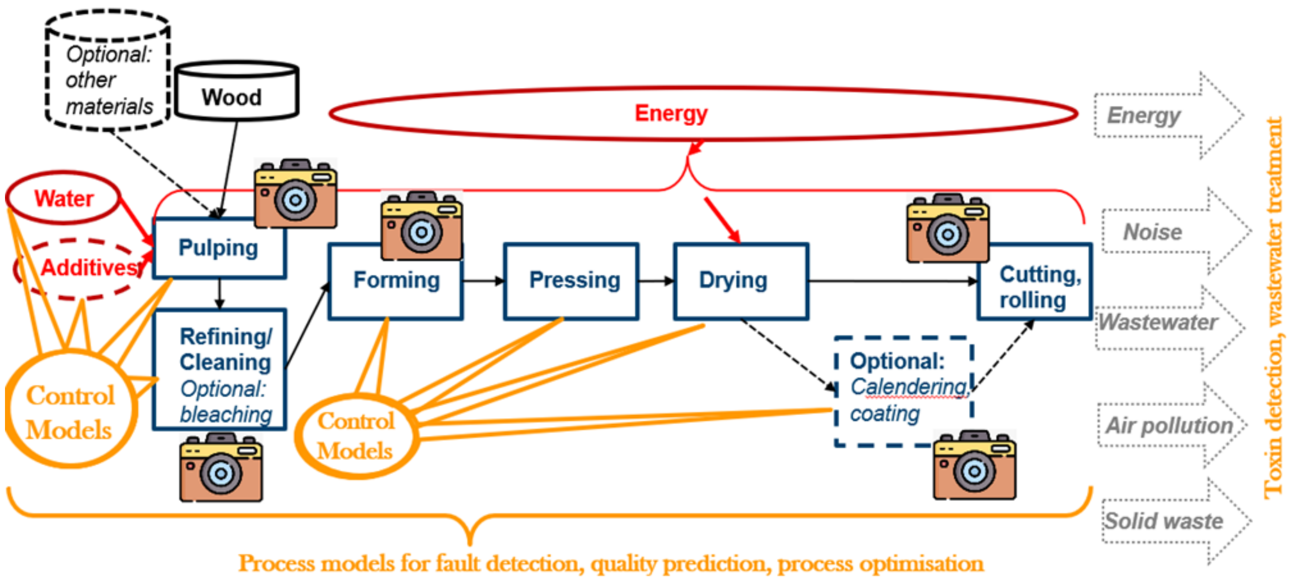

Figure 8. Machine Learning at different stages of paper making process. Legend: red – inputs to paper making process; grey – other-then-paper outputs; dashed connections: optional processes; camera icon: image analysis; orange – other AI/ ML.

Many patents are not very concrete, they use terms “certain parameters” instead of describing these parameters or describe the complete system on high level. Similarly, patents do not describe network architectures and training data. Hence the descriptions below are also on high level.

6.5 Machine learning approaches in different parts of the process

Next we open up the main findings from the patents under several categories.

Process monitoring and detecting problems / causes

IoT and AI systems monitor multiple process parameters using paper-making machine data and various sensors. Their goals are to predict potential problems and/ or detect causes for potential and actual problems, such as root cause analysis for paper breaks and predicting “time to break”.

Often, such systems utilise complex AI models, trained on large datasets. For example, one of the patents stated that AI model was trained on 3 years data. In this patent, training data included historical and simulated parameters of the process (quality of pulp, pulp to water mixing ratio, wetness factor, speed of drives, paper web drying time, amount of air flow, drive temperature, grade of manufacture etc.) having the abnormal patterns are labelled with (1) a root cause for the break in the paper web; and (2) estimated time to break the paper web. During operational phase this system not only determines a root cause for the break in the paper web or estimates time to break in the paper web, it also collects more data and updates models.

Less complex approach is monitoring parameters and using anomaly detection methods to recognise when parameter value dangerously deviates from its usual value. To build such models, one needs a lot of data of correct machine operation to create a “fingerprint” of proper operation, but less data of problematic cases than the above-described more complex approach.

