



D2.1 Baseline report on key technology features for support solutions

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List of abbreviations

<i>Abbreviation</i>	<i>Explanation</i>
AGV	Autonomous Guided Vehicles
AI	Artificial Intelligence
API	Application Programming Interface
AR	Augmented Reality
AWS	Amazon Web Services
BMS	Battery Management System
CE	Circular Economy
D	Deliverable
ERP	Enterprise Resource Planning
GCP	Google Cloud Platform
HBC	Hellenic Bottling Company
IoT	Internet of Things
IT	Information Technology
LCCP	Lexmark Cartridge Collection Program
LECP	Lexmark Equipment Collection Program
ML	Machine Learning
MRO	Maintenance, Repair and Operations
OEM	Original Equipment Manufacturer
OST-HMD	Optical See-Through Head Mounted Displays
PCB	Printed Circuit Boards
PDM	Product Data Management
PVDF	Polyvinylidene Fluoride
SQL	Structured Query Language
T	Task
TPA	Transfer Path Analysis



1. Executive Summary

This document is a result of Task 2.1 'Identify the key technology features for support solutions and define their current baseline'. This report defines a baseline of industry best practices in technologies (i.e., Internet of Things for tracing, tracking and condition monitoring, machine learning for decision making, image processing and augmented reality for value recovery) implemented for industrial value recovery processes in general and their adaptability for industrial sectors targeted in DiCiM. In doing so, this report compiles the existing knowledge and experience of the demonstrators and technology providers to understand the current state and outline the desired state for the technology implementation.

Currently, the convergence of the Internet of Things (IoT), condition monitoring and the circular economy has given rise to innovative solutions that improve value recovery processes and advance sustainability. Prominent instances of IoT technology application in terms of part manufacturing, refurbishing, or recycling can be seen in the heavy machinery industry with Caterpillar, in the food industry with Nestlé, in the automotive industry with Tesla and Volvo. In the realm of household appliances, the Internet of Things (IoT) is being effectively integrated to serve the concept of Circular Economy (CE), as demonstrated by Miele and Bosch. In DiCiM

Questar Auto Technologies, Infosys, BMW Group, and LG use AI and machine learning to enhance the efficiency of decision-making, inspection, and sorting in value recovery processes. There are several image processing-based inspections and sorting options available in the market. These solutions utilize computer vision techniques to detect and analyse defects in components, automate visual inspection tasks, and improve quality control processes in various industries. However, specific examples of industrial application of image processing in decision making, inspection and sorting for CE could not be found.

When looking at industrial applied Augmented Reality (AR) solutions to support assembly and sorting processes, it shows that assembly processes were supported using projective, tablet-based and glasses-based devices, with projective solutions being the most used. The industries where these assembly AR solutions were applied to covered ship building, aerospace, automotive and manufacturing. No applications for the white good industry targeted in DiCiM could be found. For sorting processes only glasses-based AR solutions could be found. These solutions were covering warehouse application for various industries, though not in particular for automotive spare parts and whitegoods, which is the target industry in DiCiM. All solutions had in common, that they provided instructions and only very few had a sort of validation process, that the task was carried out correctly. None of the solutions provided user specific instructions based on their individual skillset.

It was analysed how Siemens, TechDoc, Caterpillar and Ricoh have adapted their data management platform to fit the needs for the remanufacturing processes. However, an open access platform such as intended to build in DiCiM does not exist for the white good industry and car spare parts industry.



2. Introduction

2.1. Document Scope

This document is a result of Task 2.1 'Identify the key technology features for support solutions and define their current baseline'. This report defines a baseline of industry best practices in technologies (i.e., IoT for tracing, tracking and condition monitoring, ML for decision making, image processing and AR for value recovery) implemented for industrial value recovery processes in general and their adaptability for industrial sectors targeted in DiCiM. In doing so, the report will also compile the existing knowledge and experience of the demonstrators and technology providers to understand the current state and outline the desired state for the technology implementation.

This task is correlated with Task 2.2 'Target technologies development and adaptation requirements', by providing the baseline of industries best practices for the key technologies used in DiCiM. Further, results from the requirements analysis carried out in WP1 were used for defining the desired state for the key technologies.

2.2. Methodology

As the main goal of this report is to research the baseline of industry best practices for the key technologies used in DiCiM (i.e., IoT for tracing, tracking and condition monitoring, ML for decision making, image processing and AR for value recovery) regarding their implementation for industrial value recovery processes, we decided to only consider best practices reaching at least TRL7. Because of this targeted TRL we decided against searching for research papers as they are usually only describing solution on TRL2-5. Instead, we only investigated grey literature, i.e., websites, case studies and e-books of best practices. However, these publications are always published by companies, and the solution providers respectively for their customers. Therefore, the descriptions of the capabilities of the described best practices solution must be taken very cautiously as the presented results are not validated by an independent source. The intend of these publications is advertising their solutions. It is therefore safe to assume, that there are practical problems and technological insufficiencies which are whitewashed or obliterated in the publications. Further, we included solution examples from linear production that were deemed to be transferable to a circular production.

For the description of the state of the art of the key technologies used in DiCiM within the consortium, we described relevant technologies and results from linear and circular production approaches of past project on TRL4 and higher.

2.3. Document Structure

Following the introduction section 3 describes the state of the art of key technology features for value recovery. This section constitutes the main content of this deliverable and contains four elaborate subsections each dedicated to one key technology (IoT for tracing and tracking, machine learning and image processing, augmented reality, data management platforms). We aimed to provide a representative overview of industry best practices for value recovery. In section 4 the relevant capabilities of the consortia members are provided in respect to DiCiM's goal and technologies. Section 5 describes a brief high-level description on the adaptation of the key technologies to the need of the demonstrators. The deliverable finishes with a concise conclusion of its content.



3. State of the Art of Key Technology Features for Value Recovery

This section represents the main contribution of D2.1 by providing industries best practices for the key technologies used in DiCiM to facilitate value recovery operations for the white goods, printers and automotive spare parts industries. Each subsection is dedicated to one key technology: IoT for tracing and tracking, machine learning and image processing, augmented reality, data management platforms. The examples are representing exemplarily the state of the art of the targeted key technologies from grey literature and not scientific publication. Due to the high TRL adaption in industry, that is targeted to present in this section this is inevitable. Due to the different adaptation of by various industries of the key technologies some subsections contain more and some less examples. Lastly, we tried to find relevant best practices from the demonstrator industries targeted in DiCiM, although sometime none could be found.

3.1. IoT for Tracing, Tracking and Condition Monitoring

The concept of value recovery within the circular economy has gained traction, emphasizing the extraction of maximum value from products, components, materials and resources at the end of their life cycle. In parallel with this trend, the Internet of Things has emerged as a powerful technology that enables real-time data collection, seamless communication, and intelligent decision making. Together, the two fields provide various opportunities to optimize value recovery processes.

This section explores the intersection of IoT and the circular economy framework. It should be noted, however, that it can be difficult to obtain specific industry reports on this particular topic, as data is often sparse or unavailable due to ongoing development. Therefore, this review will primarily focus on highlighting solutions that are at least partially related to the topic, given the available information.

3.1.1. *Cat Connect and Car Reman by Caterpillar [1–3]*

Caterpillar's Cat Reman and Cat Connect programs demonstrate how the company, a leader in the construction and mining equipment industry, is effectively combining circular economy principles and the Internet of Things (IoT) to enhance value recovery processes and establish a sustainable ecosystem. The Cat Connect program leverages the power of IoT technology to provide real-time data and insights into Cat machine performance and health. Using cutting-edge digital technology, this platform integrates sensors, software, and services to collect and analyse critical information such as hours of operation, fuel consumption and load profile. Cat Connect facilitates proactive maintenance, optimizes machine performance and streamlines personnel management. The ultimate goal is to minimize downtime, control costs and maximize operational efficiency.

On the other hand, the Cat Reman program focuses on the remanufacturing and rebuilding of products to extend their lifespan and reduce waste. Caterpillar introduced this program back in 1973, making it an early pioneer in applying recycling and reuse principles within the circular economy framework. Through a meticulous process, Caterpillar restores products to a like-new condition, conforming to the latest specifications, thereby reducing ownership and operating costs for customers. Remanufacturing involves meticulously restoring used products to their original performance specifications, effectively prolonging their life cycle and minimizing waste.



By prolonging the equipment's lifespan, minimizing waste, and enabling informed decision-making through real-time data, Caterpillar is actively contributing to the creation of a more sustainable and resource-efficient ecosystem. However, it is worth noting that the available information does not provide details regarding the existence or practice of data sharing between these two programs.



CAT

1

Figure 1: Cat Connect IoT solution by Caterpillar¹.

3.1.2. Tesla's Battery Recycling Initiative [4–7]

Tesla has demonstrated a strong dedication to integrating Internet of Things technologies to enhance efficiency, sustainability, and cost-effectiveness. A significant focus area where Tesla leads is battery recycling within the circular economy framework. Tesla's electric vehicles rely on lithium-ion batteries, which have a limited lifespan. Throughout a Tesla vehicle's lifecycle, IoT-enabled sensors embedded within the battery system continuously capture essential data, providing real-time insights into the battery's condition. These sensors, integrated into Tesla's battery management system (BMS), monitor critical parameters such as temperature, voltage, current, and state of charge. By collecting and relaying data, the sensors enable the BMS to optimize battery performance, regulate temperature, and prevent issues like overcharging or over-discharging. Additionally, the sensors detect anomalies within the battery pack, facilitating prompt corrective actions or driver notifications.

When a battery reaches the end of its life, Tesla leverages the data acquired from these IoT sensors to make informed decisions about appropriate actions. Some batteries can be refurbished and repurposed for stationary energy storage systems, while others undergo advanced recycling processes. This approach not only prevents hazardous waste disposal but also reduces the need for raw material mining, aligning with sustainable practices. Tesla's integration of IoT technology into battery recycling and management processes demonstrates the company's commitment to the circular economy. By optimizing value recovery, minimizing

¹ <https://cranemarket.com/blog/wp-content/uploads/2017/03/Cat-Connect.jpg>

waste, and reducing environmental impact, Tesla reinforces its position as a serious and sustainable contributor to the electric vehicle industry. Through their closed-loop recycling process, collaborations with recycling partners, and ongoing research, Tesla showcases a responsible approach to managing electronic waste.

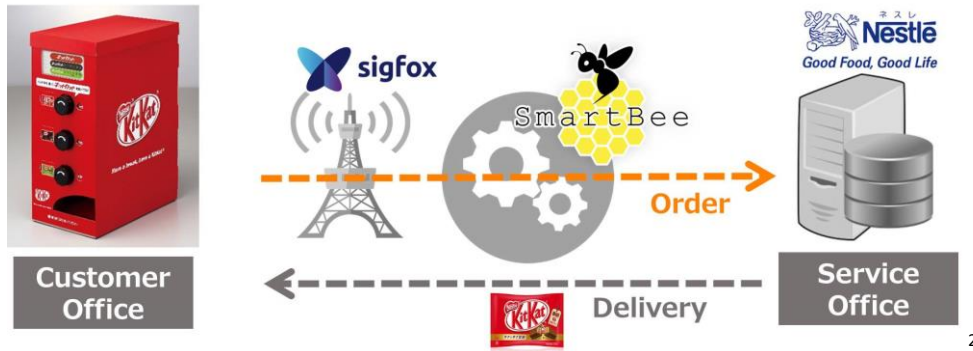


Figure 2: IoT solutions in automotive industry [8]

3.1.3. IoT solutions by Nestlé [9–11]

Nestlé has actively embraced advanced technologies under the Industry 4.0, with a specific focus on seamlessly integrating IoT solutions into its supply chain and manufacturing operations. Firstly, these solutions contribute to the improvement of product quality by ensuring that goods are stored and transported under optimal conditions, thus guaranteeing compliance with stringent food quality and safety standards.

An example of a successful intersection of IoT and the circular economy framework can be seen in Nestlé's collaboration with Telefónica Business Solutions, which has brought about a transformative effect on Nestlé Professional's coffee business. By leveraging IoT telemetry, Nestlé gains the ability to closely monitor the operational parameters of its coffee machines, leading to enhanced customer experiences and improved operational efficiency. Further Nestlé's plans to involve utilizing this technology to control crucial machine aspects, including remote configuration, predictive maintenance of failing components, and even personalized adjustments to the strength and flavour of dispensed drinks.



2

Figure 3: An example of IoT based solution by Nestlé²

3.1.4. Volvo Group IoT management of AGV fleet [12, 13]

The Volvo Group manufacturing facility in Lyon, France, faced the challenge of reducing operational costs and improving maintenance service for their Autonomous Guided Vehicles (AGVs) used in engine production. When the voltage of the AGV batteries dropped below 22V, the production chain would be blocked, resulting in a loss of approximately two engines per week. To address this issue, the IoT team at Volvo Group Digital & IT implemented a wireless system for predictive maintenance using LoRaWAN technology.

Each AGV was equipped with a LoRaWAN sensor that periodically transmitted battery voltage data. With this system in place, the maintenance team received regular notifications when the battery levels dropped below 23V or when battery failures occurred. This allowed them to proactively move the AGVs to the charge point without disrupting the production line or organize interventions in case of battery failure.

The predictive maintenance system, consisting of LoRaWAN sensors, a private LoRaWAN network, a maintenance platform, and real-time status displays throughout the factory, provided the Volvo Group with significant benefits. The AGVs' health could be monitored in real-time, reducing production downtime and engine losses. Additionally, the connected factory environment enabled the integration of other sensors for various purposes, such as temperature and humidity sensors for painting quality improvement and pressure difference sensors for monitoring filter clogging.

²https://encrypted-tbn1.gstatic.com/images?q=tbn:ANd9GcSXu4YlSaFP4YI-sNiI6fjdDQOVVyVMDMHu8QMs_XhIraWHz-h



Figure 4: IoT supported AGV fleet by Volvo Group³

3.1.5. Bundles [14]

Bundles is a Dutch start-up that was founded in 2014 and specializes in commercializing household appliances using servitized business models. They offer pay-per-month and pay-per-use contracts to their customers, wherein the customers do not purchase the appliances but rather pay for the laundry service provided by Bundles. This approach allows customers to use high-quality household appliances without the need to buy them, resulting in potential cost savings of up to 1500 euros compared to buying new appliances outright.

The company employs a circular supply chain model, where they take ownership of the appliances at the end of the contract, refurbish them if necessary, and then sell them back to another customer. If a product cannot be repaired, Bundles collaborates with their OEM partner, Miele, to reuse spare parts. This approach promotes sustainability and environmental benefits, as the appliances offered by Bundles are all highly energy-efficient (A+++ ranked) and the contracts facilitate reusing and recycling practices.

Bundles leverages digital technologies such as IoT (Internet of Things) and Big Data to enhance their services. The household appliances they provide are equipped with sensors that collect data on machine condition, energy consumption, and water usage. This information is transmitted to Bundles' online platform and made available to customers. The utilization of IoT enables Bundles to offer additional benefits to their customers, including maintenance services and personalized advice on optimizing appliance usage.

In summary, Bundles' innovative approach to commercializing household appliances through servitized business models, combined with their circular supply chain, digital technologies like IoT, and collaboration with an OEM partner, helps provide cost-effective and environmentally friendly solutions for their customers.

3.1.6. AquaFresco [14]

AquaFresco is a water-saving mechanism developed by three MIT graduate students to reuse wastewater from washing machines. It won the third prize in the "Water Innovation Prize

³ <https://assets.volvo.com/is/image/VolvoInformationTechnologyAB/Empty-AGV?wid=1024>

Competition" in 2014. The system utilizes a polymeric filter to clean and recover 95% of the water used in a washing cycle, allowing it to be reused multiple times. The device can be paired with different types of washing machines and is designed to be connected to three or five machines simultaneously.

The AquaFresco system is currently being tested by three hotels and three laundry services in the US. The system's efficiency can be further enhanced by integrating IoT technology to control water quality. This innovation offers both environmental and economic benefits by reducing water consumption and pollution. Large-scale implementation of the AquaFresco technology can lead to significant cost savings, with estimates suggesting that a hotel spending \$10,000 per week on water and detergents could save \$500,000 per year by using the AquaFresco system.

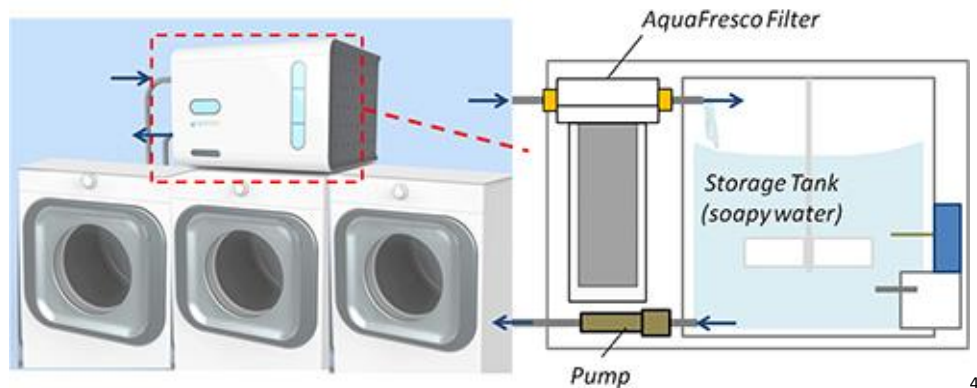


Figure 5: AquaFresco filter installation concept [15]

3.1.7. WeWash [14]

WeWash is an IoT-related project that originated as a spin-off within the multinational company Bosch, known for producing automotive and household appliance spare parts. The initiative was conceived by three Bosch members who developed an app to streamline the sharing of washing machines. After proposing the idea to Bosch in 2014 and gaining support, they established their own company a year later.

The main objective of WeWash is to encourage sharing and reduce the overall number of washing machines in the market. To use the app, customers must register on a dedicated platform, which enables them to check the availability of shared washing machines, make reservations, and track the status of their wash cycle. This sharing approach incorporates digital technologies, transforming the usage phase of washing machines.

To utilize WeWash, users need an IoT kit that is easily adaptable to various types of washing machines. The IoT kit is installed between the device and the power plug, enabling remote connectivity and control. Additionally, WeWash accepts credit card payments, simplifying the transaction process for users.

⁴ https://alum.mit.edu/sites/default/files/slice/uploads/2015/12/AquaFresco2_edit.jpg



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Figure 6: WeWash logo [16].

3.1.8. Summary

The convergence of the Internet of Things and the circular economy has given rise to innovative solutions that improve value recovery processes and advance sustainability. Prominent instances of IoT technology application in terms of part manufacturing, refurbishing, or recycling can be seen in the heavy machinery industry with Caterpillar and the automotive industry with Tesla.

Moreover, IoT solutions have been successfully incorporated into supply chains, combining marketing strategies with condition monitoring on machines to anticipate maintenance issues before critical components fail. Nestlé and Volvo Group serve as prime examples of this integration.

Furthermore, within the realm of household appliances, the Internet of Things (IoT) is being effectively integrated to serve the concept of Circular Economy (CE), as demonstrated by Bundles - Miele, AquaFresco, WeWash-Bosch. Notably, prominent manufacturers such as Whirlpool, Electrolux, and Miele are actively striving to transition towards CE. While the precise utilization of IoT (and potentially machine learning) in this context has not been explicitly found in literature, their business models and strategies are elaborated in Bressanelli et al. [14].

3.2. Image Processing and Machine Learning for Decision Making, Inspection and sorting

Image Processing and Machine Learning for Decision Making, Inspection and Sorting is a broad topic that covers many applications and techniques. Image processing refers to the techniques and algorithms that manipulate and analyse digital images, such as enhancing, compressing, segmenting, detecting, recognizing, and classifying objects. Machine learning is the use of algorithms and data to learn from experience and make predictions or decisions. Machine learning can be applied to image processing to perform tasks such as feature extraction,

⁵https://assets.bosch.com/media/global/stories/annual_report_2016/wewash/wewash-wallbox-vde_res_640x360.webp

classification, detection, segmentation, etc. This section shows some examples of the state of the art of image processing and machine learning for decision-making, inspection, and sorting.

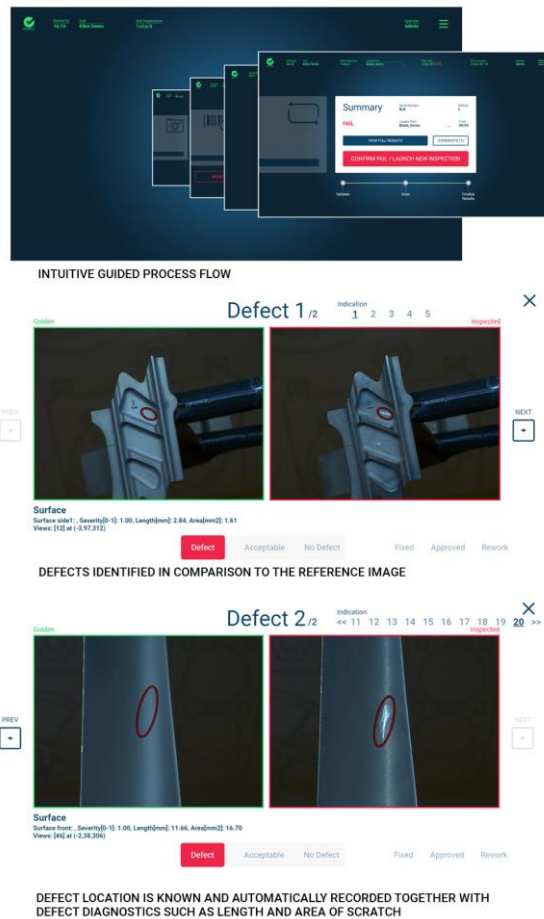
Image processing and machine learning are two fields that have advanced significantly in recent years, enabling a wide range of applications for decision making, inspection and sorting. The combination of image processing and machine learning can provide powerful solutions for decision making, inspection and sorting problems that involve complex visual data. For example, image processing can pre-process the images to extract relevant features, reduce noise and improve quality, while machine learning can use the features to make predictions, recommendations or actions based on the data.