Training AI/ ML models to output control parameters

In this approach, AI/ ML models are trained only for a certain stage of the paper-making process. Patents cover various stages separately from each other.

First, there are many patents related to producing pulp, for example:

- controlling operation of a plant for producing deinked pulp from waste paper -> Neural Network (NN) is trained to output e.g. content of adhesive contaminants or ash percent based on input material characteristics, measured by e.g. spectrometer
- controlling pulp washing system -> NN is trained to output rate of rinse water
- determine the point in time during pulp cooking at which the viscosity and/or kappa number of the pulp produced have predetermined values -> NN predicts cooking time
- predictive control of brown stock treatment at a pulp mill: generating control signals for actuators associated with defoamer flow rate, vat dilution rate, washer speed, based on detected variations between actual values and target values for the entrained air level and vat level
- adjust the blade speed and pressure of cutting machine to thickness and hardness of straw
- controlling other pulp productions parameters: temperature, pressure, valve closure, centrifuge speed, speed of mixing filler and pulp

Then, there are also patents for next stages:

- controlling the moisture content of a paper web in a drying section ->a model (linear) provides an amount of water to be evaporated or a heating requirement.
- Patent describes construction of the roller, allowing to adjust its weight quickly. NN is trained to predict desired weight of the roller based on paper gloss (assessed via image analysis). Since patent uses gloss data to adjust roller weight, patent authors were mainly addressing

paper calendaring stage. However, rollers are used also on other stages of the paper making process (for example, pressing to remove water), and the same adjustable rollers can be used also on other stages

There is also patent to use NN to output position correspondence between actuators and measuring points for every raw material recipe, which can be applied to different stages of paper-making process.

Training AI/ ML models to output paper quality parameters

In this approach, model is trained to predict quality parameter; then control value is determined based on desired quality value and its difference with the actual quality value. For example, programmable logic controllers can be used for setting control values.

Again, there are many patents for pulp production, for example:

- estimating an optimal dosage of bleaching agent in pulp production -> NN generates a predicted brightness value of pulp.
- estimate beating degree or pdf shape of fiber length distribution -> fiber cutting can be adapted.
- enzyme blend is selected based on expected fiber quality.
- NN is trained to obtain model of the best recipe of dynamic consistency information when not only wood, but also leaves, bamboo etc. are used in pulp production; then matching of long and short fibers, use of additives etc. is done.

There are also patents for other stages, for example:

- headbox opening is selected based on predicted paper weight.
- based on predicted paper strength, various parameters are adapted.
- image analysis allows to evaluate coating quality, then pressure of the arm in a coating machine is adapted using programmable logic controller (PLC).
- NN outputs information concerning a mechanical quality parameter of the xylem-based material. This information is used to generate signals for controlling the process.

Predicted quality can be used in also in other ways in the process, such as

- prediction of corrugated cardboard production speed at the wet end can make overall process more efficient because dry end is relatively independent.
- measuring fibre orientation can help to control formation profile.
- analysing thermal data can help to determining force data; detecting tear can help to regulate heat.

Paper quality control and control of other outputs

In this approach, AI models do not predict paper quality; they evaluate current paper quality. One patent describes estimating quality based on process data, but most of other patents describe use of video and/ or infrared cameras:

- In pulp production: using image analysis to detect (in order to remove) damaged or diseased straw parts in pulp

- During the process: monitoring of paper edges on the belt
- Evaluating quality of the final product via image analysis: corrugated cardboard quality, coating.
- Using image analysis for paper sorting
- Using image analysis to evaluate quality of paper rolls when paper is unwinded from master rolls and winded to other rolls

There are also patents for using various sensors to avoid undesirable situations and ensure safety, such as

- Detecting contaminants and toxic gazes
- Acoustic emission system and method for predicting explosions in dissolving tank

Optimisation

Optimisation algorithms are machine-learning methods, known already for long time. They require domain knowledge to define cost function and use data to adapt model parameters to minimise cost function. They are used in patents for optimising use of a paper machine (in this case, usually energy costs are included into cost function together with machine usage other costs) and its different parts (in this case, cost function utilises knowledge about operating this part, and cost function may include for example probability of defects). Examples of such patents are:

- Optimising production volume and financial profit per day using pulp/ wood price, cooking time, wood mass per boiler etc.
- Optimising recovery boiler parameters, based on process model
- Continuous overall regulation of a single-layer or multi-layer headbox of a paper, board or pulp-draining machine, based on optimisation of cost function
- Optimising process for refining lignocellulosic granular matter such as wood chips based on relations between moisture content, density, light reflection or granular matter size and refining process operating parameters such as transfer screw speed, dilution flow, hydraulic pressure, plate gaps, or retention delays, at least one output controlled (such as primary motor load or pulp freeness), and at least one uncontrolled output (specific energy consumption, energy split, long fibers, fines and shives)
- Online optimisation of batch digesters in the pulp industry. Chip quality, size, moisture content and cooking liquor concentrations keep changing with the batches. Due to disturbances in the steam generation system, availability of steam for heating the digester contents also changes
- Optimising energy of the drying system, which is the most energy-consuming part. Changes in paper weight, paper machine speed, wire pressure section parameters, etc. affect the evaporation efficiency of the drying section. Energy is optimised using genetic algorithm and machine constraints (e.g., impossible values)

6.6 AI driven process stability monitor for VTT’s new pilot dry forming paper machine

Forest industry is facing market challenges as the price of the manufactured products are increasing. This is due to global turmoil and Ukrainian war, which have increased the energy price and **also** weakened the availability of fiberwood. Thus, industry needs renew itself and find more energy, water efficient processes which can withstand new kinds, recycled or mixed fiber sources to maintain competitiveness in the market.

VTT is leading an Energy First initiative [18], where new paradigm for paper making is developed. The core idea is to create paper with minimal amount, or almost without water, which decreases heavily the energy needed to dry paper web during the process as with normal water or foam based approaches. Instead of mixing fibers with water or foam to create pulp, the fibers can be mechanically dispersed using hammering and then web is made with air flows. Water needed for hydrogen bonding is sprayed on the web. The use of energy and water is thus heavily reduced, which then results in lower price of the end products.

Figure 9. VTT pilot line at Jyväskylä Finland.

Dry web forming technology is experimentally tested in pilot level with the new machine built at VTT Jyväskylä premises close by the earlier paper pilot lines with traditional technologies.

The challenge that rises, is that as the machine and technology are both new there are no experience on how machine should be operated. It would be advantageous if AI could assist on machine ramp-up phase as well as during later normal operation. For example, by assisting human operator to find those machine parameters that lead stabile process. Or, predicting resulting paper quality whilst the process is running.

Currently, the development cycle relies on trial-and-error, where confirmative quality tests are done in the laboratory after the process, which then indicate what needs to be done for the next trial. If the paper quality and/ or machine stability could be forecasted in reliable manner during the test run, it would shorten the development cycles considerably and decrease resource consumption during development.

A prototype AI model was developed to identify when process is in stabile condition quicker than human operator. At the time, new paper machine was not operation, but data was available from the existing foam process machine. With that data, AI-data pipeline could be established and model trained with data that have some basic similarities that are also expected from the new machine.

The input data consisted of a total of 70 variables, of which 22 were directly adjustable by the operator and 48 were measurements obtained from various components in the process.

The AI model was initially based on tree-based models such as XGBoost or Random Forest, but during the development, it was found that the data was heavily biased towards unstable conditions and data from the stable condition was scarce. After several trials and attempts to draw as much from the data as possible, it was concluded that neither the XGBoost model nor the Random Forest model could provide needed answers. Instead, new approach was done with autoencoders, which are an unsupervised method of categorizing data. Autoencoders are a deep learning architecture that consist of an encoder and a decoder.

The objective of the autoencoder is to encode and then decode a message so that information is conserved as much as possible. The difference between the original and decoded messages are then compared, which provide the estimation error. This estimation error is then used to label the process as stable or unstable. By using the autoencoder model, we were able to categorize the paper machine process as stable or unstable without requiring the scarce label information.