3.2.1. Image Processing for Decision Making, Inspection and sorting

There are multiple options available in the market for image processing-based inspection and sorting. Below, you will find a brief overview of some relevant examples:

- **Maximo Visual Inspection by IBM [17]:** This is a software that puts the power of computer vision AI capabilities into the hands of quality control and inspection teams. It makes computer vision, deep learning, and automation more accessible to technicians as it's an intuitive toolset for labelling, training, and deploying artificial intelligence vision models.
- **Kitov.ai Inspector [18]:** This is a software that uses a hybrid model of AI and classical 3D computer vision to find product defects such as cosmetic defects (scratches, dents, discoloration, etc.) and mechanical defects (worn, untightened, or defective screws, labels, pins, etc.) Inspector is the production-time inspection platform. For each inspection contained in the inspection plan and for each part, Inspector will capture a high contrast image and run the desired detector. Inspector runs in a browser-based application following an intuitive process flow that guides the operator through each step – from loading a new inspection plan to summarizing and exporting a final report





6

Figure 7: Kitov.ai Inspector Software [18]

- **ZEISS Automated Defect Detection [19]:** This is a software that uses artificial intelligence and computed tomography to detect and analyse defects in components quickly and reliably. It can be used for various industries such as injection moulding, battery, medical, or additive manufacturing.
- **AI Inspect by Mitutoyo [20]:** This is a software that uses AI and machine learning to learn the visual differences between normal and defective pixels in any set of correlated images. It can be used for various applications such as surface inspection, dimensional measurement, pattern recognition, etc. It can detect defects such as scratches, dents, stains, etc.
- **Quality control with Visual Inspection AI by Google Cloud [21]:** This is a cloud-based solution that automates visual inspection tasks using AI and computer vision. It allows manufacturers to easily build and deploy custom models for defect detection without coding or AI expertise. Mobile phone printed circuit board (PCB) inspection Electronics manufacturers use Visual Inspection AI to simultaneously inspect dozens of individual components on high volume s PCB to detect missing, misplaced, or damaged components, screws, springs, and soldering issues.

⁶ <https://kitov.ai/wp-content/uploads/2023/04/Inspector3.jpg>



7

Figure 8: PCB inspection example of google cloud [21]

3.2.2. Machine Learning for Decision Making, Inspection and sorting

There are numerous industrial implementations of machine learning in various sectors for tasks such as decision making, inspection, and sorting. Below, we provide an overview of some relevant examples:

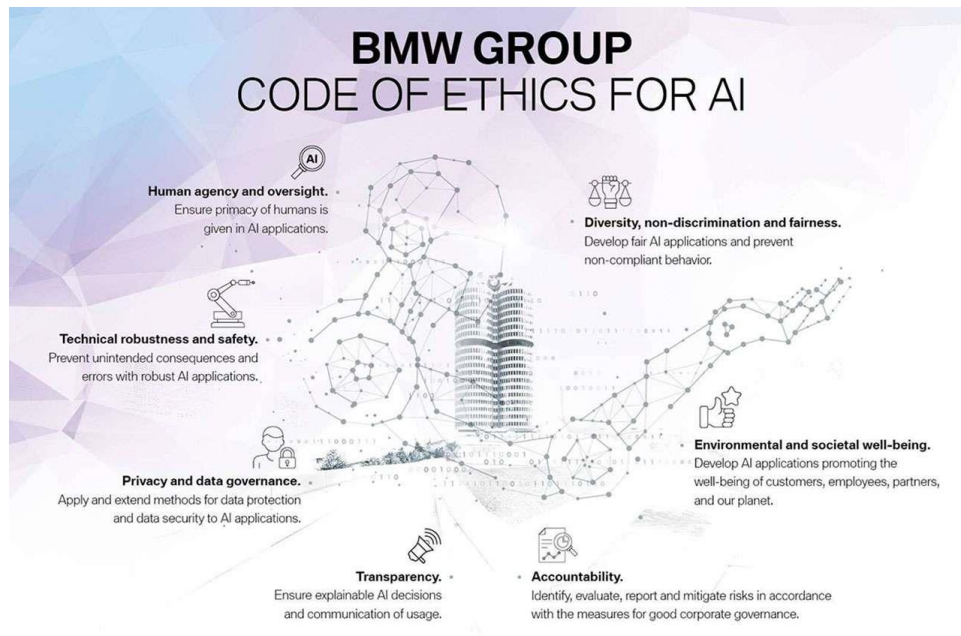
- **Questar [22–25]:** Questar Auto Technologies, an AI-driven predictive vehicle health company, is at the forefront of revolutionizing vehicle maintenance practices by integrating AI and advanced analytics into their Vehicle Health Management Platform. Their platform harnesses the power of AI and data collected from sensors to proactively detect potential malfunctions in vehicles, enabling predictive maintenance and reducing repair costs. In a recent pilot program with Israel's Kavim Public Transportation company, Questar's VHM platform successfully identified major malfunctions in 10% of the tested buses that were not detectable through traditional error codes. These malfunctions included issues with the exhaust systems and particulate filters, impacting emission filtration. By detecting these malfunctions early, Questar minimizes vehicle downtime, resulting in substantial cost savings for fleet operators. Furthermore, Questar's AI-powered approach to vehicle maintenance enables fleet owners to move away from traditional fixed-time maintenance schedules and transition towards a more targeted and data-driven maintenance strategy. By leveraging AI and predictive analytics, fleet operators can identify and address maintenance needs before they escalate into costly repairs or safety risks, resulting in reduced resource consumption and improved operational efficiency. Questar's comprehensive suite of solutions has been successfully deployed in over 350,000 vehicles across more than 20 countries, providing constant, meaningful insights to automakers, suppliers, and fleets. By integrating AI and deep learning capabilities with data collection and management expertise, Questar empowers the automotive ecosystem to convert vehicle data into actionable insights, facilitating informed decision-making and driving the adoption of sustainable practices within the industry.

⁷https://lh3.googleusercontent.com/Wg-3_yNBm7Jyj3mKwCLw5k5mP5xURSBDiTLJoBSAvpGaNQV8uch1G5mOFQbpcKiXOTWb2OzrueoH=e14-rw-lo-sc0xfffff-h800-w953

- Infosys** – Revolutionizing Vehicle Maintenance Efficiency [26]: In light of the escalating costs associated with maintenance, there is often a temptation to delay scheduled maintenance. However, this approach typically leads to even higher expenses and increased periods of downtime. Fleet maintenance managers commonly rely on preventive maintenance or original equipment manufacturer (OEM) guidelines, which serve as effective measures against unscheduled repairs. However, the exorbitant costs and resulting vehicle downtime associated with preventive maintenance cannot be disregarded. To address this challenge, Infosys has developed the Vehicle Maintenance Workbench (VMW), an integrated platform that harnesses the power of advanced AI and ML optimization algorithms to enhance fleet maintenance efficiency and safety. The VMW's innovative capabilities enable it to forecast potential failures in advance, empowering maintenance managers to schedule preventive maintenance automatically for their respective garages. With its sophisticated algorithm, the workbench seamlessly manages over 5000 maintenance tasks, providing comprehensive insights into vehicle utilization and downtime within seconds. The failure prediction feature of the Infosys VMW offers a complete overview of the fleet's status, distinguishing between vehicles requiring immediate service and those deemed safe for continued operation. It promptly alerts maintenance teams about potential engine and transmission failures, brake issues, battery life concerns, tire conditions, axle problems, and steering irregularities. These alerts empower maintenance activities to be proactive in nature, preventing major breakdowns and minimizing unexpected downtime. When a vehicle arrives at the garage for inspection based on a predictive maintenance alert, it undergoes a thorough examination tailored to the specific type of alert. This meticulous approach ensures that any necessary repairs are promptly executed, maintaining the overall health and performance of the vehicle. In cases where no issues are found, the technician updates the planner accordingly, marking the vehicle as "no" and providing relevant comments in the remarks section before saving the details. These recorded details are then utilized by the machine learning model to continuously refine and enhance the accuracy of future failure predictions, ensuring the optimal maintenance of the fleet.
- BMW group** [27–30]: BMW Group effectively utilizes artificial AI across various sectors to enhance its operations. As a leading manufacturer of automobiles and motorcycles, BMW integrates AI into research and development, supply chain management, production, and after-sales services. AI plays a crucial role in BMW's production sector, enabling various processes such as automated image recognition, nameplate checks, dust particle analysis, and prevention of pseudo-defects. These AI-driven applications ensure real-time monitoring, stringent quality control, and quick identification of deviations from established standards. By harnessing AI technology, BMW optimizes production efficiency, reduces errors, and upholds superior quality standards. The automated image recognition system evaluates component images during production, comparing them to established standards, allowing for prompt corrective actions. AI-powered nameplate checks verify the correct placement of required parts, ensuring accurate assembly. Dust particle analysis helps prevent the misinterpretation of flaws, enhancing overall product quality. By implementing AI in these areas, BMW maintains a high level of precision and efficiency in its production processes. One notable application of AI at BMW is predictive maintenance on their production lines, a proactive approach facilitated by sensors, data analytics, and AI algorithms. This shift from traditional rule-based maintenance allows for the timely detection of potential system failures. By continuously monitoring equipment and status data, AI predicts and identifies maintenance needs before issues arise, enabling proactive component replacement and scheduled maintenance during planned production downtimes. This predictive approach optimizes repair processes, minimizes costs associated



with unscheduled downtime, and extends the service life of tools and systems. Moreover, by preventing system failures and optimizing maintenance schedules, BMW promotes resource efficiency and reduces waste in its production operations.



8

Figure 9: BMW Group – Ethics for AI⁸

- LG and AI solutions** [31, 32]: LG is using the power of AI in the appliance industry and promote sustainability. By integrating AI into their appliances, LG among other things improving daily tasks through predictive maintenance. One notable application of AI is LG's proactive customer service, which utilizes AI in smart appliance models. This feature detects and alerts users to potential problems before they escalate. For instance, it can identify issues like decreased cooling performance in refrigerators or reduced airflow in dryer vents. By notifying users of these issues early on, AI helps prevent appliance damage and prolongs their lifespan. Moreover, LG's AI technology offers solutions and recommendations to users based on the detected issues. It can provide quick fixes for minor problems that users can address independently or schedule appointments with service professionals for more complex repairs. Additionally, AI sends routine maintenance reminders, such as running specific cleaning cycles or replacing filters, ensuring optimal performance and efficiency.

⁸ <https://mediapool.bmwgroup.com/cache/P9/202010/P90403207/P90403207-seven-principles-for-ai-at-the-bmw-group-1755px.jpg>





Figure 10: LG Smart Home ThinQ⁹

3.2.3. Summary

Questar Auto Technologies, Infosys, BMW Group, and LG are harnessing the power of a AI and machine learning to enhance the efficiency of decision-making, inspection, and sorting in value recovery processes.

Questar and Infosys employ AI and sensor data to proactively detect potential malfunctions in vehicles, enabling predictive maintenance and reducing repair expenses. BMW Group integrates AI across various operations, spanning from production to after-sales services, leveraging it for predictive maintenance purposes as well. LG utilizes AI in its appliances, enabling the detection and notification of potential issues, thus preventing appliance damage and prolonging their lifespan.

Through the utilization of these advanced technologies, these companies optimize their maintenance practices, reduce costs, and foster sustainability within their respective industries.

There are several image processing-based inspection and sorting options available in the market. These solutions utilize computer vision techniques to detect and analyse defects in components, automate visual inspection tasks, and improve quality control processes in various industries. Some notable options include Maximo Visual Inspection by IBM, Kitov.ai Inspector, ZEISS Automated Defect Detection, AI Inspect by Mitutoyo, and Quality control with Visual Inspection AI by Google Cloud.

However, within the field of image processing, there are still numerous challenges and opportunities for further research and development. Some of these challenges include:

- Managing large-scale, high-dimensional, and heterogeneous data efficiently in terms of storage, processing, and analysis methods.
- Developing robust, accurate, and interpretable models that can handle issues such as noise, occlusion, illumination variation, and domain adaptation.
- Ensuring the privacy, security, and ethical considerations related to the data and models used in sensitive or critical applications.

⁹ https://www.lgnewsroom.com/wp-content/uploads/2022/08/LG-ThinQ-Smart-Home_01-scaled.jpg

- Evaluating the real-world performance, reliability, and impact of the models on practical problems and scenarios.

Considering these challenges, image processing remains a promising field for enhancing decision-making, inspection, and sorting processes across various domains. However, it requires careful design, implementation, and evaluation to ensure its effectiveness and suitability for specific problems.

Therefore, image processing and machine learning are two fields that have a lot of potential for improving the decision making, inspection and sorting processes in various domains. Though, they also require careful design, implementation, and evaluation to ensure their effectiveness and suitability for specific problems. However, specific examples of industrial application of image processing in Decision Making, Inspection and sorting could not be found.

3.3. Augmented Reality for Assembly and Sorting

In recent years AR has been applied productively in many industries and use cases. This is why the description focuses on representative examples for assembly and sorting, structured by the used AR technology. Applications for other tasks like remote support, inspection, maintenance are listed. AR-applications for marketing or consumers as users are not provided as the application area and usage context is too far out of focus from the DiCiM target applications.

3.3.1. Glasses-based Assembly Solutions

3.3.1.1 *Assembly in Automotive Industry: Teamviewer [33]*

WS System GmbH is a automotive supplier based in Stuhr, Germany. They offer its industrial customers services in the areas of component assembly and product packaging. WS System decided to improve its assembly processes with TeamViewer's frontline solution xMake. WS System needed a hands-free solution to optimize the assembly process, and a solution that would simplify the training of new employees and be easily scalable for other processes. WS System adapted and implemented the TeamViewer Frontline freehand solution xMake on two assembly lines and xMake was fully integrated into the company's IT landscape via a PLC interface. Each assembly step is now confirmed by external sensors such as scales, light sensors buttons or video object recognition, allowing the quality assurance process to begin during assembly. VUZIX smart glasses guide workers through assembly processes using a graphical user interface, with seamlessly integrated sensor-based step confirmation for hands-free work. The introduction of TeamViewer Frontline solutions has improved the performance of WS System's assembly and training processes. It has also improved process quality and reduced error rates. In addition to process speed and error rate, the was also able to improve ergonomics through hands-free operation of the smart glasses.

The following links showcase industrial applications of glasses-based AR, but for other applications than assembly, like inspection, remote support or maintenance:

- <https://www.ptc.com/en/-/media/files/pdfs/case-studies/fujitsu-leveraged-augmented-reality-case-study.pdf>
- <https://www.ptc.com/en/-/media/files/pdfs/case-studies/howden-vuforia-studio-case-study-feb-2019.pdf>
- <https://www.ptc.com//en/-/media/files/pdfs/case-studies/bid-group-ar-spotlight.pdf>
- <https://www.amaxperteye.com/xperteye-essential/>



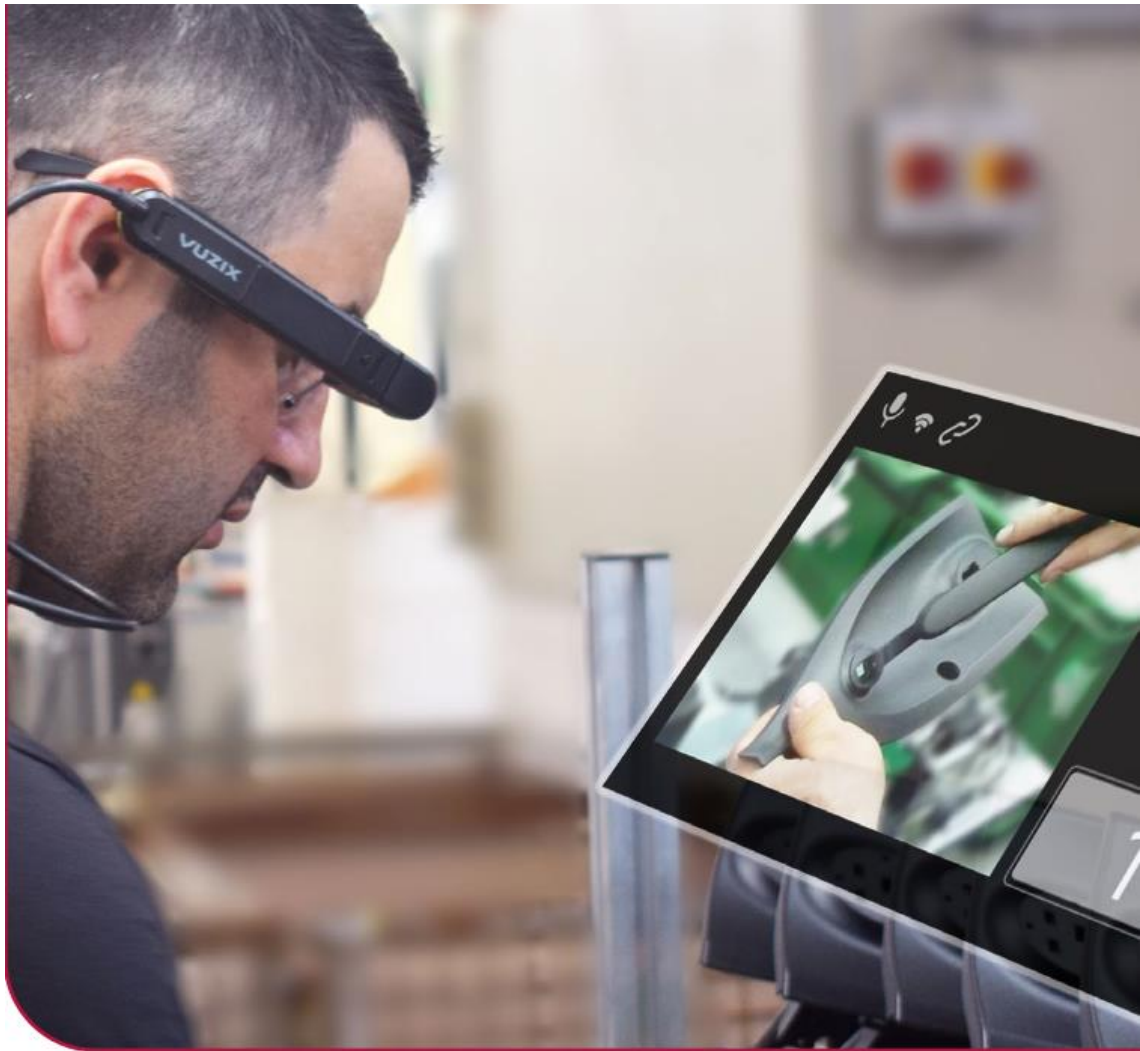


Figure 11: AR-Glasses for assembly of automotive parts by Teamviewer [33]

3.3.2. Projective-based Assembly Solutions

3.3.2.1 Assembly in Manufacturing Industry: LightGuide [34]

TNO, Bronkhorst High Tech, Omron and TE Connectivity have integrated an operator support system into a manual assembly workstation using LightGuide Systems AR projected work instructions. TNO has integrated LightGuide AR software into an operator support system at a flexible manual assembly workstation. This system projects work instructions which helps operators to perform assembly tasks. LightGuide projection allows the correct compartment to be illuminated and assembly instructions to be projected onto the product or work surface. Operators can quickly see which part to remove from which compartment and how to assemble it. Operators also receive direct feedback if an incorrect part is removed. Critical actions can be manually confirmed using virtual buttons projected onto the work surface. The system can be easily connected to external systems such as (3D) vision, cobots, PLCs and MES. Production data, such as assembly times and quality information, is captured at each step and written to a database for further analysis. TNO conducted measurements in three companies to determine the effectiveness and efficiency of this system compared to digital work instructions via monitors. The effects on the employees' workload and their experience with the projection

system were investigated. A total of 35 employees participated, and the results of this study are very promising: reduction of total cycle time by 57%; reduction of removal time by more than 70%; no errors when removing parts using LightGuide support (this error percentage was 8,000 ppm); no part placement errors using LightGuide instructions (this error percentage was 80,000 ppm for digital work instructions); compared to on-screen instructions, projected work instructions reduced workload for experienced operators by 25%.

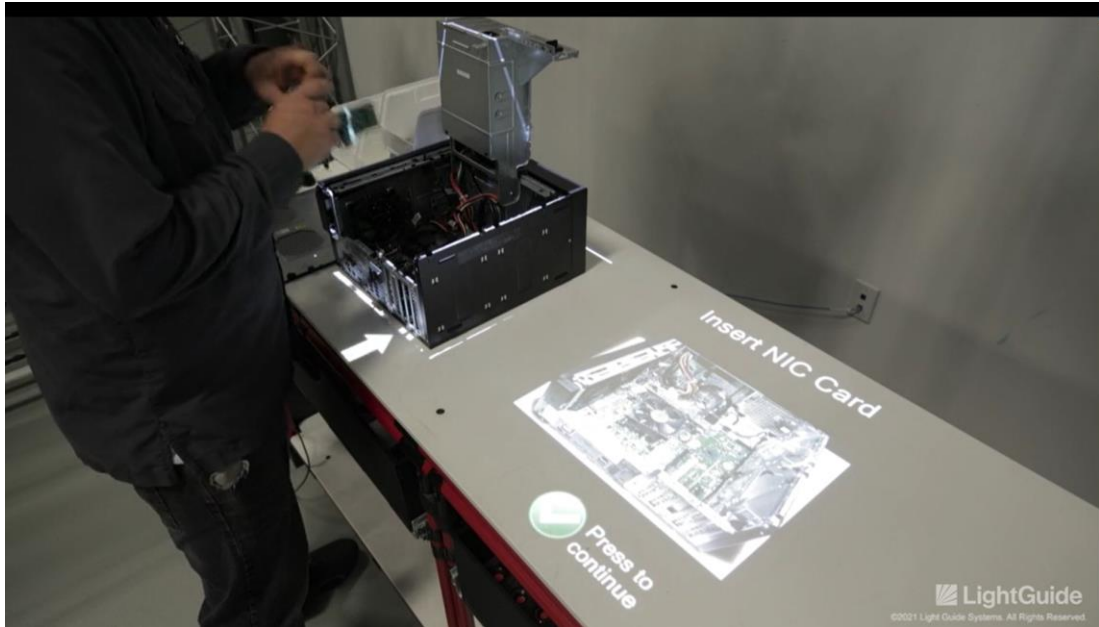


Figure 12: Projective AR Workstation by LightGuide Inc., USA¹⁰

3.3.2.2 Assembly in Aerospace Industry: DIOTA [35]

Before the robots start drilling and milling on the Rafale jet the operators must place various pins at specific positions to ensure that the wing has a good structure. This is a lengthy preparation process with the risk of risk of error due to the complexity of the task and the changing configuration from one operation to the next other. Rafale wing assembly requires sequential and complementary interventions by the robot and the human operator for staking, drilling and milling. For the robot to perform appropriate drilling and milling operations on the wing, operators first ensure that the aircraft structure is well secured to its frame without interfering with the robot's trajectory. To this end, pins of various sizes are placed at specific locations on the wing prior to any intervention by the robot. The configuration of the changes with each phase of the process. The variability of the pinning configuration is a source of complexity for the operators. In order to identify the localization and references of the pins for their installation on the wing, the operators constantly compare the real part with papers and draw marks with pins, tape, pieces of paper, etc. With this method, localization and reference errors are inevitable, even for the most experienced workers. Therefore, Dassault Aviation implemented a solution that would help operators avoid errors and make it easier to understand instructions. To guide operators, they decided to use DIOTA's Digital-Assisted operator solution for projecting instructions about pinning directly on the wing. In this way, the operators visualize directly on the wing the pinning configuration according to the process phase.

¹⁰ <https://www.lightguidesys.com/why-lightguide/>

The following links showcases other industrial applications of projector-based AR assembly support:

- <https://www.lightguidesys.com/resource-center/case-study/hydraulic-manufacturer-achieves-zero-defects-with-ar-work-instructions/>
- <https://arkite.com/case-studies/case-study-pcb-assembly-guidance-in-manufacturing/>
- <https://arkite.com/case-studies/barco-one-platform-for-all-digital-work-instructions/>
- <https://www.extend3d.com/en/infocenter/case-studies/>

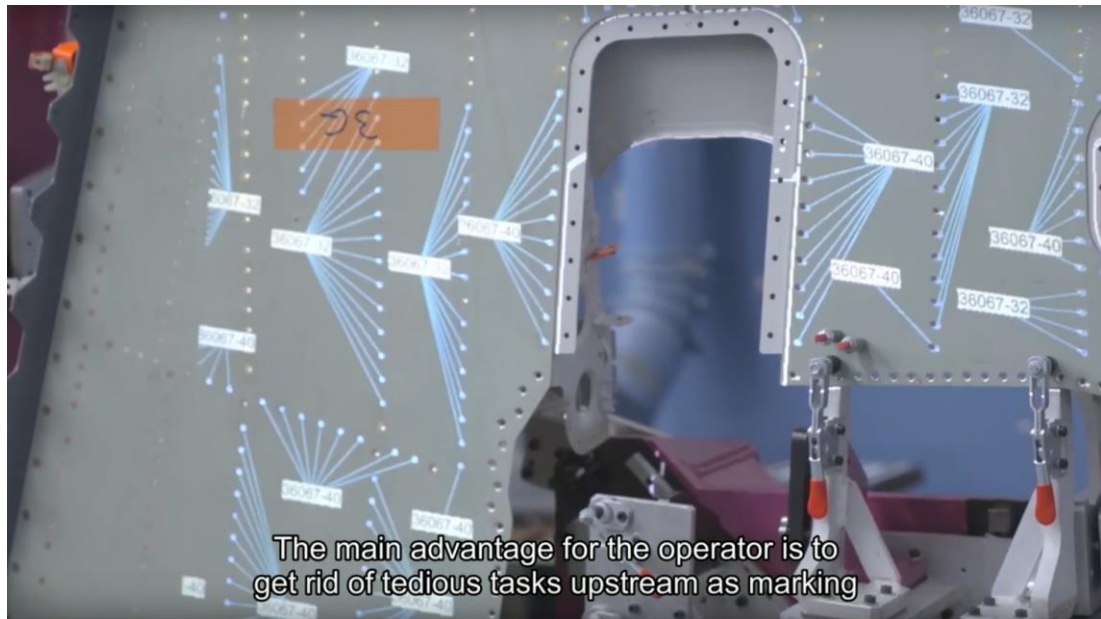


Figure 13: Projective AR for Aerospace by DIOTA¹¹

3.3.3. Tablet-Based Assembly Solutions

3.3.3.1 Assembly in Aerospace Industry: DIOTA [36]

The MRO (Maintenance, Repair and Operations) process of aeronautical equipment is carried out according to specific rules and not repetitive. It results in the application of work instructions that are highly dependent on the configuration of products arriving for repair. Each general overhaul, which is carried out every 10 years, is a special case. In this context, fully contextualized work instructions related to the configuration of the product to be repaired and the configuration to be delivered after the repair are necessary to ensure compliance with the airworthiness requirements and to guarantee the expected quality level. The operator's interpretation of these regulations represents a particularly important design work, even if they are experienced. For this reason, Safran Landing Systems has tried to simplify the use of the maintenance manuals and to reduce the mental burden of the workload by using DIOTAs AR solutions. The goal was to ensure the use of the work instructions for the particular configuration of the landing gear to be delivered. To achieve this, the operator is now guided at each step by AR instructions at each step. The overlay of 3D models for critical and complex

¹¹ <https://www.youtube.com/watch?v=jBZ8gZ36ZmY>

tasks allows for customization to match the operator's skill level through a simplified representation of assembly or inspection operations.

Several gains have been measured that contribute to the overall efficiency of MRO operations.

- Increased productivity: shorter inspection time, less rework, faster start-up.
- Improved overall quality and traceability of operations.
- Improved communication with the end customer through comprehensive and personalized reports.
- Ergonomics and working comfort, reduction of mental stress.



Figure 14: Tablet AR for Aerospace by DIOTA¹²

3.3.4. Glasses-based Sorting Solutions for Warehouses

3.3.4.1 Picking in Beverage Industry: Coca-Cola [37]

Coca-Cola Hellenic Bottling Company (HBC) is one of the largest bottlers for The Coca-Cola Company, with sales of more than two billion cases per year. At Coca-Cola HBC's distribution center in Thessaloniki, Greece, a team of 12 pickers collects orders for several products. Crates, shrink-wrapped bottles and cans are packed onto pallets for delivery trucks. Tablets on pallet jacks and radio frequency scanners are used for picking. To streamline its processes, Coca-Cola HBC chose to implement TeamViewer frontline solution xPick, which runs on rugged RealWear HMT-1 smart glasses. Pickers are presented with pick items, pick locations and quantities directly in their field of view. To confirm that they have picked at the correct location, they use the glasses to scan a QR code above the pallet with the smart glasses' camera. This leaves the picker's hands free for the task at hand. After two months of implementing the vision picking solution, picking performance increased by approximately six to eight percent, with the goal of achieving 100 percent accuracy.

¹² <https://www.youtube.com/watch?v=Dr8vkBBEzyY>



Figure 15: Head-Mounted-Displays for picking by Teamviewer [37]

3.3.4.2 Picking in Logistics Service: Picavi [38]

With more than 6,800 employees and 136 of its own network and logistics locations throughout Europe, Geis Global Logistics provides international logistics services. To handle order picking at the Gochsheim site, the company opted for Pick-by-Vision from Picavi in 2019. At the Gochsheim site, Geis works for the Intersport Group, one of the largest sporting goods retailers in Europe. Picavi provided its pick-by-vision solution with the Google Glass Enterprise 2 for the logistics company. The service team of the pick-by-vision expert took care of the integration of the technology. Pick-by-Vision is combined with the ProGlove Mark 2 back-of-hand scanner, which provides the desired flexibility for employees when picking from cardboard boxes. Picavi's Pick-by-Vision solution has greatly improved the quality and speed of picking. Productivity increased by up to 30 percent. The data glasses are also very popular with employees. They are worn during the entire working time.

The following links showcases other industrial applications of glasses-based AR sorting support:

- <https://www.opelpost.com/02/2017/smarte-helfer/>
- https://static.teamviewer.com/resources/2022/01/112021-1_TeamViewer_Case_Study_Siemens_xPick_EN-2.pdf
- <https://picavi.com/kunden/db-schenker/>
- <https://picavi.com/en/customers/krone/>
- <https://picavi.com/en/customers/leifheit/>
- <https://picavi.com/en/customers/fiege/>



Figure 16: Glasses-based AR by Picavi¹³

3.3.5. Summary

Section 4.3 looked at industrial applied AR solutions to support assembly and sorting processes. Assembly processes were supported using projective, tablet-based and glasses-based devices, with projective solutions being the most used. The industries where these assembly AR solutions were applied to covered ship building, aerospace, automotive and manufacturing. No applications for the white good industry targeted in DiCiM could be found. For sorting processes only glasses-based AR solutions could be found. These solutions were covering warehouse application for various industries, though not in particular for automotive spare parts and whitegoods, which is the target industry in DiCiM. All solutions had in common, that they provided instructions and only very few had a sort of validation process, that the task was carried out correctly. None of the solutions provided user specific instructions based on their individual skillset.

3.4. Data Management Platforms

3.4.1. Circular Information Management Platform

Open access digital platforms, in their true sense today, primarily exist within the research and publishing domains, offering open access to journals, articles, and other resources. However, in the industrial domain, finding a genuinely open access platform is challenging.

¹³<https://www.picavi.com/wp-content/uploads/2022/09/geis-logistik-google-glass-scaled-1-1024x683.jpg>



In the technology industry, "open access" might refer to open-source software, open standards, or interoperability among different systems and devices.

3.4.1.1 ***TecDoc automotive data management platform***

One of the most well-known partially open access platforms, TecDoc operates on a subscription-based model, where businesses pay a fee to access and use its database and services. The platform provides standardized, structured, and up-to-date data on millions of automotive parts, including specifications, cross-references, and fitment details. This data helps businesses find the right parts for specific vehicles, making it a valuable tool in the automotive aftermarket.

While TecDoc is not considered an open access platform in the sense of being freely accessible to the public, it does play a significant role in facilitating information sharing and collaboration within the automotive industry. By providing standardized data to various stakeholders, it helps improve efficiency and accuracy in the process of identifying and supplying automotive parts.

3.4.1.2 ***Siemens Mindsphere open digital platform***

Siemens Mindsphere which was recognized as a leader in *Open Digital Platforms for Cloud-centric Industrial IoT* due to its interoperability with industrial sensors, open API/Dec tools, data connectivity/aggregation from various sources/equipments, open data model and adherence to industrial open standards such as OPC UA (Open Platform Communications Unified Architecture). Current state of the art OEMs within circular value information management includes companies like heavy duty machinery maker CAT and electronics and printer maker Ricoh. These and similar global manufacturing enterprises have implemented processes to support a circular approach for selected parts, components, accessories or consumables for their main products, and take-back schemes for products and in some cases major components.

3.4.1.3 ***Caterpillar's Cat Reman program data management platform***

Caterpillar's Cat Reman program demonstrates how the company, a leader in the construction and mining equipment industry, has managed to take back millions of pounds of end-of-life material every year, reaching 140 million pounds in 2022 [3]. Compared to the manufacture of new parts, the Caterpillar remanufacturing process [39] uses 65-87% less greenhouse gas emissions, 65-87% less energy and 80-90% less raw materials.

The Remanufacturing Process and its relationship with the Product Lifecycle at Caterpillar are illustrated in Figure 17. The remanufacturing process begins when a component nears the end of life and the customer returns the used component, or core, to the dealer for credit. To be eligible for a (partial) credit, the used part needs to be fully assembled and complete, display no non-operational damage and not been visibly cracked, broken or welded.

Caterpillar's data management platform seamlessly integrates with various data sources throughout the remanufacturing process. It collects real-time data from sensors, monitoring equipment, and production systems, capturing valuable insights on equipment condition, usage patterns, and performance metrics. By consolidating this diverse data, Caterpillar gains a holistic view of their remanufacturing operations, enabling informed decision-making and process optimization. [40]



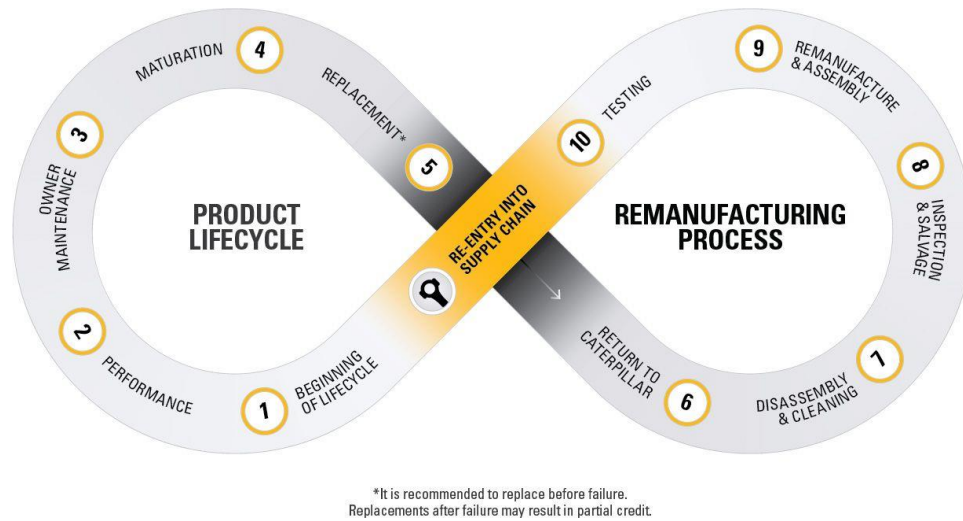


Figure 17: The Product Lifecycle and Remanufacturing Process at Caterpillar¹⁴

One of the key advantages of Caterpillar's data management platform is its ability to leverage predictive analytics. By analysing historical and real-time data, the platform employs sophisticated algorithms to identify potential failures and proactively schedule maintenance activities. This predictive maintenance approach reduces unexpected downtime, maximizes equipment uptime, and optimizes the allocation of resources, resulting in enhanced remanufacturing efficiency.

Efficient supply chain management is critical to successful remanufacturing operations. Caterpillar's data management platform integrates with their supply chain systems, providing real-time visibility into inventory levels, demand patterns, and logistics. By analysing this data, the platform enables accurate forecasting, streamlined inventory management, and optimized material flow, minimizing lead times and ensuring the availability of critical components for remanufacturing processes.

In the context of remanufacturing, compliance with environmental regulations and reporting requirements is paramount. Caterpillar's data management platform incorporates robust features for tracking and reporting relevant environmental metrics, such as energy consumption, waste generation, and emissions. This functionality ensures Caterpillar's adherence to sustainability targets and facilitates transparent reporting to regulatory bodies and stakeholders.

3.4.1.4 Ricoh remanufacturing process data management platform

Figure 18 illustrates the remanufacturing process of Ricoh and in various steps in the process data plays an important role.

Ricoh has established evaluation and diagnostics technologies to optimize quality, cost, and delivery in our remanufacturing business. Evaluation and diagnostics technologies are pivotal for generating earnings. Evaluation technology determines the reusability of used products

¹⁴ <https://s7d2.scene7.com/is/image/Caterpillar/CM20220728-cao04-39a2d>

based on assessments of their residual usability and other factors. It enables Ricoh to cut transportation costs by shipping only products that can be remanufactured from collection sites across Japan to the Ricoh Eco Business Development Center. Diagnostic technology assesses the conditions of prospectively reusable products. Products are categorized in different conditions, putting them on reclamation lines by level to streamline production. [41]



Figure 18: Remanufacturing process at Ricoh¹⁵

Ricoh’s Comet Circle, is a system that outlines the company's involvement in product lifecycles and those of third-party entities. The Comet Circle is powered by the Ricoh Asset Cascade, which is supported by a capable Enterprise Resource Planning (ERP) tool. The Asset Cascade assists on-site teams in making informed business decisions by identifying the best approach for reclaiming hardware, consumables, and parts to bring them back into the Ricoh system. This process is crucial for the success of the leasing model and the concept of 'selling a printed page'. Through tracking and usage measurement, every component is closely monitored, providing detailed insights that accurately determine the retained value of individual parts. [42]

Common for Caterpillar and Ricoh are the focus on finding profitable business models, integrate circularity into existing business processes as sales, service and repair, rental and supporting processes or business units. End customers wishing to benefit from refurbished components or reused products can seamlessly use normal contact points and solutions, to achieve the same thing but with used parts or products. Circular value information management solutions span over various systems, process and organizational units.

Common for these enterprises is also the size of these companies and the budgets they have at hand for investing in circular value information management solutions. It seems very few smaller manufacturers have clear focus on circularity, which to some extent also is verified by surveying Signifikant’s existing customers.

¹⁵https://www.ricoh.com/-/Media/Ricoh/Sites/com/sustainability/environment/circular_economy/initiative_recycle/img/initiative_recycle_img_05.png



Researching vendors within circular value information management solutions, there are no obvious product vendors of such platforms. Rather it is many pieces to build a full solution; ERP (Enterprise Resource Planning) processes, logistics planning, parts optimization, pricing software, service planning tools etc. Creating circular value information management solutions involves integrating processes over several such systems. Typically, standards as ANSI RIC001.1-2016 are used for terms and definitions for the business processes. ANSI RIC001.1-2016 defines processes and terms on a high level to make it clear in which way the remanufacturing process and differentiate remanufacturing from other practices

In our market research we have concluded that circular value information management solutions are tailormade for the major enterprises that are successful.

Direction of a more standardized circular value information management solution will need to create the needed business models to support reverse logistics of used parts, components or products, the integration into remanufacturing in needed cases, and into the sales and delivery process for offering alternatives to end users.

3.4.2. Data Platforms for Storing and Analysing large amounts of Data

The previous subsections have presented relevant industrial applications of IoT devices or IoT platforms that allow for the data acquisition from a big variety of assets and environment. These devices generate vast amounts of data that can be analysed to extract valuable insights, improve decision-making processes, and create new business opportunities. However, managing, processing, and extracting value from such large amounts of data can be a challenging task. Therefore, combining IoT devices with a well-designed data architecture can help organisations overcome these challenges and effectively manage, process, and extract value from big data generated by IoT devices. This combination can unlock the full potential of IoT technology, providing organisations with a competitive edge and enabling them to make data-driven decisions that can improve their business outcomes. Below, the big-player data platforms in the market will be briefly analysed.

3.4.2.1 Google Cloud with BigQuery warehouses [43]

Google Cloud Platform (GCP) is a cloud computing platform that provides a variety of services for storing, processing, and analysing data. One of the key services offered by GCP is BigQuery, a fully-managed, cloud-native data warehouse that enables users to store and analyse large datasets using SQL-(Structured Query Language)-like queries.

BigQuery allows users to quickly and easily analyse massive amounts of data without having to worry about the underlying infrastructure. The service automatically scales to handle petabytes of data, and supports real-time data ingestion for streaming data.

In addition to the basic BigQuery service, GCP also offers BigQuery data warehouses, which are optimized for handling complex queries and large data sets. These warehouses allow users to segment data by project, department, or use case, and provide separate compute and storage resources for each warehouse. This enables users to scale their queries and storage independently, depending on their specific needs.

BigQuery data warehouses also provide additional security and access control features, allowing users to control who has access to their data, and how it is accessed. This can be particularly useful for organizations that need to comply with strict security and privacy regulations.



3.4.2.2 **Microsoft Azure with Apache technologies (Hadoop, Spark) [44–47]**

Azure is Microsoft’s cloud computing platform, widely used across the industry as a complete Data Platform offering a variety of services. One of the key capacities of Azure is support for Apache technologies such as Hadoop and Spark.

Apache Hadoop is an open-source big data platform that enables distributed processing of large data sets across clusters of computers. With Azure, users can easily deploy and manage Hadoop clusters, either on-premises or in the cloud. This allows organizations to scale their data processing capabilities on demand, without having to invest in additional hardware.

Apache Spark is an open-source data processing engine that can be used for large-scale data processing, machine learning, and graph processing. With Azure, users can also deploy and manage Spark clusters, either on-premises or in the cloud. This allows organizations to take advantage of Spark's powerful data processing capabilities, without having to manage the underlying infrastructure.

In addition to Hadoop and Spark, Azure also supports a wide range of other Apache technologies, such as Kafka, Storm, and Cassandra. This makes it easy for organizations to integrate their existing Apache-based data processing workflows with Azure, or to build new workflows using these technologies.

3.4.2.3 **Amazon Web Services [48]**

Amazon Web Services (AWS) is a cloud computing platform that provides a range of services for storing, processing, and analysing data. Its range of services and tools, along with its flexibility and scalability, make it a popular choice for organizations of all sizes and industries.

AWS provides several storage options, including object storage (Amazon S3), block storage (Amazon EBS), and file storage (Amazon EFS). These storage options can be used to store both structured and unstructured data, and can be accessed using a variety of APIs and protocols.

AWS also offers a range of services for processing and analysing data, including:

- Amazon EMR - A managed service that enables users to run big data frameworks like Apache Hadoop, Spark, and Presto on AWS.
- Amazon Athena - A serverless, interactive query service that allows users to analyse data in Amazon S3 using standard SQL.
- Amazon Redshift - A fully-managed data warehouse that enables users to store and analyse large amounts of data.
- AWS Glue - A fully-managed extract, transform, and load service that makes it easy to move data between different data stores and applications.
- Amazon Kinesis - A platform for streaming and processing real-time data at scale.