A potential view of the Process stability monitor can be seen in Figure 10. On the left side, the process is labelled as stable, whereas on the right side it is labelled as unstable. The red horizontal bars depict the operator-determined stable areas. In future development, we could opt to using a moving average or deviance within a timeframe instead of the absolute estimation error, as differences in the source and target material cause different baselines of estimation error.

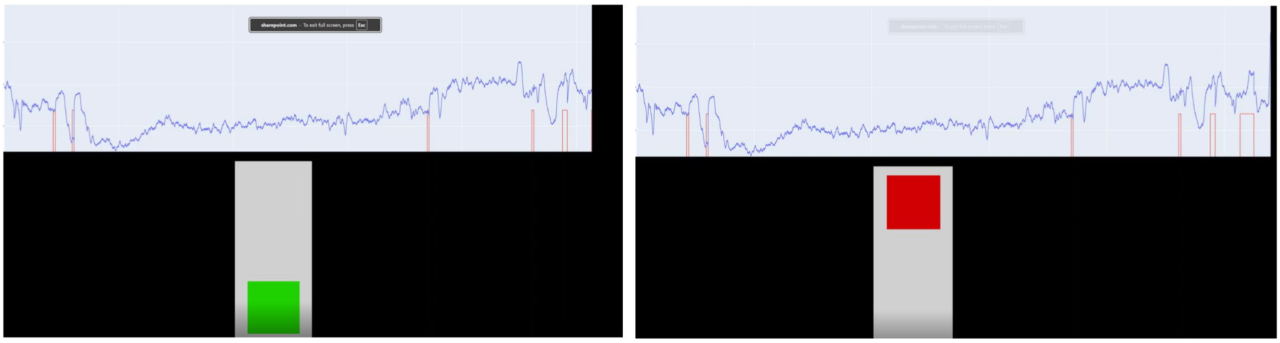

Figure 10. Process stability monitor with traffic lights.

The future work is needed for:

- Collecting the data for the new dry forming machine: both machine data and operator comments (needed as ground truth to test the developed unsupervised AI methods and to develop semi-supervised and fully supervised AI methods to see if the AI accuracy can be improved compared to the unsupervised methods). To this end, special care needs to be taken (1) to develop convenient for the operators tools to obtain their comments and (2) to accurately synchronize machine data with the operator comments.
- Tuning unsupervised AI/ ML models, developed for the old machine, to serve the new machine, by training the models on new data, then testing and then tuning model parameters and/ or selecting best features. Testing will first utilize the obtained operator comments as ground truth; after that data visualizations for the rest of the data will be presented to the Jyväskylä team to jointly assess the models.
- Developing new semi-supervised and fully supervised AI/ ML models and testing their accuracies in the same way as accuracies of the unsupervised models. This part of work is feasible because typically semi-supervised and fully supervised AI models are more accurate than unsupervised models, and the higher the model accuracy, the less resources are wasted.

7. Conclusions

The main outcomes of the project were a) Minimum Viable Closed-Loop in Remanufacturing with identified IPR possibilities for VTT AI research, b) AI service for paper machine process stability monitoring and c) Visual Language model implementation on steel part defect detection.

Knowledge created in GG_CAI is utilised and further developed in remanufacturing related BF_FREIMAN research project. In addition, a software notification was made on the develop AI paper process stability model. Discussion continues on further developing AI model for accelerating new paper machine process development at VTT Jyväskylä pilot paper making facility. Knowledge developed in project on visual language fundamental AI models can be utilised in EU projects such as landmark HEU_MANUGAIN project (submitted, under review) developing fundamental AI models for Europe.

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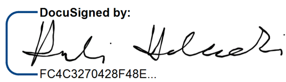
Heli Helaakoski heli.helaakoski@vtt.fi Research manager, Cognitive production industry Security Level: Email, Account Authentication (None), Authentication	 Signature Adoption: Drawn on Device Using IP Address: 45.82.17.30	Sent: 16 March 2026 | 11:29 Viewed: 16 March 2026 | 13:00 Signed: 16 March 2026 | 13:00

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