AWS also offers a range of tools and services for data visualization and business intelligence, such as Amazon QuickSight and Amazon Kinesis Data Analytics.

3.4.2.4 **IBM Cloud [49]**

IBM Cloud is a cloud computing platform popular for its security and compliance features, making it a popular choice for organizations in regulated industries or those with strict security requirements.



IBM Cloud provides several storage options, including object storage (IBM Cloud Object Storage), block storage (IBM Cloud Block Storage), and file storage (IBM Cloud File Storage). Both structured and unstructured data are supported through different APIs and protocols.

IBM Cloud also provides a wide array of data analysis tools, including:

- IBM Cloud Pak for Data [50] - An integrated platform that provides tools for data management, data science, and AI/ML modelling.
- IBM Watson Studio [51]- A cloud-based platform that provides tools for data preparation, model development, and deployment of machine learning models.
- IBM Cloud Data Engine [52] - A serverless, interactive query service that allows users to analyse data stored in IBM Cloud Object Storage using standard SQL.
- IBM Cloudant [53] - A fully-managed NoSQL database service that can handle large-scale workloads and support high-velocity data ingestion.
- IBM Streaming Analytics [54] - A platform for streaming and processing real-time data at scale.

Tools and services for data visualization and business intelligence are also included, such as Cognos Analytics and Watson Discovery.

3.4.2.5 ***Snowflake [55]***

Snowflake is a cloud-based data platform that provides a fully-managed service for storing, processing, and analysing data. Snowflake is designed to handle large-scale data workloads and its unique architecture and separation of storage and compute resources make it a popular choice for organizations that need to process large volumes of data quickly and efficiently.

As we mentioned, one of the key features of Snowflake is its ability to separate storage and compute resources, which allows users to scale both sides independently. This means that users can add or remove compute resources as needed to handle fluctuations in data processing demands, without having to worry about the underlying storage infrastructure.

Snowflake also provides a unique architecture that separates data processing into three layers: storage, compute, and services. This allows for high levels of concurrency and scalability, as well as efficient resource utilization.

Snowflake provides several storage options, including object storage (S3, Azure Blob Storage, and Google Cloud Storage), and supports a variety of data formats, including JSON, Parquet, and CSV. Snowflake also provides a range of services for processing and analysing data, including SQL-based queries, machine learning, and data visualization.

In addition to its scalability and flexibility, Snowflake is also known for its security features. Snowflake is built on a foundation of advanced security measures, including end-to-end encryption, data protection policies, and multi-factor authentication.

3.4.2.6 ***Tableau [56]***

Tableau is a data visualization and business intelligence platform that helps people see and understand their data. It allows users to create interactive dashboards, reports, and charts that can be used to gain insights and make data-driven decisions.

One of the key features of Tableau is its ability to connect to a wide range of data sources, including spreadsheets, databases, and cloud services. This makes it easy for users to bring in their data from multiple sources and create a unified view of it.



Once the data is connected, users can use Tableau's drag-and-drop interface to create visualizations and dashboards without needing to write any code. Tableau offers a variety of visualization options, including bar charts, line charts, scatter plots, and heat maps, and users can customize these visualizations to meet their specific needs.

Tableau also offers advanced analytics capabilities, including forecasting, clustering, and trend analysis, which can help users gain deeper insights into their data.

In addition to its data visualization and analytics capabilities, Tableau also offers collaboration features that allow users to share their dashboards and visualizations with others. Users can also collaborate on projects and share insights in real-time.

3.4.2.7 **Databricks [57]**

Databricks is a cloud-based data platform that provides a unified environment for data engineering, data science, and business analytics. Databricks is built on Apache Spark and offers a range of features and tools for managing and analysing large-scale data workloads.

One of the key features of Databricks is its collaborative environment, which allows users to work together on data projects in real-time. Databricks provides a notebook interface for writing and executing code, and users can work together on notebooks and share their work with others. This makes it easy for data engineers, data scientists, and business analysts to collaborate on data projects and share insights.

Databricks also provides a range of tools and services for managing data workloads, including data preparation, data exploration, and data processing. Users can work with a variety of data sources, including structured and unstructured data, and can use Databricks' machine learning capabilities to build and deploy machine learning models.

Another key feature of Databricks is its scalability. Databricks can handle large-scale data workloads and can automatically scale resources up or down based on demand. This makes it easy for organizations to handle fluctuations in data processing demands.

3.4.2.8 **Teradata [58]**

Teradata is a data platform that offers a suite of tools and services for managing and analysing large-scale data workloads. It is designed to handle data warehousing and analytics workloads for organizations across various industries and sizes.

Teradata's key strength is its ability to scale resources up or down based on demand, enabling organizations to handle changes in data processing requirements without worrying about underlying infrastructure. It provides data warehousing capabilities such as data integration, quality management, and management of large volumes of structured data, allowing for data analysis through SQL-based queries.

Apart from its data warehousing capabilities, Teradata also offers advanced analytics features including machine learning and predictive analytics. This enables organizations to gain deeper insights into their data, facilitating informed decision-making.

3.4.3. **Summary**

Data is one of the key components for an efficient remanufacturing process. You will need to store information on the original product, its components, its usage during the lifetime and the target products. In the industrial domain, finding a genuinely open access platform is challenging. In the technology industry, "open access" might refer to open-source software,



open standards, or interoperability among different systems and devices, such as what Siemens and Techdoc have today. While Caterpillar and Ricoh have adapted their data management platform to fit the needs for the remanufacturing processes. However, an open access platform such as we intend to build in DiCiM does not exist for the white good industry and automotive spare parts industry.

When it comes to data storage, a thorough review of the big player data platforms in the market has been presented. It is clear that there are various data architectures and best practices available that can help organisations effectively manage, process, and extract value from big data. The DiCiM partners recognise the importance of leveraging these best practices to ensure the successful implementation of its IoT network and data architecture. By following the best practices learnt from this study, the DiCiM project can build a robust and scalable data architecture that will enable it to effectively manage the big amounts of data generated by its IoT devices. This will not only help our end users improve their operational efficiency but also enable them to extract valuable insights from their data, providing a competitive edge in the marketplace. Ultimately, DiCiM's commitment to utilising best practices in data architecture will ensure that it remains at the forefront of innovation and technology in the IoT landscape.



4. Consortia's current State of Key Technology Features for Value Recovery

This section describes the existing knowledge inside the consortia regarding the key technologies used in DiCiM to facilitate value recovery operations for the white goods, printers and automotive spare parts industries. Each subsection is dedicated to one key technology: IoT for tracing and tracking, machine learning and image processing, augmented reality, data management platforms. The examples are representing exemplarily solution from linear and circular production that are relevant for the developments in DiCiM.

4.1. IoT for Tracing, Tracking and Condition Monitoring

4.1.1. ULFS

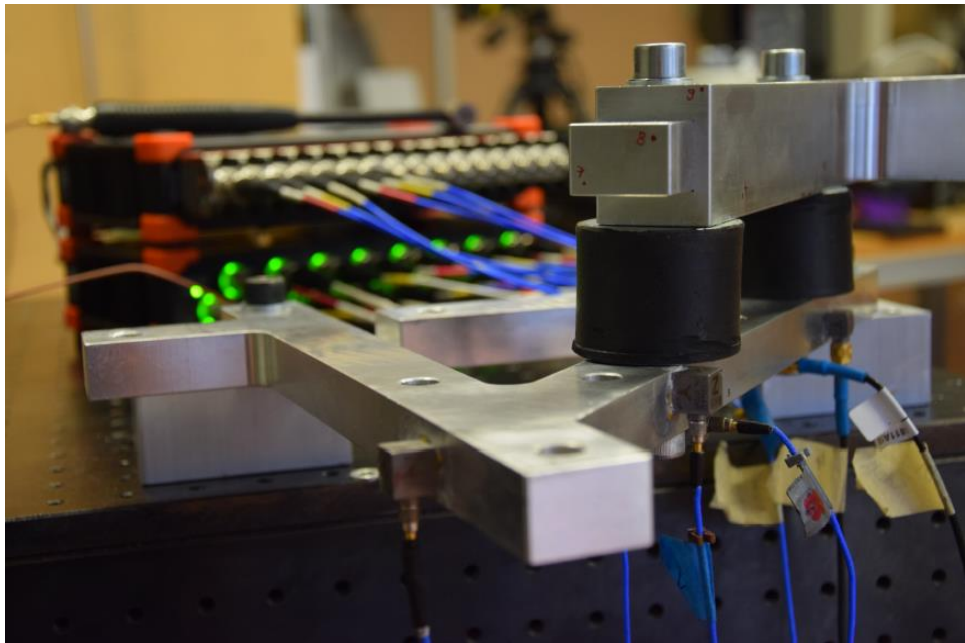


Figure 19: Experimental setup for validating condition monitoring methods using TPA.

Advanced signal processing and structural analysis techniques:

Recently, ULFS has made significant progress in developing algorithms for tracking and tracing sensor data and their signal processing. In particular, our research efforts have led to the creation of an open-source Python library called pyFBS, which includes numerous solutions for this domain. This library has been instrumental in advancing the field, and we will now explore two notable applications relevant to our project.

The first application involves the use of acquired sensor data to detect structural changes. Structural changes can be detected by implementing modal identification algorithms or sub-structuring techniques. By analysing the sensor data, it is possible to accurately identify modifications or changes in the structural integrity of the monitored system.

In addition, the open-source code includes transfer path analysis (TPA) methods that enable real-time condition monitoring and identification of problematic transmission paths for noise



and vibration. This includes detecting changes that occur within these paths during operation. By employing TPA, it is possible to identify the major sources of noise and vibration within a system and develop effective remediation strategies.

4.1.2. Gorenje

By leveraging IoT, Gorenje has a vision to enable users to monitor and control their appliances remotely, providing a seamless and connected experience.

In terms of status and error monitoring, Gorenje appliances are equipped with sensors and connectivity capabilities that enable near-real-time data collection. These sensors can monitor various parameters of the appliance's operation, such as water temperature, spin speed, and detergent levels. This data can then be transmitted to ConnectLife a cloud system which connects everything - from major to small domestic devices from all Hisense Group Brands – Hisense, Gorenje, ASKO, ATAG, and Pelgrim. It connects users to their homes and provide them with a new and unique smart home experience. The user can access the appliance data on the cloud via Web application or via Mobile application. The Web application is intended for the users who also have access to the service menu on the appliance. In the web application are all the data about the machine. It provides the overall status of the device, product information and possibility to call a repair service. Additionally, the statistics of most used programs will also be gathered in the web application. The Mobile application is intended to be used by end customers at home, for small businesses users and in common laundry rooms. Application enables users to connect through QR code to the appliance. This than allows users to access the status of their appliances from anywhere at any time and remotely monitor the operations of the appliances.



Figure 20: ConnectLife platform

Moreover, Gorenje's connectable appliances possess advanced error detection mechanisms. These mechanisms can identify and diagnose potential issues or malfunctions, such as water leaks, motor failures, or excessive vibrations. When an error is detected, the appliance can automatically notify the user, either through a mobile notification or an alert on the appliance's display. This proactive approach allows users address problems promptly, minimizing downtime and potentially reducing the need for costly repairs.

Overall, Gorenje's implementation of IoT and status/error monitoring in their washing machines is a way to increased convenience, improved user experience, and timely identification of issues, leading to enhanced efficiency and customer satisfaction.

4.1.3. Lexmark

4.1.3.1 Streamline Processes

Today’s businesses are vaster in size and scope than ever before, and are constantly faced with the daunting task of managing information from two connected, but different sources: print and digital. At Lexmark, we know that it’s when these two sources collide and intersect that information errors, security breaches and process delays often occur. That’s why our solutions were designed to bring paper and digital information together and streamline processes, regardless of source. Our solutions resolve print management inefficiencies, address security breaches and threats, and enhance business process automation to tackle your unique information challenges.

4.1.3.2 Cloud Fleet Management

Lexmark Cloud Fleet Management makes it possible for service providers to remotely monitor, manage and secure your print environment—all without ever visiting on site. Fewer visits means less fuel for service fleets, resulting in overall energy savings.



Figure 21: Empower workplace flexibility with an advanced connectivity suite

4.1.3.3 In-Store Capture

Lexmark In-Store Capture’s [59] technology designed for retailers and Lexmark’s smart MFP platform streamlines paper-based processes, driving greater efficiency and improving security while reducing energy usage.

The foundation of our MPS solution is the Lexmark Global IoT System, an interconnected printing and scanning ecosystem that leverages predictive support to increase uptime and cloud-native services to eliminate IT infrastructure.

Lexmark’s Supply Chain Document Optimization solution can support and simplify your digital transformation initiatives. Whether your goal is to embrace industry 4.0 or gain greater visibility

D2.1 Identify the key technology features for support solutions and define their current baseline in your logistic processes, Supply Chain Document Optimization reduces manual, paper-based tasks that delay logistics operations.



16

Figure 22: Omnichannel efficiency for the retail supply chain¹⁶

Lexmark’s Retail Publishing Solution handles all aspects of the signage process—from design and distribution to management and measurement. Publish shelf-edge signs, labels, fact tags, digital signs, electronic shelf labels (ESLs) and more, all from a single, easy-to-use platform. Most importantly, you can reduce installation burden on associates so they have more time to focus on customers.



17

Figure 23: A complete signage platform for greater sales lift¹⁷

4.1.3.4 Optra IoT Platform

With Optra IoT Platform [60], you can harness the power of the IoT to operationalize data from your connected devices and grow your business into an intelligent enterprise. Using this platform, Lexmark has achieved 70% of support issues resolved remotely, reducing the need for services to go on-site. When issues are resolved remotely, it reduces onsite service visits which reduces service vehicle fuel consumption.

¹⁶<https://www.lexmark.com/content/dam/lexmark/images/custom-images/y2017/supply-chain-optimization-for-retail.jpg>

¹⁷<https://www.lexmark.com/content/dam/lexmark/images/vthumbnail/y2020/retail-signage-1238810399-365x245.jpg>



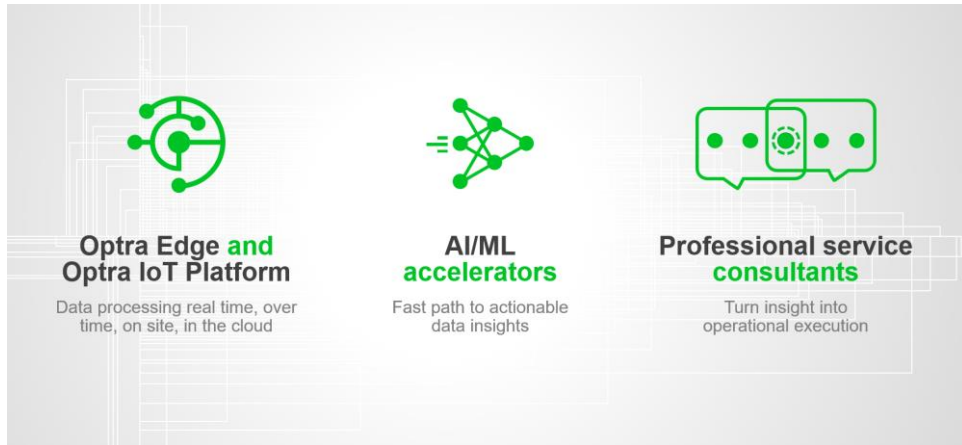


Figure 24: The perfect pairing of edge and cloud for fast results

4.1.3.5 Optra Edge

Optra Edge [61] executes AI applications closer to the source at the point of need, providing powerful local computation ability without the cloud, reducing or eliminating travel time for data processing, improving energy and resource management, and preventing large machine downtime and service interruptions for increased productivity.



Figure 25: Edge computing technology that executes AI applications at the point of need to drive productivity, cost savings and competitive advantage



4.1.3.6 RETURN & RECYCLE

Lexmark continuously seeks new ways to reduce its footprint. While making great strides in waste reduction at our global manufacturing facilities, Lexmark also provides an opportunity for our customers to reduce their waste and increase the number of Lexmark products that are reused and recycled. By incorporating Life Cycle Assessment results in our product design process, we develop sustainable products that combine high standards of performance, efficiency and environmental stewardship through each life cycle stage. At the end of product life, Lexmark recovers components and parts to reuse or recycle via our customer return methods: the Lexmark Cartridge Collection Program (LCCP) [62] and the Lexmark Equipment Collection Program (LECP) [63].

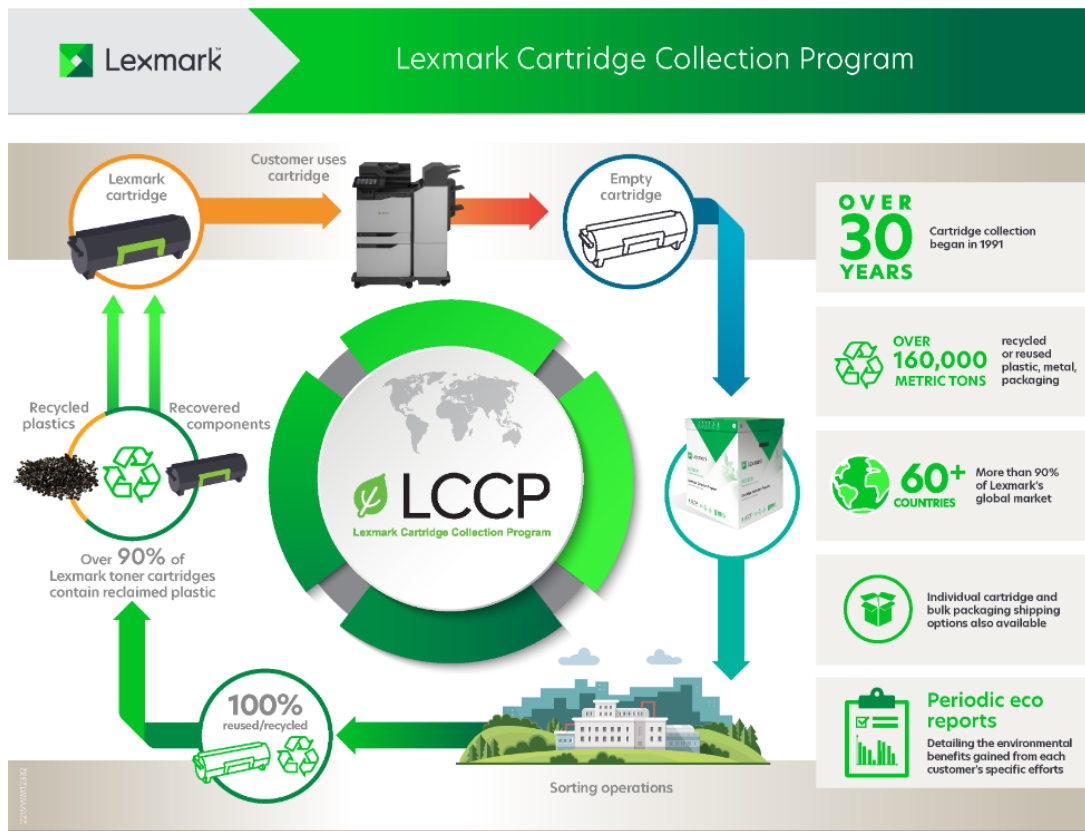


Figure 26: Lexmark Cartridge Collection Program

4.1.4. C-ECO

C-ECO is inspecting, evaluating and sorting used parts from automotive industry on behalf of its customers which are producing companies intending to remanufacture the products or dealers who intend to return the used products and to receive back a prepaid incentive matching to a prior sale of a matching product in the past. This service is offered globally in dedicated so called inspection-centres. Usually, these used parts are not traceable nor trackable as they are not digitally connected in any way after they are dismantled from the vehicles. To meet the described challenge, every part which enters C-ECO's global network is labelled with a barcode or QR-code which is printed in the inspection-centres. This code is referencing the inspection of this unique used product and connects it with all data collected in C-ECO's systems. This is involving the identified type and version of the used product, its status compared to defined



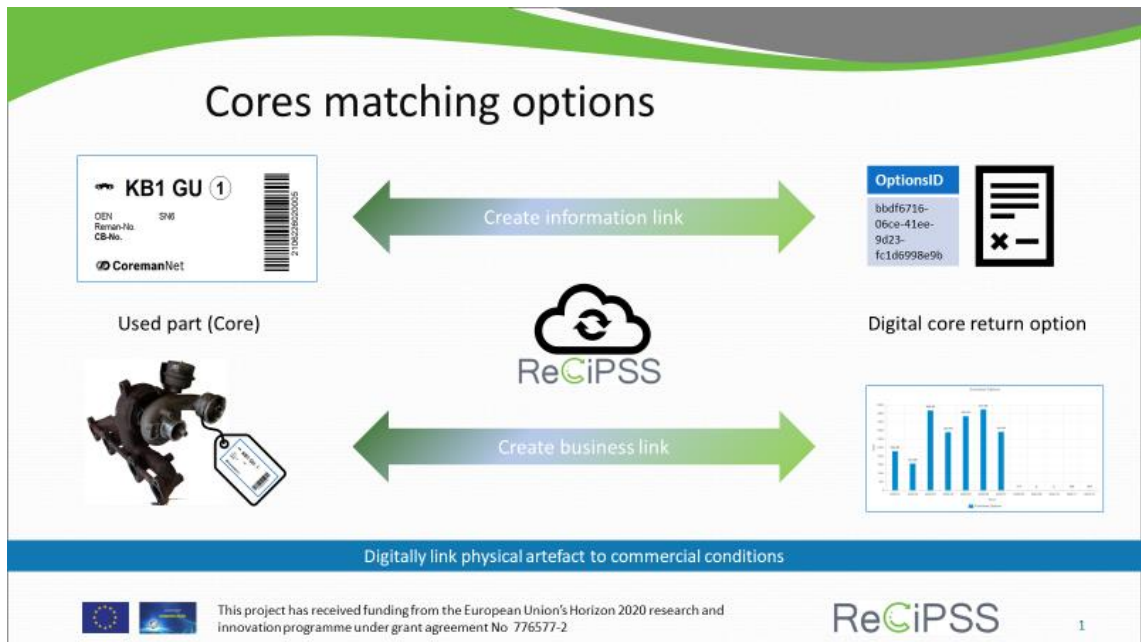
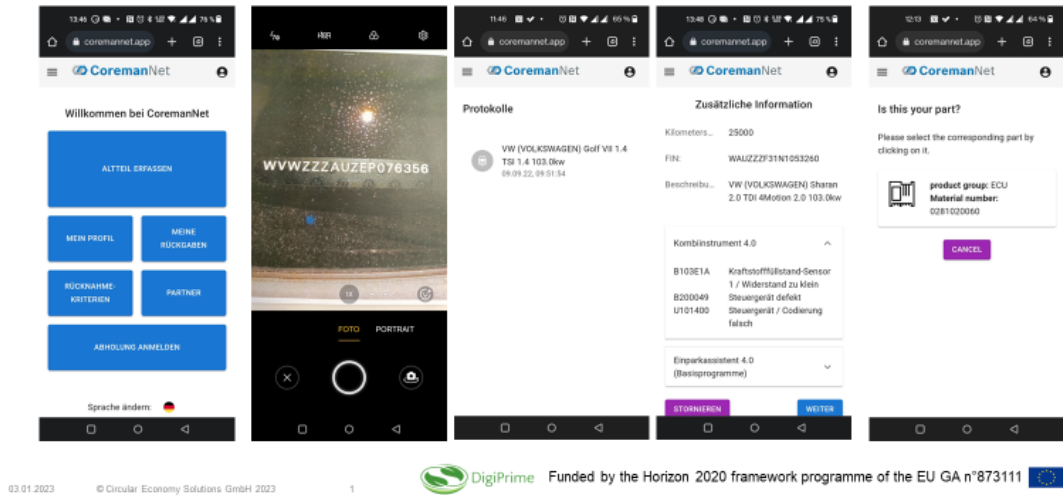


Figure 27: Digitally link physical artefacts to commercial data

In H2020-project DigiPrime (www.digiprime.eu), C-ECO was developing a mobile application which should connect the used parts already in the automotive workshops with data originating from on-board-diagnosis of the vehicle right after dismantling it. Here the challenges are that connection to the vehicle and its data will be lost when part is dismantled and returned and that in general no printing of labels to support reverse-logistic is supported on mobile devices. In order to link diagnostic data from the vehicle to the used product, OCR-technology is used to match the vehicle identification number and link it to asynchronous transmitted diagnostic-data in C-ECO's cloud platform. This allows tracing back technical information of the products last usage environment to the used products.

CoremanNet App: Check-in and link to data



03.01.2023 © Circular Economy Solutions GmbH 2023

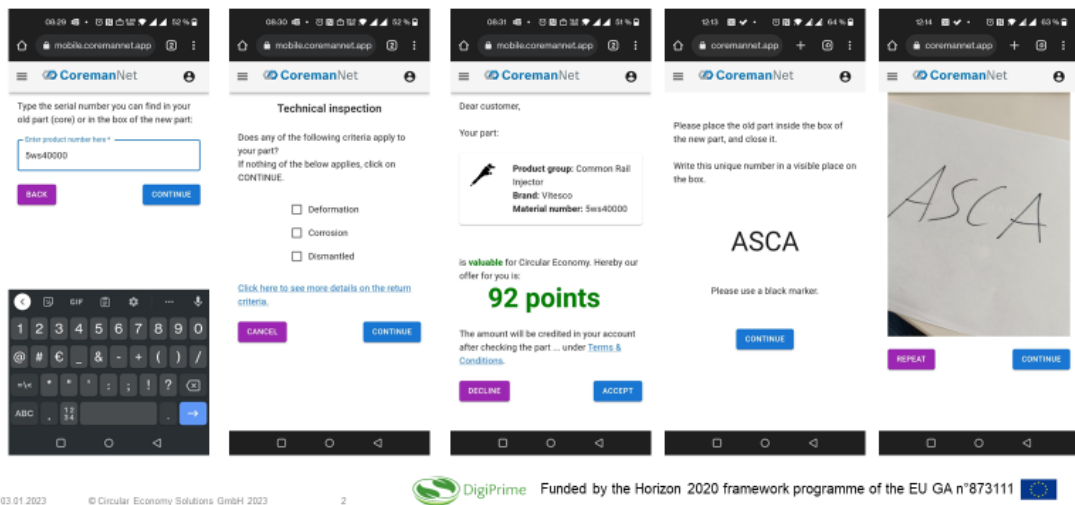


Funded by the Horizon 2020 framework programme of the EU GA n°873111

Figure 28: OCR used on mobile device to link diagnostic data to used products

To support tracking of the used parts from the workshops, C-ECO creates an alpha-numerical code in the mobile app, which the worker can put in hand-writing on the packaging of the returned product before dispatch. This code is then read in via OCR-technology to verify it is readable and to be substituted by a printed label as soon as the product is received in one of C-ECO's inspection centres.

CoremanNet App: Evaluation and marking



03.01.2023 © Circular Economy Solutions GmbH 2023



Funded by the Horizon 2020 framework programme of the EU GA n°873111

Figure 29: OCR used on mobile device to mark used products for tracking by handwriting

4.1.5. Arçelik

Arçelik offers a diverse and innovative product range that caters to various needs. From intercommunicating smart home systems to environmentally friendly solutions, our goal is to



create a more connected world. Arçelik's ecosystem provides users with practical and innovative features, including remote controls, software updates, program downloads, and instant notifications for connected appliances.

The **HomeWhiz mobile application** is designed to make controlling and monitoring smart home devices effortless from anywhere. It simplifies the user experience by providing accessible smart solutions through a single interface. Customers can download individual programs based on their specific needs.

Arçelik's collaborations involve working with Amazon DRS and Finish 365. Arçelik is developing a smart order feature for HomeWhiz that determines the detergent purchasing cycle, leading to energy and water savings by reducing unnecessary consumption and offering smart assistance for technical issues.

Energy management is crucial, especially for devices. HomeWhiz provides an eco-friendly solution by collecting data and offering smart suggestions to users for more efficient energy consumption.

To ensure responsible energy usage, Arçelik designed a fully automated, energy-saving system for smart home appliances and white goods via HomeWhiz. By collecting information and user habit data, HomeWhiz can make intelligent decisions, such as automatically turning off an air conditioner when a window is opened or switching off smart bulbs when no one is at home. The application also allows users to monitor and control ambient temperature and humidity remotely. [64]

Arçelik's connectivity features include a **Power Cut Alert**, which informs customers when there is an electrical outage and when the refrigerator's communication is disrupted. Arçelik also provides customers with useful tips and tricks, such as information on energy consumption due to frequent door opening, troubleshooting for error codes, and food placement guidance for optimal refrigerator usage.



Figure 30: Screenshots from HomeWhiz mobile application²⁷

¹⁸ https://www.arcelikglobal.com/media/3529/homewhiz_ease_screen.jpg

4.2. Image Processing and Machine Learning for Decision Making, Inspection and sorting

Image processing and machine learning algorithms can be used simultaneously, generating a perfect synergy in order to develop inspection systems. The process involves the analysis of images of a product or material for the defects or anomalies detection; and then using machine learning algorithms to identify and classify the different kinds of defects.

These are the general steps when we are using image processing and machine learning for inspection:

1. Image acquisition: Capture images of the product or material being inspected. This can be done using different kinds of cameras.
2. Image pre-processing: The images are pre-processed to improve quality. This can include noise removal, brightness and contrast adjustment and scaling the image size scaling.
3. Feature extraction: Extract features or characteristics from the image that are relevant to the inspection task. These can include: colour, texture, shape...
4. Defect detection: Using machine learning algorithms, the system is trained to detect defects or anomalies in the images. This is done by comparing the features of the image to those of known defects.
5. Defect classification: Once a defect is located, the system can use machine learning algorithms to classify it based on the type of defect.

4.2.1. IRIS

IRIS have participated in several European projects in which all or most of the referred topics have been tackled. In SUPREME, a project that aimed to optimize powder metallurgy processes IRIS studied the case of using thermal cameras and machine learning to reduce energy consumption in metallurgic processes.



Figure 31: Thermal camera image processing

Another European project that involved image processing, machine learning inspection and identification was MULTICYCLE (www.multicycle-project.eu), it aimed to introduce an advanced

and sustainable recycling process as well as the value chains for plastic-based multi-materials. IRIS developed a near-infrared camera-based system with its classification software to sort multiple plastic materials from waste streams.

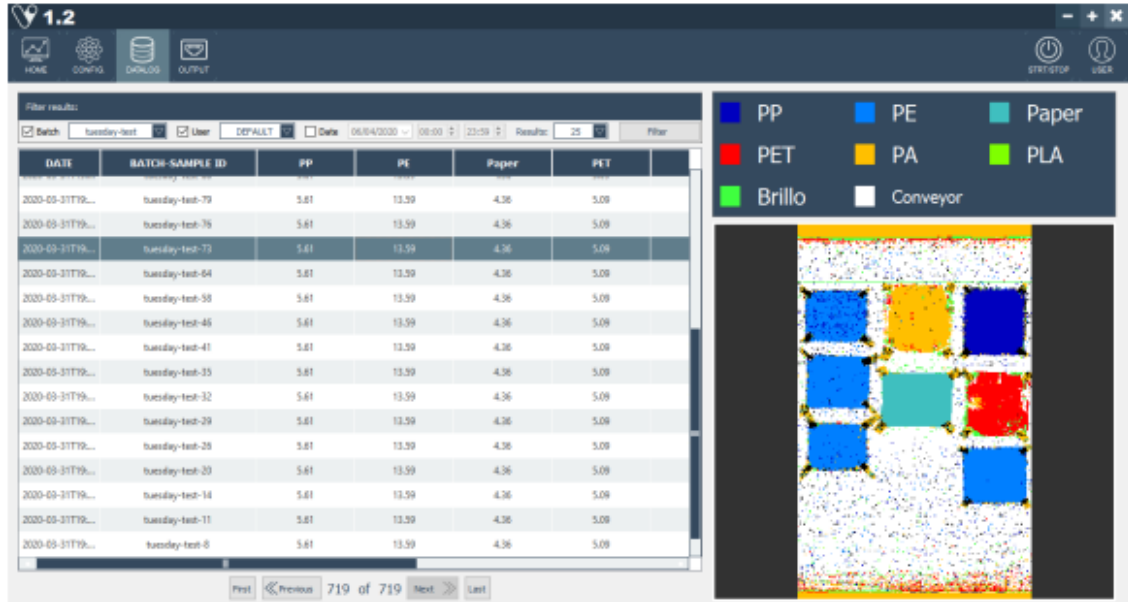


Figure 32: IRIS acquisition and prediction software for NIR HSI images

IRIS Technology develops turnkey industrial machine vision systems for a wide range of applications. Visum DeepSight™ combines machine learning models and algorithms with a lighting and optical system. The deep learning technology and the machine vision system of Visum DeepSight™, unlike deterministic algorithms, allows to obtain results where traditional machine vision systems are not capable. Has many applications in industry, such as the detection of foreign bodies or defective units in food, packaging control, labeling, intolerable color differences in different products, objective quantification of faults or defects in order to calculate a fair price for the various quality grades of a product.

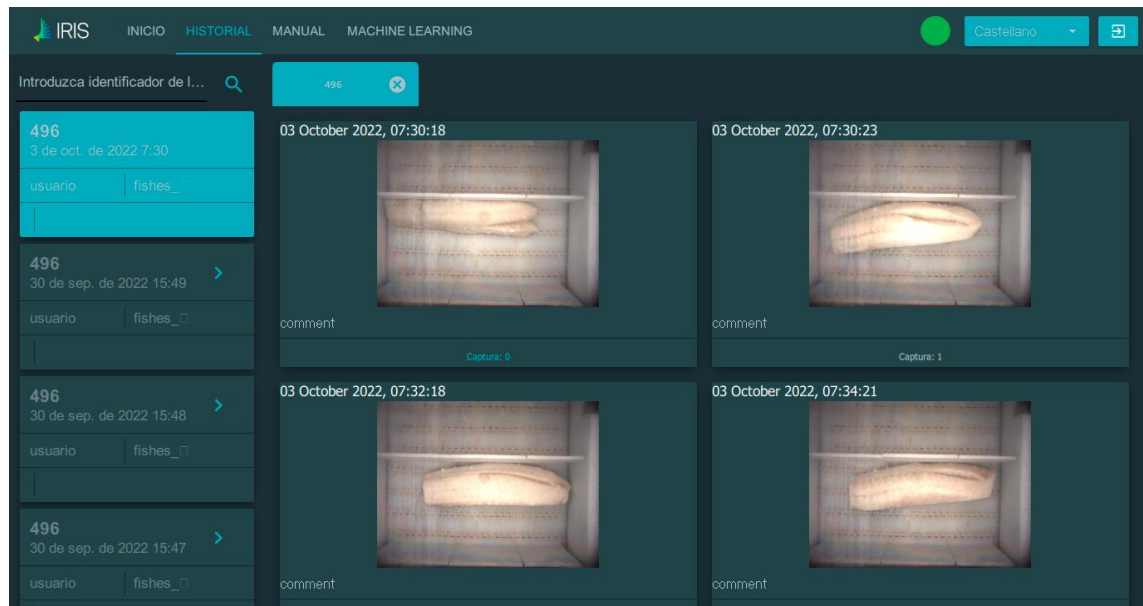


Figure 33: IRIS Visum DeepSight™ software for food quality sorting

4.2.2. IDENER [65]

Idener's expertise in machine learning modelling is a cornerstone of its innovative approach to problem-solving. Machine learning, a subset of artificial intelligence, involves the development of algorithms that allow computers to learn from and make decisions based on data. This process involves the creation of models that can predict outcomes, classify data, or even understand complex patterns. These models are trained using large datasets, and their performance improves as they are exposed to more data over time.

For machine learning and AI-related developments, Idener is currently developing the AI-Core platform. AI-Core extends this view incorporating complementary modules for machine learning, systems modelling, advanced control and mathematical optimization – all working in coordination. The engine is built on top of a hyperconverged storage and processing infrastructure. This features real big data processing capabilities, handling huge amounts of diverse information as fast as it is possible – a requirement for some applications, while in others a guarantee for future upscaling. Security and privacy by design are also core to the implementation, enabling reliable solutions for industrial and public sectors.

As an example use case, Idener leverages this core technology to create predictive models that can forecast energy consumption in machines, as demonstrated in the DENiM project. This project, which aims to develop an interoperable digital intelligence platform for industrial energy management, relies heavily on Idener's machine learning models and related services to optimise manufacturing routines and provide a decision support system for operation managers. [66]

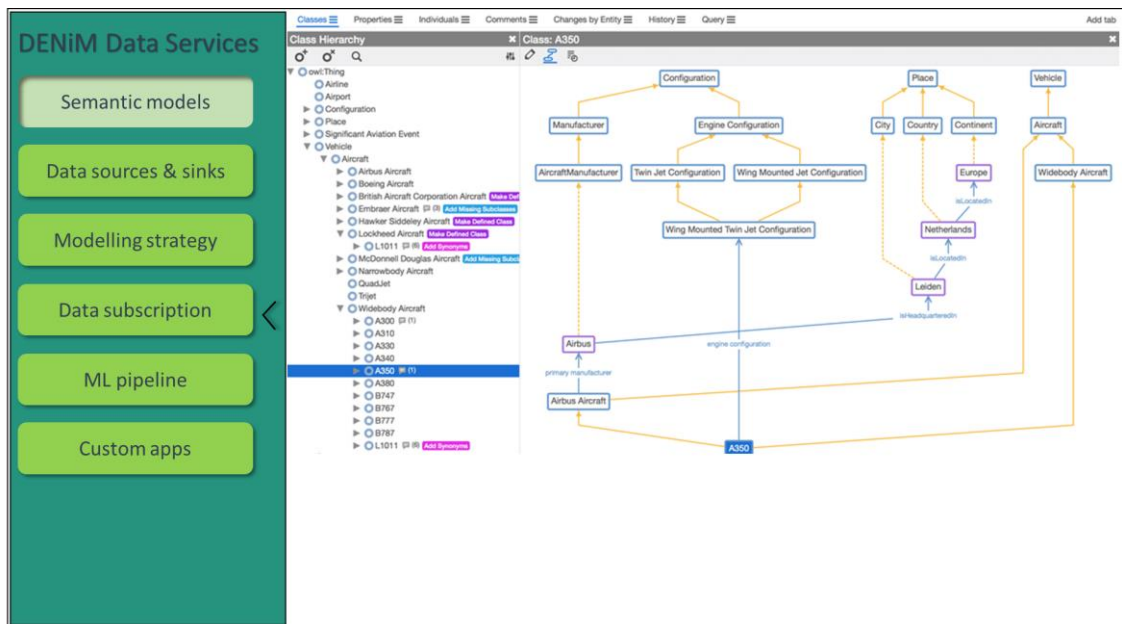


Figure 34: Mock-up of DENiM data services supporting machine learning development

Similarly, in the CITYLOOPS (www.cityloops.eu) project, Idener applies machine learning to develop innovative measures designed to promote circular economy outcomes in relation to construction and demolition waste, soil material and organic waste flows in the city of Seville (Spain).

These projects exemplify how Idener's proficiency in machine learning modelling can be applied to diverse contexts, highlighting the company's adaptability and innovative approach to leveraging technology for problem-solving.



4.2.3. ULFS

Innovative sensor integration and application:

In addition to ULFS theoretical contributions, practical experience has also been gained through collaboration on industrial projects. An important example is the successful integration of polyvinylidene fluoride (PVDF) sensors in washing machines, whose main objective is to provide real-time monitoring of operating conditions. This solution has been patented, which underlines its novelty and potential importance in the industry.

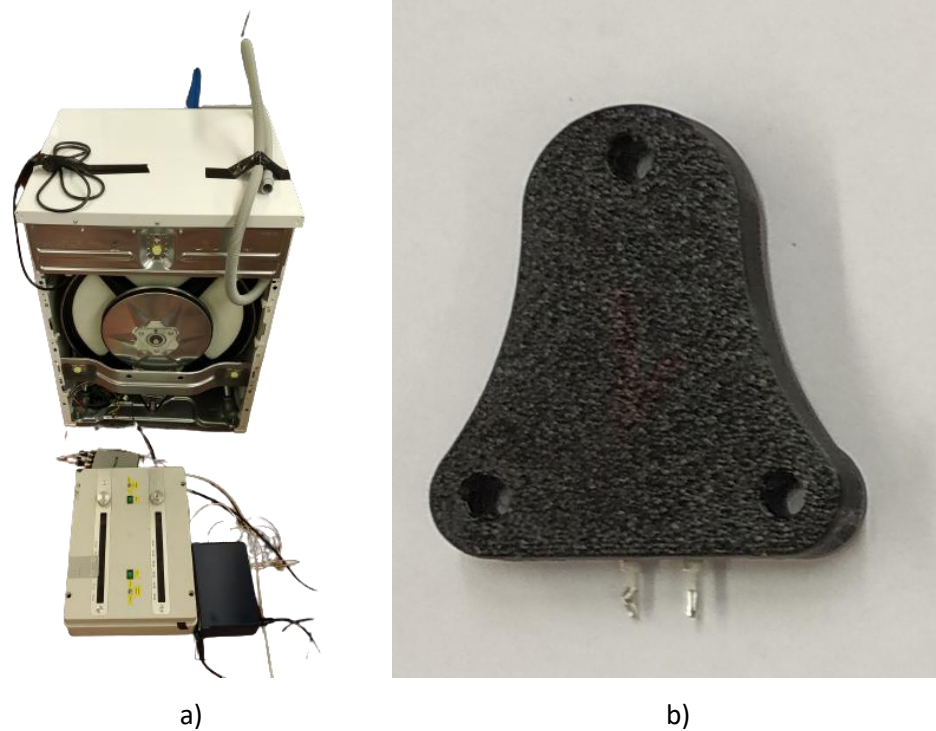


Figure 35: Integration and Calibration of a Custom Sensor: a) Experimental Setup on a Washing Machine; b) The integrated sensor.

Building on our achievements, we are currently working on a collaborative project with partners to develop a comprehensive condition monitoring system tailored to a specific industrial application. Together with our partners, we are actively developing all key components of the system, including a novel sensor, the corresponding AI algorithms for decision making and open-source software solutions for manipulation and overview.

4.2.4. Gorenje

Gorenje integrates image processing technology into their ovens to offer advanced features like food recognition and anti-browning detection. This cutting-edge functionality enhances cooking precision and simplifies the user experience.

Using a combination of cameras and image recognition algorithms, Gorenje ovens can identify different types of food placed inside. The oven's image processing system will be able to analyse visual cues such as shape, colour, and texture to recognize common food items, such as vegetables, meats, and baked goods. This capability eliminates the need for manual input of cooking parameters and ensures optimal cooking settings for specific dishes.



Figure 36. Smart Oven Bio24 with Camera and AI based Functionalities

Additionally, Gorenje's ovens utilize image processing to detect the degree of browning or doneness during the cooking process. By continuously analysing images captured inside the oven, the system can estimate the level of browning or crisping on the surface of the food. This information enables the oven to adjust cooking parameters, such as temperature and duration, to achieve the desired level of browning as per user preferences.

The integration of image processing technology in Gorenje ovens not only enhances cooking accuracy but also simplifies the cooking process for users. With automated food recognition and anti-brownage detection, users can confidently rely on their oven to deliver consistent and delicious results, saving them time and effort.

In summary, Gorenje's implementation of image processing in their ovens demonstrates Gorenje ability to include and transfer the technology to the part recognition and part monitoring.

4.2.5. Lexmark

IoT fuels Lexmark innovation. Driving print into the digital age enables Lexmark to solve customer problems in amazing new ways.



Figure 37: Transforming your business with the right IoT platform

Today the average Lexmark printer is equipped with more than 120 sensors dedicated to collecting data. This data is gathered from the millions of Lexmark devices under management worldwide and stored in the proprietary Lexmark IoT Hub — a single, globally managed print

D2.1 Identify the key technology features for support solutions and define their current baseline services platform that feeds intelligence to Lexmark’s R&D and customer service functions, helping us build better products and solutions, and better serve our customers.

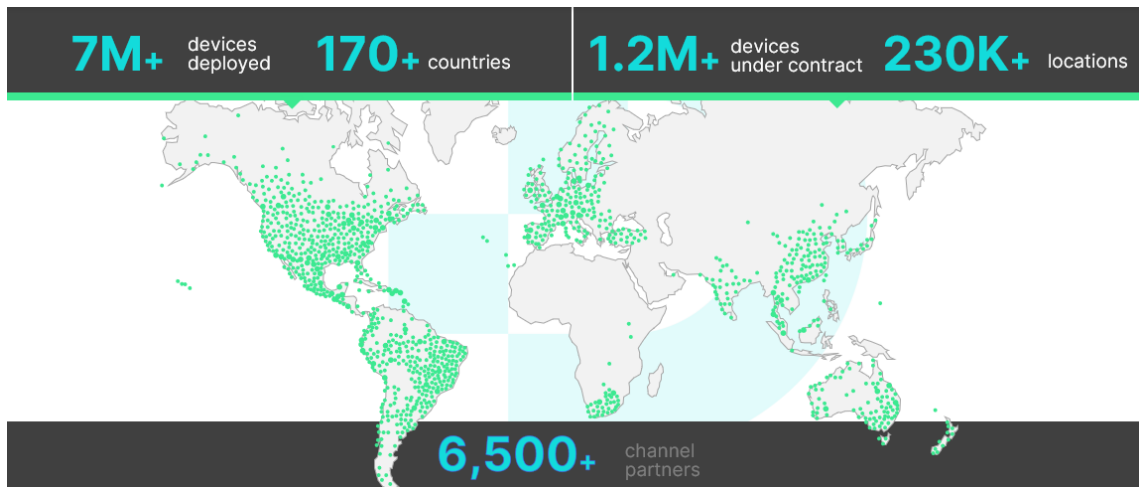


Figure 38: Lexmark's global reach

Out of the 7M+ printers sold to the global market, 15-20% of the devices are operated under the Managed Print Services (MPS) business model and are interconnected via Lexmark’s cloud technology. Printers sold to the open market represent 80-85% of the devices that are not connected to the Cloud Fleet Management Platform, therefore Lexmark has limited visibility of these devices. In this field, we see development opportunities where Lexmark aims to connect more non-MPS products to the cloud which would allow us to keep on track of usage and condition data for data assessment and processing purposes.

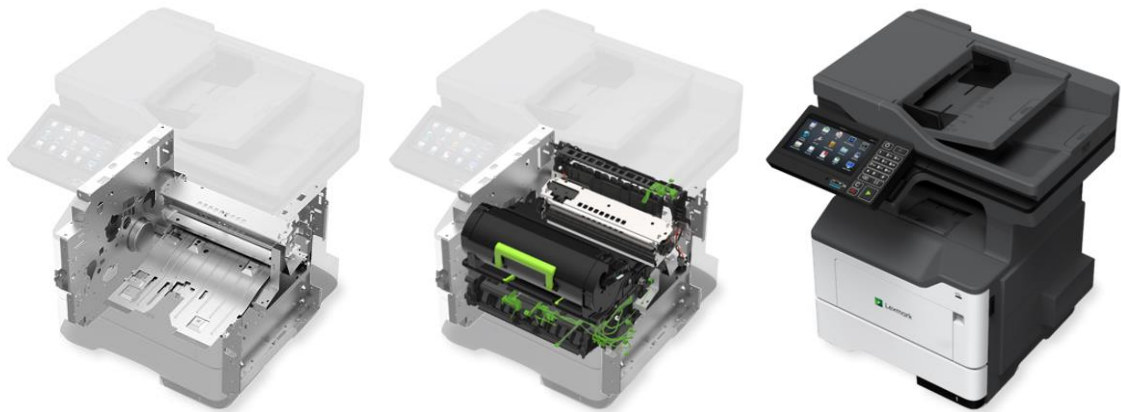


Figure 39: Lexmark printer is equipped with more than 120 sensors

More than a million Lexmark devices provide useful product data.

Toiling away in various industry sectors, the intelligent, sensor-equipped Lexmark devices that customers ask Lexmark to manage are continuously generating the data we need to make our products more durable, repairable, and reliable.

This powerful application of big data analytics expedites problem resolution, reduces unnecessary service calls, and maximizes uptime. For R&D, it also drives a deeper understanding of product operation and improves future sustainable product design.

Lexmark’s insight starts with the sheer quantity of data we gather from the intelligent Lexmark printers and multifunction devices customers ask us to manage in 200,000 locations around the world. We continually monitor over 100 data points from alerts and sensors inside each Lexmark device in this global pool, such as how much power it draws, operating temperature, the speed which the paper is moving, and how the user interacts. Besides many other solutions, there is a motor in the print engine, which is responsible for revolving the PC drum, we can see the lead time from powering it on till reaching the nominal revolution speed, also continuously measuring the used current. If either the time gets longer, or the current increases over a certain level, the smart predictive algorithm can recognize the need for the replacement before the printer produces any malfunctions or shows any error messages. Lexmark’s unique analytics engine not only captures, interprets, and analyses device data, but uses sophisticated algorithms to detect symptoms of an impending issue. Predictive analytics can make data-driven forecasts of what a Lexmark device will do next, and automatically generate service requests. Whether we make a fix through settings changes and firmware updates or deploy a technician prepared with specific, detailed information based on data collected directly from the device, Lexmark can address potential issues before they create a disruption at the customers’ premises.



Figure 40: Lexmark Optra Edge: Sense anything. Analyze instantly. Act intelligently.

With the Optra IoT Platform, predictive services have a unique innovation potential. Using a treasure trove of performance data gathered from devices, users will have a handle on precisely what is causing their devices to fail, how, and when. With the power of data analytics and insights enabled by the Lexmark IoT solution, customers can anticipate device failures and disruptions before they occur — and even resolve the issues remotely before they become aware that there is an issue.

Decisions about when devices in the field should be replaced are difficult. When the timing is wrong customers might lose revenue, and users would be burdened with needless change and disruptions.

By operationalizing the data streaming from connected devices, customers can free themselves of these risky decisions.

The Optra IoT Platform brings reporting dashboards full of data and insights around device utilization, costs, service history, and more — over the lifetime of each device.

The Optra IoT Platform enables data-driven decision-making and empowers customers on whether they should replace a device, refresh their entire fleet, or continue with repairs.

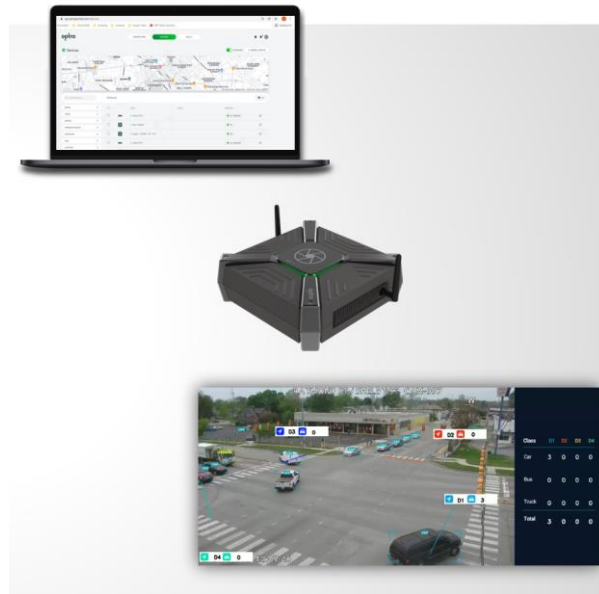


Figure 41: An end-to-end edge computing platform that brings the promise of AI to your business operations

Organizations are awash in data — but using that data to improve their business and gain a competitive advantage requires capital and highly technical skills that many businesses don't have at the ready.

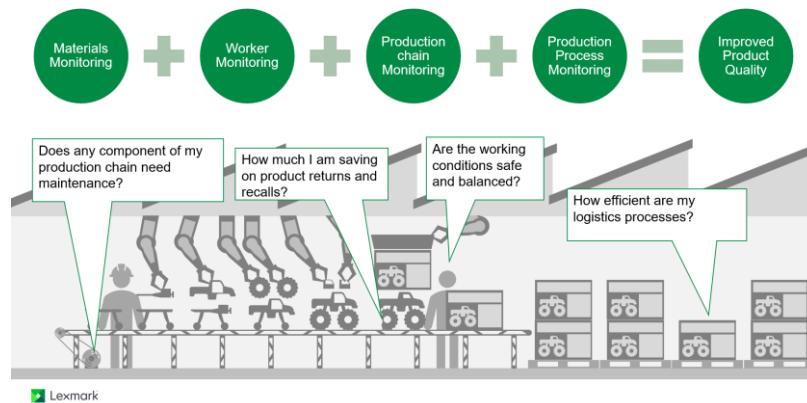


Figure 42. Revolutionizing the way manufacturing is managed and executed

Optra Edge is a user-friendly, user-focused platform combining edge compute hardware, a low code/no code cloud-based management portal and pre-built AI/ML applications that make it fast and easy to turn real-time data into real-time action combined with image-processing solutions.

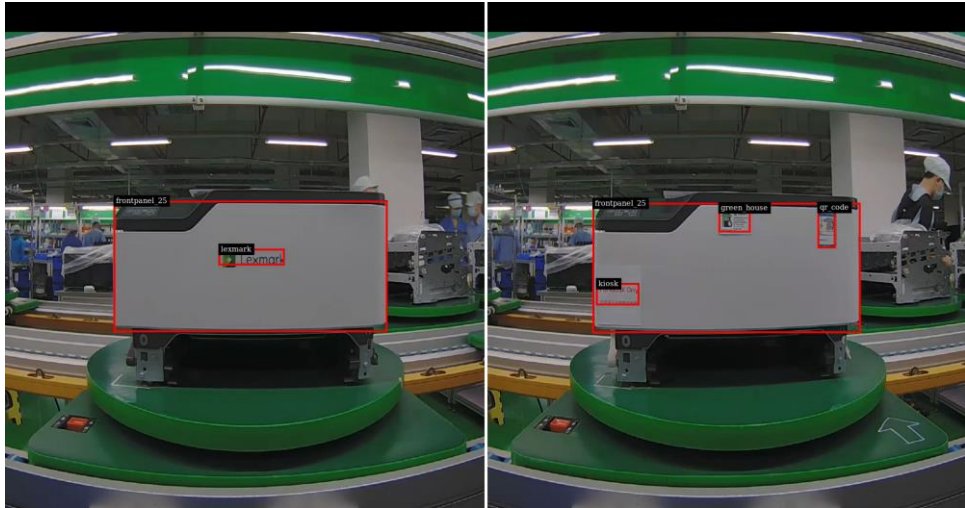


Figure 43: With Optra Edge, cameras and sensors on the factory floor can collect and process vast amounts of data, generating valuable insights instantly

4.2.6. C-ECO

The identification of used products is a major component in C-ECO's service offer for the automotive aftermarket. As the used products after a use phase in the vehicle are often missing labels or they are not readable anymore as the parts are dirty, corroded, painted or otherwise damaged, C-ECO has developed a system which is using image-processing, digital sensor data and machine learning to support the identification and sorting of used car parts. The development was conducted together with research partners in a project which received funding by Germany's Federal Ministry for Research and Education (BMBF). The system has been integrated into C-ECO's inspection workstations and applied for testing period in full productive use in one location.

ARTIFICIAL INTELLIGENCE

Analyse and combine data from different sources

Data from various digital sensors, e.g. cameras, depth-imaging, scale,...



Human senses and cognitive capabilities



Business context data (e.g. purchasing or return-behaviour)



Combine individual strengths of human and machine for better results:
AI must support human-beings, not replace them!

Figure 44: EIBA – using digital sensor data and AI on identification of used car parts

DAS EIBA SYSTEM



Figure 45: EIBA-system prototype

4.2.7. Arçelik

Datafarm Smartfix solution developed by Arçelik, utilizes machine learning modelling to predict faults in refrigerators in advance. It is used for tracking the white good at customer remotely and analysing the cooling and functional parameters in order to understand the malfunctioning and finding service solution earlier. In addition, by analysing data and labelling errors, the system can recommend spare parts before the issue occurs, streamlining the repair process. We also provide customer satisfaction by fast and effective troubleshooting and can collect data for further projects.

Arçelik is also conducting various camera-equipped refrigerator projects that will create added value for the customers. These projects aim to enhance the user experience and provide valuable features using advanced image processing and artificial intelligence technologies.

We can collect image data from the white good of customer and analyse the customer habits in order to supply input to design of new products. By this way we are going to improve customer experience, satisfaction by design and troubleshooting in the case of failure.

After bacteria removal process in refurbishment centre, bacteria level determination is performed by swabbing method and using ATP measuring device. However, this method takes long time (40min per product). In DiCiM we aim to improve this process.

4.3. Augmented Reality

4.3.1. Past AR Projects

TUC has developed various AR applications for maintenance, assembly, marketing, packing and machine operation in the past years. Although, no value recovery processes were supported with AR, it is possible to adapt known approaches and methods to this use case. In the following subsections selected highlight projects are presented.

4.3.1.1 *VirMont*

In the context of a growing variety of products, small and medium-sized companies are faced with the challenge of efficiently carrying out production processes and comprehensively planning workplaces. Virtual technologies offer a high potential for relieving the workload of direct employees and integrating them into the planning process. In the VirMont project, the targeted use of virtual and augmented reality was tested. Virtual and Augmented Reality (VR/AR) in different phases of the product development process. Based on the analysis of the context of use and the requirements, a VR planning and learning system and an AR assistance system were developed in a user-centric manner. The development of the AR assistance system for the support of assembly processes follows two central objectives: To prepare and provide data in such a way that they can be used in the same way for a virtual reality training application or, if necessary, to integrate it from the VR planning and training application into the can be integrated into the AR assistance system. The aim of the AR application is thus the user-friendly visualization of the individual assembly steps so that they can be carried out correctly on an ongoing basis, as well as the integration of employee experience in order to improve assembly processes and quality assurance in the long term.

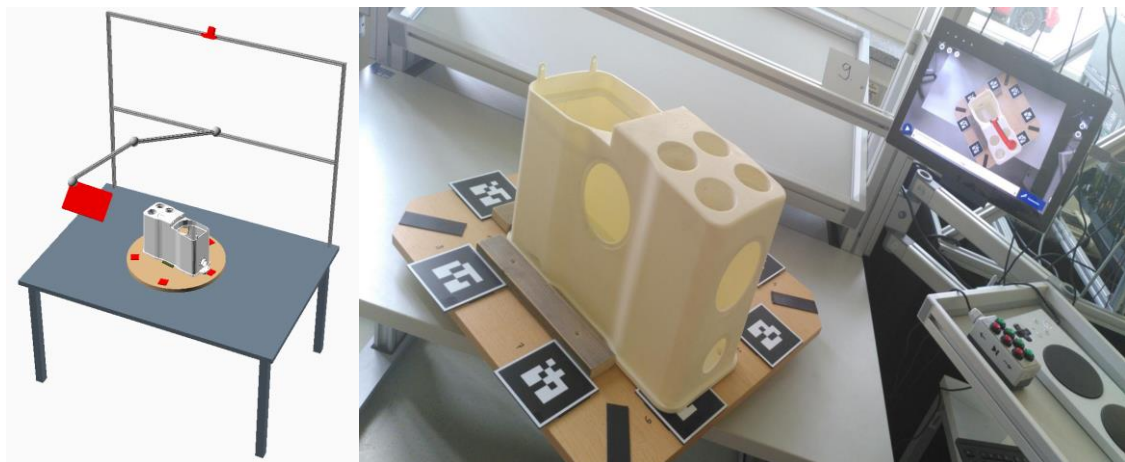


Figure 46: Schematic representation of the workbench with camera, tablet and mounting plate and (left); setup in the laboratory of the TU Chemnitz - a prototype of a pump housing of the company Zehnder Pumpen GmbH can be seen on the mounting plate, the tablet and the two hardware controllers (right).

4.3.1.2 *ServAR*

The ServAR project aimed to create the prerequisites for the successful use of augmented reality in service for mechanical engineering. For this purpose, an AR software platform was developed for the user that offers the same functionality and operating concept on different end devices, such as data glasses and tablets, and can integrate company data. In addition, research was

conducted on data glasses in combination with a hardware-based tracking module that are suitable for industrial use. On the manufacturer side, methods and processes were researched and developed to integrate the system into corporate processes and provide required data. Based on this, software support was developed that can generate the necessary data and managing it consistently in a PDM (Product Data Management) system to enable the overall process of planning, documentation and maintenance to be carried out efficiently.

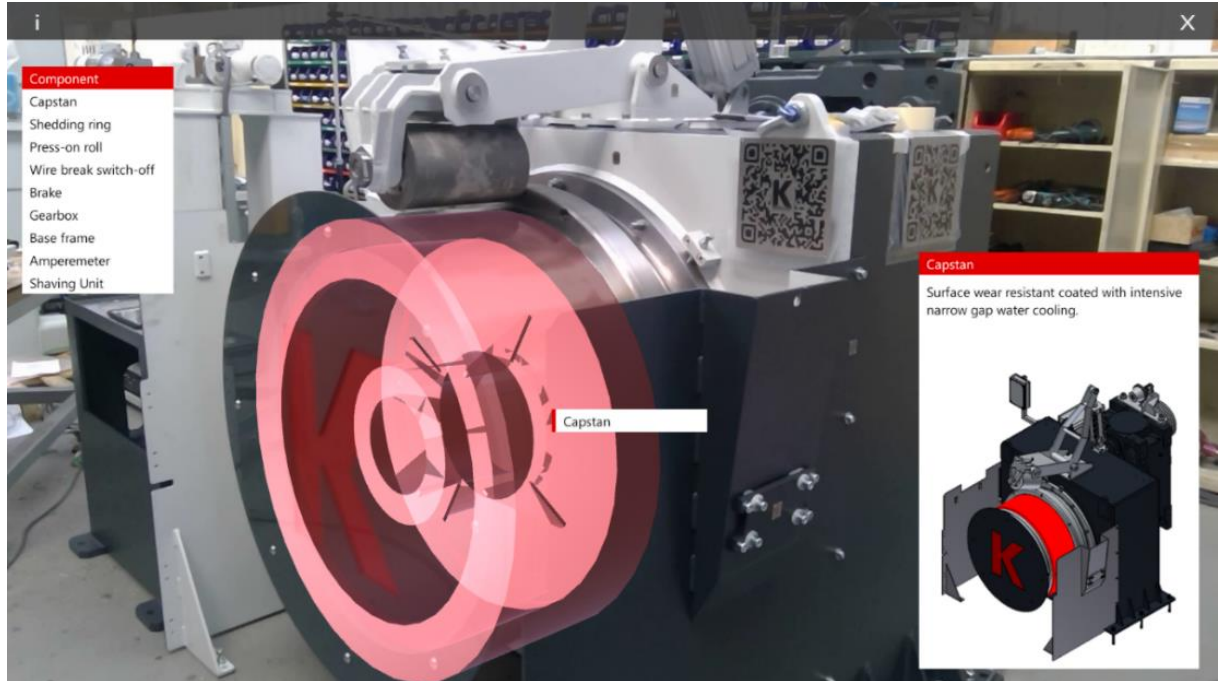


Figure 47: AR support application for a wire pulling machine

4.3.1.3 DigiTry

In die design, the usual procedure is to derive the contours of the die active parts from the component contour. Based on this component contour, the corresponding die contour is created by a constant offset, which usually corresponds approximately to the material thickness. Springback effects, which can vary for each specific sheet material, are carried out by adjusting the punch and die contour and are still taken into account in the design by what is known as overbending. However, forming sheet material typically results in different thinning or stretching and/or thickening of the sheet material distributed over the part geometry. The reworking of the dies is called spotting. The tool surfaces or the blank are coated with spotting paste. After closing the die, the component areas with different surface pressures/support points stand out. Surfaces with excessive surface pressure displace the paste. Surfaces that are not in contact, e.g. due to sheet thinning, appear darker. The manual process reveals surfaces that exert too high or too low local surface pressures on the part to be formed. The aim of the project was to create a spotting simulation based on 3D reconstructed data and to project the results onto the die using AR. A projective AR system was developed by TUC which includes semi-automatic calibration and referencing. Point clouds from 3D scans and additional information can be displayed in the correct position. The system offers gesture and mouse/keyboard control. Different processing steps can be defined by a customizable colour scale. It is also possible to process any number of data sets/instructions.

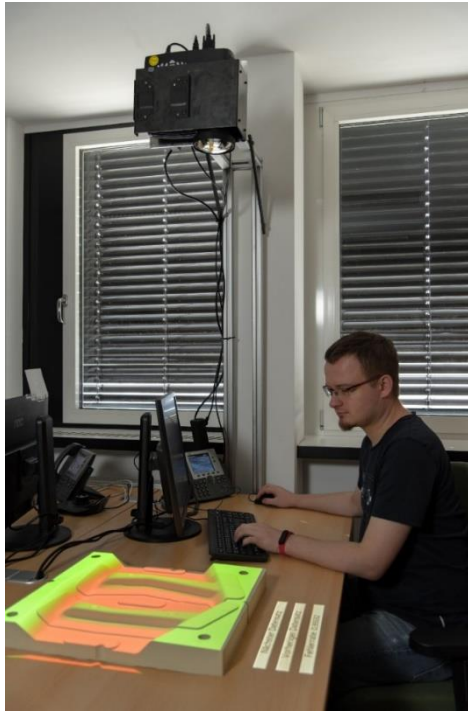


Figure 48: Test setup of the projective visualization

4.3.1.4 **PreCoM**

In the Horizon2020 project PreCoM (Predictive Cognitive Maintenance Decision Support System) TUC started in 2017 with the development of two tablet-based AR applications, which have been evaluated in three industrial use cases during a 14-month period: a paper tissue machine, largescale milling machine for wind power plant hubs and grinding machines for high precision gears. Two AR applications were implemented, (1) to provide step-by-step-instructions (AR Guidance System) and (2) to enable remote service support (AR Remote Service System). The requirements analysis at the beginning of the development process showed that the AR Guidance System should enable new or unexperienced maintenance staff to perform medium to high complexity tasks by following step-by step instructions that usually only a very few highly experienced workers would do. The step-by-step instructions were created by digitizing and customizing existing paper-based instructions and enhancing them with superimposed 3D-models, texts, pictures and videos. In addition, live machine and sensor data (e.g. axis positions) is accessible in the AR Guidance system, reducing walking time to the machine control. Further, documentation functionalities were integrated allowing the workers to create videos and pictures with notes and drawings that can be integrated in the instructions for future use or for other maintenance activities. The workers or maintenance engineers are able to create the step-by-step instructions themselves using an authoring system, so that no AR expert is needed for content creation.

The AR Remote Service System was implemented to allow the local maintenance staff to start a voice/video stream with internal or external experts using a tablet or desktop PC. Both are able to augment the video stream with drawings, text notes and 3D-models, take screenshots and videos as well as sharing documents.

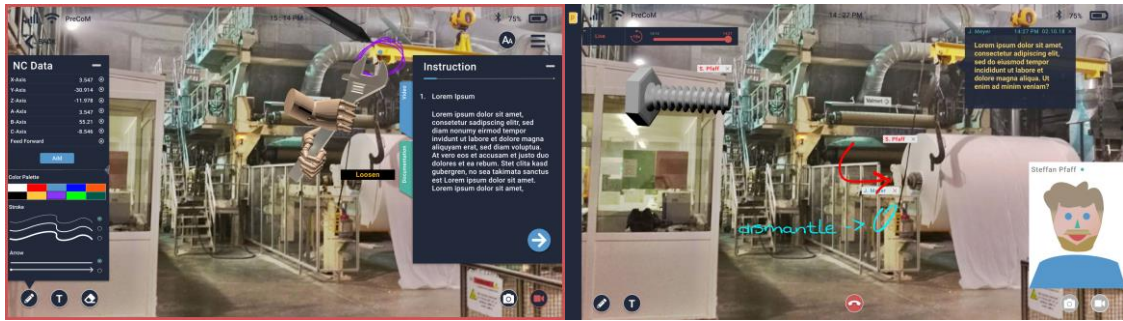


Figure 49: AR Guidance System (left) and AR Remote Service System (right) demonstrated in an industrial maintenance scenario

4.3.1.5 Bosch Rexroth Hannover Messe

In collaboration with Bosch Rexroth and the Fraunhofer Institute for Machine Tools and Forming Technology IWU, TUC has created an AR application that brings the complex products for servo presses closer to the trade visitors of the HannoverMesse. Using their smartphone or tablet, interested visitors learn interesting facts about the exhibits. Depending on which product the camera of the mobile device detects, the corresponding information is displayed, supported by videos and 3D models. The eye-catcher of the booth is a real, highly simplified frame of a press with components and assemblies from Bosch Rexroth. If a trade fair visitor holds his tablet in front of the frame, it is superimposed by a virtual press whose virtual ram works synchronously with the real transfer unit and produces a virtual component. Both the AR model and the transfer unit installed in the press frame are controlled via a real controller. By cutting and blanking individual parts, functions are visualized that are not visible on a real press. During operation, thanks to the newly developed augmented reality solution, important information about the press, the process and the products can be displayed in a targeted manner, in real time and directly on site. In addition, the press can even be controlled via the tablet.



Figure 50: Augmented Reality application for the servo press components of Bosch Rexroth at HannoverMesse

4.3.1.6 HARPO

AR in industrial applications is often used in logistics, especially in commissioning. Another field is pack optimization for trucks, containers, pallets, or boxes, where the goal is to visualize an optimized packing schema to reduce the amount of shipped air as much as possible. Sometimes, where a customer can select many differently sized articles, the issue of finding an optimally

sized box for shipping arises. Although the specific pack process is different in each company, there are some similarities to a higher level. The packing process can be combined with commissioning, in which case the articles are directly packed from the shelf into the box. TUCs hardware setup uses a PC with a monitor visualizing the pack schema using the video stream of a Microsoft Kinect V2, which is fixed above the packing place. The AR pack optimization system architecture comprises a database, a pack optimization module, a detection module, and the AR visualization. The database stores and supplies data for the rest of the system comprising size information of the packed articles and available boxes with their top-down height profiles and the list of articles of an order. These pieces of information are periodically updated from a warehouse management system. Afterward, that information is used by the pack optimization to calculate the pack schema, which is then stored in the database. The detection module uses the geometry information from the database for detecting and tracking, by processing the video image of the Kinect V2. During the packing process the detection module checks for packing errors, e.g. in case an article is at the wrong place. The AR visualization projects the article shape as a filled polygon in the video stream. The polygons fill colour is interpolated from red to green indicating the detection certainty of the current article: not detected (red) and in place (green)

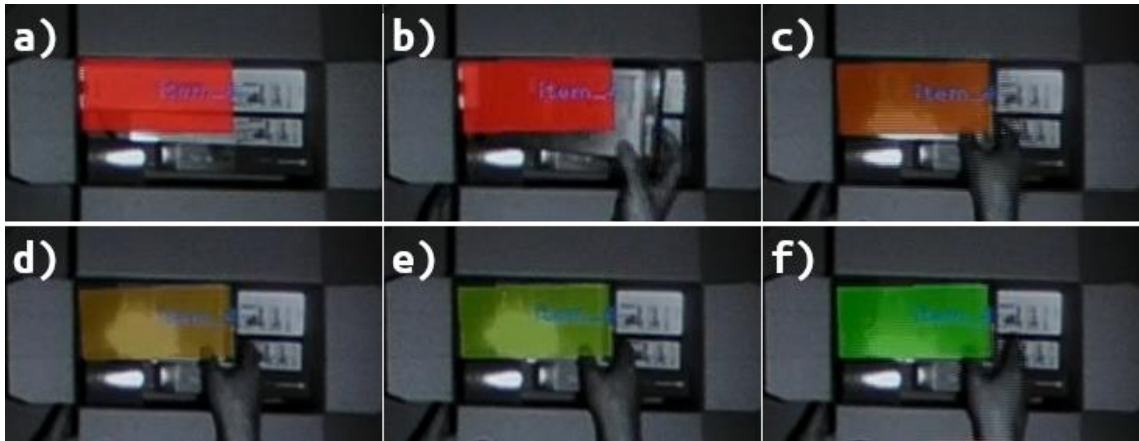


Figure 51: Packing process gradually accepting the article from a) not detected to f) accepted

4.3.2. Utilized AR Hardware

As already teased in the description of highlight AR projects, TUC has experience with developing AR applications for various AR hardware, so that always the best available technical set up is used. So far, most AR applications are based on tablets because of their large screen size, ease of integrating/using other software (Email, Office software, Browser, ERP-Clients, etc.), input capabilities, battery life and documentation functionalities (images, videos). Further, they also exist in rugged version for demanding environments, e.g. paper mills, one of the demonstrators during in the PreCoM project.

TUC developed certain smaller applications with HoloLens 1 & 2. Aside from the cumbersome and restricted development capabilities, no use case could be identified by TUC where the HoloLenses could be productively used in the manufacturing context. Further, the Epson Moverio and custom-made monocular data glasses were explored by TUC to present text instructions.

In terms of spatial AR, TUC used projections on forming tools to visualize false-colour measuring results. These projections are used by workers for finishing the geometry of the forming tool by grinding it via hand.

4.3.3. Utilized AR Software

All of TUCs AR applications are Microsoft Windows-based. In terms of tracking TUC uses most of the time third-party tracking libraries like Metaio, ALVAR, AR Toolkit or Vuforia. However, for special needs also own tracking libraries for ArUco markers or geometry-based tracking have been implemented. TUC has developed one AR-framework based on Ogre3D written in C++ which was commercialized by avireia GmbH a spin-off from TUC. Projects like ServAR (see section 4.3.1.2) or VirMont (see section 4.3.1.1) were developed by using this framework, as it allows for the easy integration of third-party software, like PDM systems or the integration of live machine data. Originating from the PreCoM project (see section 4.3.1.4) the Unity-engine based AR Guidance System and AR Remote Service System were also spun out to avireia GmbH for exclusive commercialization. A characterise many of TUCs AR applications share is that they include documentation functionalists and machine control integration. Later, is either used to show live data from a machine in the AR application or to even remotely execute commands on the coupled machine via the AR applications.

4.4. Data Management Platforms

4.4.1. Circular Value Information Management Platform

4.4.1.1 C-ECO Platform

Remanufacturing is a widespread standard-business in automotive aftermarket. Nevertheless, there is no commercial IT-solution available in the market that exclusively supports the value recovery activities inter organizational. Most of the large companies rely on Enterprise Resource Planning (ERP) systems which are designed for linear manufacturing systems and only include very limited functions for circular value recovery. Cases where internally developed software is used, they are designed for and limited to intra organizational collaboration and do not support data sharing across the value chain. These “information islands” prevent an efficient inter-organizational allocation of used parts to value preserving and recovering activities such as re-using, refurbishing or remanufacturing. As part of the ReCiPSS project, C-ECO developed an automotive part data management platform that supports core management basing on financial incentives. This platform incorporates so called core-return-options which are enabling an efficient tracking and management of financial incentives to motivate the return of used products (see also section 4.1.4). The concept of core-return options provides the potential to facilitate the structured return of used products for value recovery in any complex market environment where producers have only limited access to the users of their products and little control over the reverse-supply chain. The core-return-options platform is not limited to specific OEM’s or industry and real-time connected to C-ECO's worldwide network of inspection-centres as an infrastructure for reverse-logistics. This allows to offer a comprehensive service to dealers and producing companies for a circular economy which is focussed on extended product use, basing on the digital management of commercial incentives for the return of used products.



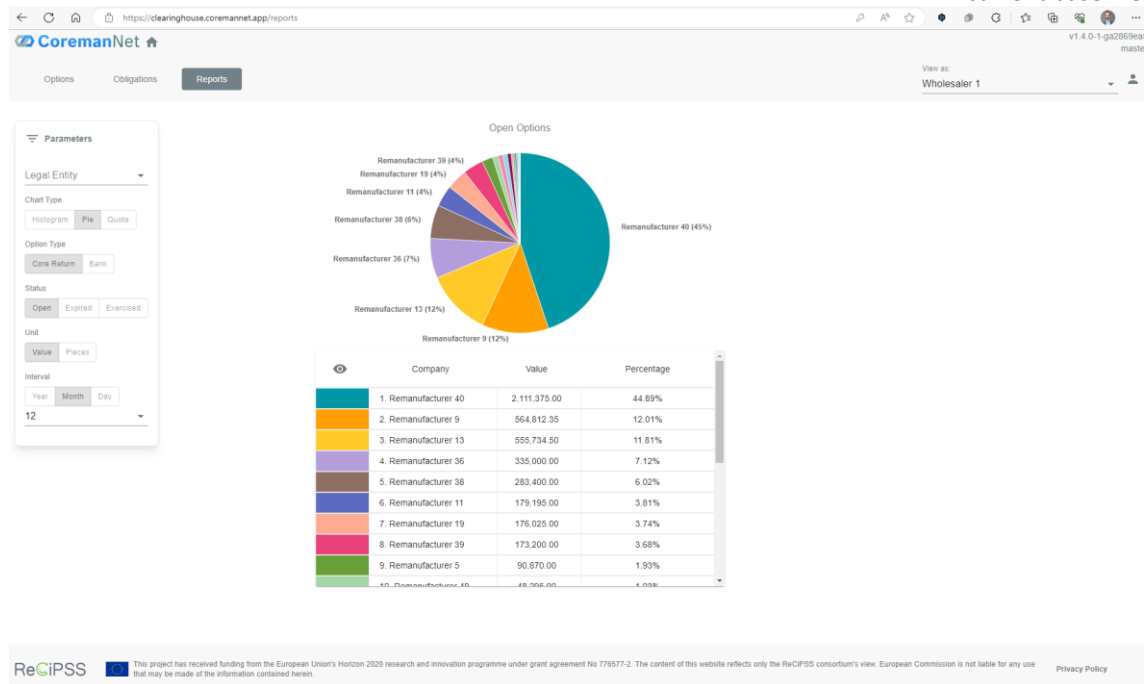


Figure 52: The C-ECO Automotive part data management platform

4.4.1.2 Signifikant Platform

Current state is that several processes within the remanufacturing processes do exist, but typically spread over several solutions with no interconnection and with gaps. ERP handles logistics and warehouse stocks, pricing etc. Reverse logistics is typically handled by ERP, or by third party operators using proprietary solutions, visual examination supported by custom solutions or niched applications. Redistribution and sales sometimes handled in existing B2B eCommerce, custom solutions or, most often, not at all. Proof of authenticity normally not existing. The interconnectivity is typically weak, and process support partially not existing.

The current Signifikant Aftermarket Business platform (see illustration Figure 53) is well suited to fulfil the information needs for all aftermarket processes in the traditional non-circular business models. It includes two main areas:

1. Structured aftermarket data, (in blue), which contains of
 - Product information
 - Keeping detailed information of technical documentation for all products, both old and current models. The information includes the bill of material for each version of the product, the product structure, service documentation, usage documentation, service kits, replacements.
 - Machine register
 - Keeping detailed information of all produced and delivered machines/tools/appliances together with their technical information. The information is kept up to date after delivery by updating the technical information after maintenance and repair.
2. Customer and user specific information (in orange), like



- Orders, claims and support tickets
These information types will cross reference the information in the structured aftermarket data. For example: orders will be linked to parts and models; Claims are linked to components, error codes in technical documentation.
- Service engagements
Keeping track on the maintenance, repair, upgrades and other engagements the service personal has with the customer
- Customer prices, discounts and other data
Keeping track of the contracts that the customer has, the discount levels and delivery options, etcetera.
- IoT information
Connecting to the customer’s data lakes with usage and production information.

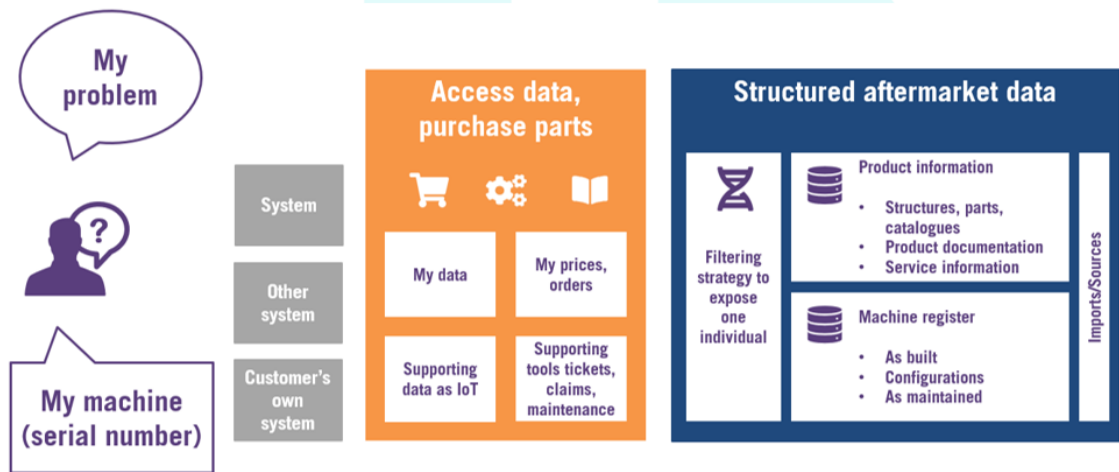


Figure 53: Signifikant aftermarket platform solution – information types overview

All of the information mentioned in the Signifikant Aftermarket Solution can be stored and owned by databases included in the Signifikant platform this is typically not the case. Most installations are very heterogeneous where information is stored in multiple systems (ERP, CRM, CCMS, PLM), but the Signifikant platform integrates all this information into one aftermarket solution.

While serving the aftermarket needs for traditional, non-circular, business models, the Signifikant platform lacks specific functionality for processes that are related to the reverse flow:

- presenting relevant and current return options to service personal when they are looking for a part or component to repair
- administrating information about returned machines, components and parts.

Another characteristic of the current Signifikant Aftermarket platform is that the installations are completely proprietary for each OEM. Data is not shared between OEMs and only shared with the OEMs own customers and users to serve their own products. To be able to tap into a shared aftermarket information database with information about possible part and component returns and availability of refurbished or remanufactured parts can potentially increase the scale and profitability of the reverse flows.

The desired state of the technology implementation to tackle the issues just mentioned will be described in section 5.4.

4.4.2. Big Data Analysis Platform

As presented in section 3.4, IoT devices and networks highly benefit from the usage of data architectures for the management of the vast amount of data that they generate. The consortium partners currently possess several technologies and know-how in the field, which are listed below:

4.4.2.1 Gorenje - Big Data Platform, Processing, and Datalake for Analytical Purposes

Gorenje recognizes the value of data in driving insights and improving their appliances and services. To harness the power of data, Gorenje has established a robust big data platform and processing infrastructure, coupled with a centralized datalake.

The big data platform employed by Gorenje is designed to handle large volumes, variety, and velocity of data generated by their appliances and customer interactions. It incorporates technologies such as distributed computing frameworks, data ingestion pipelines, and data storage solutions, ensuring scalability and efficient processing of vast datasets.

Gorenje's datalake will serve as a central repository for structured and unstructured data collected from various sources, including appliances, customer feedback, and market trends. This datalake enables seamless integration and storage of diverse data types, facilitating advanced analytics and exploration.

With the help of data processing techniques, Gorenje continues to derive valuable insights from their data lake. They employ data analytics tools and algorithms to uncover patterns, identify usage trends, and gain a deeper understanding of customer preferences. These insights play a crucial role in product development, allowing Gorenje to refine existing appliances, introduce new features, and tailor their offerings to better align with customer needs.

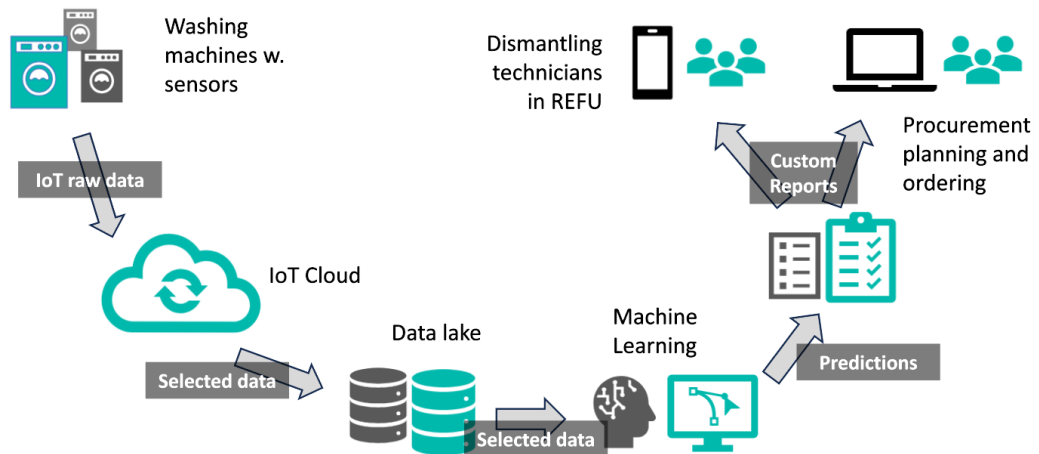


Figure 54: The flow of information from machines to REFU personnel

By leveraging a comprehensive big data platform, processing capabilities, and a centralized datalake, Gorenje empowers data-driven decision-making, fosters innovation, and continuously improves their products and services.

4.4.2.2 *Lexmark's Platform – Democratizing data to advance digital transformation journey*

Through many years of honing our approach, Lexmark has worked to understand the data-to-value journey and how it impacts our customers. We currently manage more than 1 million connected, IoT-enabled printers and devices, which translates to more than 1 TB of data a week — a huge amount of data that must be handled securely and efficiently. Several years ago, we realized that all the answers to our big business questions — such as how to predict the precise moment to ship a toner cartridge to a customer — were potentially in that data, if only we understood how to unlock the insights.

Although Lexmark is known for its strong engineering and product development skills, we wanted it to be clear that we were breaking down silos and making analytics accessible across the organization. Combining skills in programming, statistics and business acumen, the team was tasked with leveraging data science and analytics to solve the company's most difficult challenges. In the process, the centre became a resource for the entire company to work together and co-create new value for our customers.

Lexmark's technology-based approach uses artificial intelligence (AI) and predictive support to anticipate and prevent potential issues before they occur. It also provides just-in-time supplies delivery based on actual usage, not predetermined low settings. You don't need to enter a ticket, call the helpdesk or place an order. The system does it for you, eliminating the burden on your IT team. Plus, we can remotely resolve many issues.

Perhaps most important, a technology-based approach reaps the rewards of data—something a labour-based approach cannot do—especially when you can leverage the IoT.

Our IoT-enabled printers and MFPs are loaded with sensors that continuously monitor hundreds of data points including alerts, internal diagnostics and the device's inner workings.

4.4.2.3 *Idener's Edge/Cloud Continuum Scalable Platform (AI-Core) [67]*

AI-Core, an open-source-based Edge/Cloud Continuum Scalable Platform developed by Idener, provides a comprehensive solution for data management, modelling, and services integration. Its main objective is to enable data-driven decision-making and situational intelligence through efficient processing, management, and analysis of large volumes of data. Built on a Lambda Architecture-based data architecture, AI-Core can handle both real-time and batch data processing, while its Machine Learning models development, Semantics, and functional layer make it a highly scalable and flexible solution for any data-driven project.



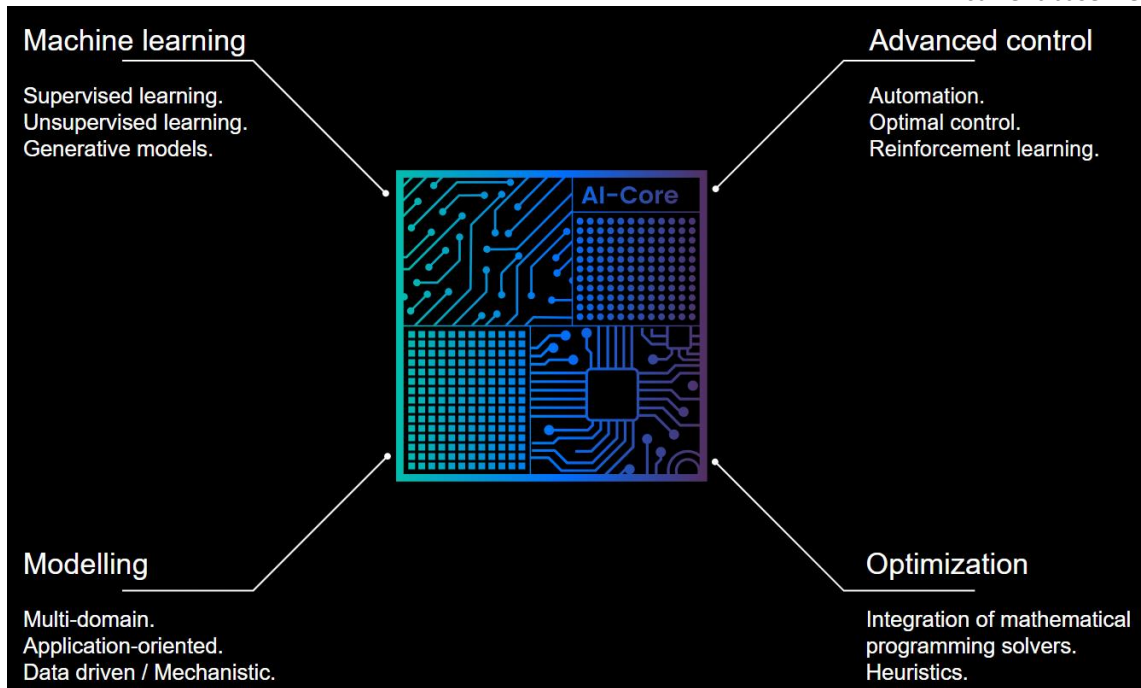


Figure 55. Idener's AI-Core in a nutshell

AI-Core connector-based approach enables it to connect with a wide range of industry protocols and batch sources, with default connectors for the most commonly used industry protocols and custom connectors for legacy or non-supported equipment. The platform offers a comprehensive and unified view of the data, enabling complex analytics and generating insights to drive informed decision-making.

Currently at estimated TRL-6, AI-Core has been tested in manufacturing, agriculture, and energy sectors and has shown great potential for use in other industries. Its adaptability to new purposes, leveraging ontologies and well-defined data interfaces, ensures that the platform remains relevant and effective in meeting the evolving needs of data-driven projects. Overall, AI-Core is a powerful and versatile platform that has demonstrated its effectiveness in various industries and has the potential to transform data-driven decision-making in many others.

5. Desired State of Technology Implementation

This section describes on a high level the desired state of the key technologies to be reached within DiCiM to facilitate value recovery operations for the white goods, printers and automotive spare parts industries. Each subsection is dedicated to one key technology: IoT for tracing and tracking, machine learning and image processing, augmented reality, data management platforms.

5.1. IoT for Tracing, Tracking and Condition Monitoring

5.1.1. *Lexmark, Gorenje, ULFS, C-ECO, Arcelik:*

In the DiCiM project, IoT solutions will be developed by ULFS for two industry demonstrators: Lexmark and Gorenje.

Under the auspices of the DiCiM project, ULFS will collaborate to cater to the unique needs of Lexmark and Gorenje.

In terms of IoT, Lexmark has already implemented a sophisticated data tracing system for its connected devices. These devices are equipped with several sensors to ensure reliable printing functionality and provide a predictive support system. While open to potential alterations in sensor architecture and strategies, the goal is to reliably aggregate relevant data from various sources, such as logs, sensor data, and others. This approach is aimed to enable insights into the overall and individual part conditions, as well as estimate the residual value of the appliance. An important challenge is to acquire data from devices that are not currently connected to the network.

Similarly, Gorenje has implemented IoT solutions in their washing machines for advanced status/error monitoring, improved user experience, and timely issue identification. With appliance data stored in data lakes and service intervention data stored separately, the first desired adaptation involves synchronizing these databases. This synchronization process involves the harmonization and integration of information from sensor-generated data with service intervention activities. Furthermore, in order to predict the condition of the appliance and its parts, Gorenje may need to adjust its data management and possibly revise its sensor architecture and storage strategies.

As C-ECO is not a producer of car spare parts themselves, the company cannot influence the design of the parts and can only work in their processes with technology which has been embedded into the parts by the manufacturers. In C-ECO's business the main challenges are in identifying, evaluating and sorting used car parts which have been put in the market and used in vehicles years ago. These products are usually not equipped with any IoT devices which could be used for identification or evaluation. Therefore, C-ECO is currently not using IoT technology in their processes and is not intending to work on that in the context of DiCiM.

Arcelik wants to explore new solution of machine learning algorithms for customer experience and troubleshooting that can later be implemented into current IOT application which is called HomeWhiz. By this way, customers and the devices will communicate with each other more and the customer can be canalised for the mindset of long and health life span of product which will contribute to circular economy.



5.2. Image Processing and Machine Learning for Decision Making, Inspection and sorting

5.2.1. Lexmark, Gorenje, ULFS, C-ECO, Arcelik:

In the framework of the DiCiM initiative, ULFS plans to address the distinct requirements of two industrial demonstrators, Lexmark and Gorenje, using AI and ML algorithms.

For Lexmark, the envisioned technology application involves using AI or ML to aid decision-making in several steps:

- Proactive maintenance decision-making - forecasting machine failures.
- Decision-making in reverse logistics: estimating demand and remotely assessing the device's condition.
- Decision-making in parts sorting centre - determining whether to reuse, remanufacture, or recycle.

In essence, an AI algorithm is needed to estimate the appliance's condition through data-driven decision-making. After determining the appliance's state, it will utilize this information to optimize reverse logistics. Subsequently, the AI algorithm will evaluate the condition of individual parts. Lastly, it will use this assessment to improve the logistics of sorting and storing these parts.

For Gorenje, the intended technology application involves using AI or ML to facilitate decision-making in multiple steps:

- Data-informed decision-making concerning spare parts demand and reverse logistics.
- Assessment of the overall appliance condition, its individual components, and their residual value.
- Decision-making about sorting of parts.

Basically, an AI algorithm is required that will first determine the demand for parts, then decide which appliances should be collected/disassembled. It should further estimate the condition of appliance parts and their suitability for reuse or refurbishment.

For C-ECO, image-processing and AR will be used in the sorting-process to train and support operators for error avoidance and more process security. The technologies will be tested in the targeted use-cases and will be analyzed regarding the potential to be applied in other domains in the company.

For hygiene test, Arcelik expects to determine the bacteria level by special camera and image process method, with the new solutions developed in DiCiM. In this way, a quicker and safer measurement will be possible. In terms of image processing studies on the compressor zone of the refrigerators will help Arcelik to decide the performance of the refurbished product. In terms Arcelik wants to use machine learning for the troubleshooting of products at the customer, with an algorithm that uses the parameters at the running product and decide the performance level. Further, Arcelik wants to collect image data from the white good at the customer to analyse their habits in order to supply input to design of new products. By this way we are going to improve customer experience, satisfaction by design and troubleshooting in the case of failure.



5.2.2. IRIS

Iris experience and knowhow in other computer vision challenges and projects such as the ones mentioned in previous sections like Visum DeepSight™ or MULTICYCLE can be used as a base point for new developments like the ones outlined here researching new AI Models for the each one of the problematics or exploring new techniques to increase camera contrast for different detection requirements. Each one of those adaptations or research are elaborated in greater detail in the subsequent points.

5.2.2.1 Cooling Performance

Image processing combining the use of thermal cameras instead of the hyperspectral cameras used in other projects and the research of new AI algorithms that are more suited for the needed task can be used to monitor the temperature of the refrigerator by analysing thermal patterns in the images. Modifications of the current technologies of MULTICYCLE can be used as said before to detect these patterns, training new models that are able to determine whether the temperature corresponds to a good or bad compressor condition can be used to check and infer if the refrigerator is working properly so it goes on the testing pipe one way or another or discard it to scrap.

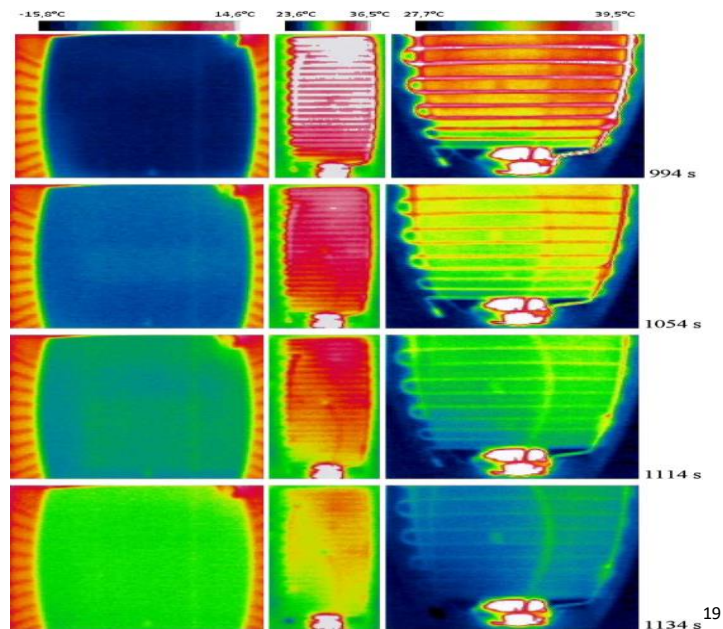


Figure 56: Thermal camera vision of refrigerator backside¹⁹ [68]

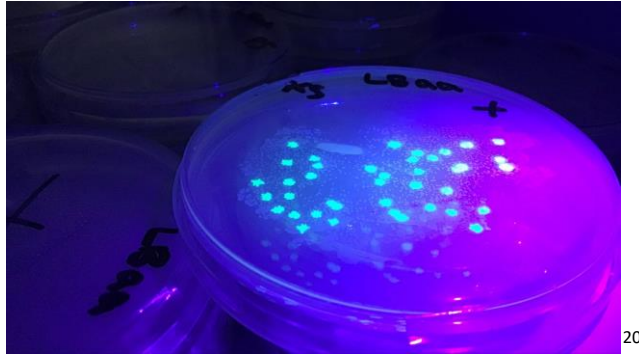
5.2.2.2 Hygiene Supervision

Current Iris digital solutions like Visum DeepSight™ in conjunction with the adaptation, modification and research of new detection Algorithms can be used to monitor the different colours on the surface inside the refrigerator to detect Mold colonies strongly associated with smell generation. This would allow us to sort the different refrigerators in order to know which ones need cleaning and which ones do not.

¹⁹ <https://ars.els-cdn.com/content/image/1-s2.0-S135943111000195X-fx1b.jpg>

The Initial approach can be to modify the detection algorithms to work with the detection of this bacteria colonies and the cameras that are required for the task. The cameras used to detect bacteria colonies would work with the visible spectra light and so on would be able to detect this bacteria colonies in the same spectrum that naked human eye is able to see.

Besides, the research of different reactive or different illumination wavelengths like Ultra Violete (UV) light or any others will be needed in conjunction with an adaptation of the AI models to work with these new conditions of light and surface colouring. Depending on the solution adopted, image dataset requirements will change.



20

Figure 57: Bacteria reacting to UV light²⁰

5.2.2.3 Paint Condition Monitoring



21,22

Figure 58: Possible scratch defect in refrigerator to be detected^{21,22}

Iris has done similar works in the pass like the mentioned with Visum DeepSight™ an adaptation of this platform for the detection of intolerable colour differences in different products or flaws in paint coating, besides different machine learning algorithms can also be researched to check the quality of the plate on the entire surface of the refrigerator and detect scratches. The analysis will be focused on the outside of the refrigerator. Product line with similar characteristics: colour, material properties like gloss or mate. Detection of clearly visible

²⁰ <https://pbs.twimg.com/media/Du3mA2GU8AMU5m3?format=jpg&name=large>

²¹ [How to remove scuffs and scratches from stainless steel? : r/Appliances \(reddit.com\)](https://www.reddit.com/r/Appliances/comments/qg9omo/how_to_remove_scurfs_and_scratches_from_stainless_steel/?context=3)

²² https://www.reddit.com/r/howto/comments/qg9omo/heres_a_tough_one_dented_fridge_fixable_or_is_my/

damages. Fringe Rotation will be needed to visualize each side of the fridge with a static camera. Different AI models will be needed to train for each of those characteristics, this will require a big image dataset. Camera and AI model will try to perform as good as human eye in terms of accuracy.

5.2.2.4 *Electrical Safety*

An adaptation of the image processing and machine learning detection algorithms of some of the Iris Solutions mentioned above, can also be used to check visible flaws in electronic components such as blown capacitors visible burnt components like resistors or connectors and flaws in the PCB itself like broken PCB parts scratches, missing holes, open circuits shorts spurs or copper exposure though solder mask.

For this Purpose, the use of a visible spectrum camera installation will be needed as well as the training of new ai models, trained just for this purpose. Electronics enclosure cover plate will be needed being removed to visualize correctly the PCB with a static camera. Different AI models will be needed to train for each of those flaws, this will require a big image dataset containing this flaw as well as an “Good” sample that has no fails. Camera and AI model will try to perform with the same level of accuracy as human naked eye.

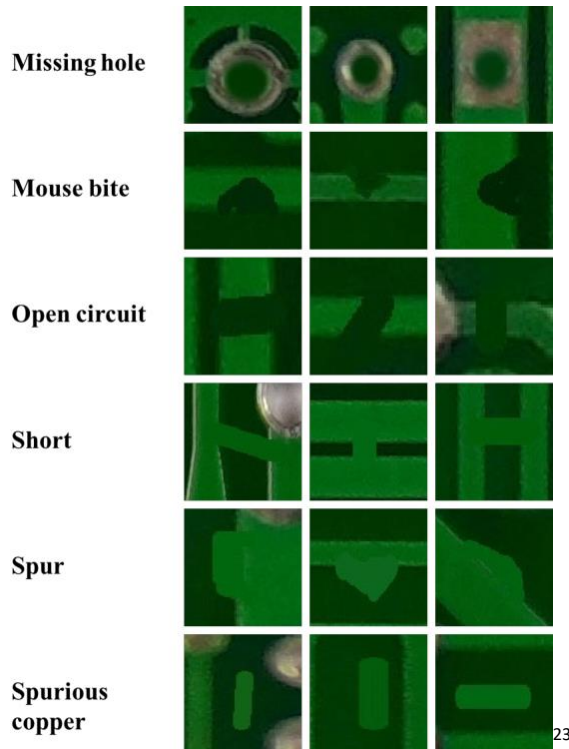


Figure 59 Samples of different visible flaws in a PCB board²³

Overall, by combining image processing and machine learning, adapting the current digital solution of Iris to the new context and requirements of each challenge it is possible to monitor the condition of a refrigerator and detect defects, anomalies or problems in its operation.

²³ <https://yscsystems.com/wp-content/uploads/2021/02/pcb-electronics-defect-inspection.jpg>

5.2.3. IDENER

The Desired State of Technology Implementation for machine learning within the DiCiM project envisages the comprehensive utilisation of machine learning's potential across various application areas. These objectives encompass:

1. Augmented Reality Application Instructions Generation for Gorenje and C-ECO: The vision for this area is to develop machine learning algorithms with the ability to be highly responsive to alterations in the environment, user behaviour, and the nuances of the specific task. Such algorithms would enable AR systems to produce instructions adaptively, ensuring these instructions are contextually appropriate, personalised, and effective. This would necessitate the application of advanced ML techniques, such as reinforcement learning for decision-making adaptability and natural language processing for the generation of human-like instructions.

2. Intelligent Assistance for Parts Sorting and Recovery across pilots: As automation increasingly becomes the norm for parts sorting, intelligent systems capable of swift identification, categorisation, and sorting of components with minimal human intervention are required. Machine learning technologies can be harnessed to enhance existing sorting mechanisms, enabling the precise and efficient sorting of parts based on various attributes, such as size, shape, colour, and material. This endeavour calls for advancements in computer vision and deep learning technologies to enable high-accuracy object detection and classification.

3. Predictive Stock Management in C-ECO: The capacity to accurately forecast stock levels based on various influencing factors could significantly improve supply chain efficiency. Machine learning algorithms could be utilised to analyse historical and real-time data from multiple sources, thereby predicting future stock requirements. These predictions could subsequently be used to optimise procurement, storage, and distribution activities. This initiative requires advanced time-series forecasting and demand prediction models, potentially utilising deep learning technologies for high-accuracy predictions.

In terms of technology development, the objective is to create machine learning models characterised by effectiveness, scalability, adaptability, and respect for privacy. This involves developing a robust machine learning framework capable of handling fluctuating data volumes, maintaining high performance across diverse use-cases, and ensuring data security and privacy.

The goal is also to support pilot cases by providing machine learning expertise and solutions tailored to their specific requirements. This may involve providing consultation, developing bespoke machine learning models, and supporting the integration of these models into existing systems. By adopting a collaborative and flexible approach, it is hoped that a significant contribution to the success of the DiCiM project can be made, while simultaneously enhancing the capability of machine learning technologies.

5.3. Augmented Reality

In DiCiM Augmented Reality solutions will be developed for the demonstrators C-ECO and Gorenje. C-ECO's business model is to inspect, and sort used car parts, so that they can be remanufactured or scrapped in case they are overused. This means that there are situations where the same type of parts have to be sorted into different boxes depending on the remanufacturer. Here, a critical point of failure arises when the parts are sorted into the wrong boxes. In DiCiM an AR sorting support application using optical see-through head mounted displays (OST-HMD) will be implemented. It supports the workers during the sorting process



with clearer visual instructions. The integrated camera in the OST-HMD will be used to identify the IDs on the parts and the sorting boxes to check their correctness. Further, TUC will try to detect the correct placement of the parts in the boxes by exploring the capabilities of AI. Although it is quite clear that it is unlikely to achieve a very high reliability for surveilling the correctness of the sorting, it will provide a benchmark of what is currently achievable and will reveal the next research steps. However, even with lower reliability, the AI results may still be used deciding to check a filled box in case the AI has detected multiple errors.

When dismantling returned washing machines for harvesting spare parts, Gorenje is faced with the challenge that each washing machine must be handled differently based on the state of its parts. TUC will use a projector to visualize the dismantling and sorting instructions directly on the washing machine. For tracking the washing machine an RGB/Depth camera will be placed next to the projector. The AR software will run on a powerful PC tower to which a touch display is connected. This allows the worker to efficiently interact with the AR application. In cooperation with IDENER, the instruction for each washing machine will be created live based on the previously made decisions about handling the washing-machines parts. Also, for this use case we will explore AI methods in order to check the correct execution of the instructions. However, the same concerns regarding the reliability of the surveillance systems apply like as the C-ECO use case.

5.4. Circular Value Information Management Platforms

5.4.1. *Signifikant platform*

Accepting the situation that there will be a large variety of needs at different manufacturers due to their positions, situations and maturity level puts a focus on how the models are described rather than the technology itself. The base must comply with the existing standards for remanufacturing and meet the needs of information sharing between processes and entities. Technology needs to be open and widely available to allow independent entities to participate, for those manufactures that need such.

Key technology features will be the business models and processes implemented in the platform, based on widely accepted terms and processes (as ANSI) and need to capture the essence of the business processes within circular manufacturing with a goal to enable, support, and to some extent automate the return and reuse of components and products. Potentially, to be explored, block chains may be used to prove authenticity of performed activities on materials.

Key technology features will also be to capture the complexity and heterogeneity of the business. Many different systems already in place at a manufacturing entity may need to exchange data with the platform and the different partners, and future potential users, will have different systems already in place. The purpose of the platform is not to replace existing processes and systems, but to serve as a glue between existing processes and systems to enable remanufacturing. In this area the key technology will need to capture the essence or core, not everything.

Finally, a key technology will be to use as widely available technical tools as possible to enable easy adaption to various systems as well as independent business entities performing service operations. In this area widely available web technologies will be key attributes.

Widely available standard technologies for managing and exchanging data can be used to achieve the technological goals of the project. The challenge lays within the business models



and information models needed to describe the information objects to be exchanged and managed within the platform and implementing these in a platform. Models need to be developed to meet the needs of the participating organizations and future usage, without trying to do everything. The business models and information objects will need to capture the essence of the business processes within circular manufacturing with a goal to enable, support, and to some extent automate the return and reuse of components and products. The challenge also lays within the complexity and heterogeneity of the business. Many different systems already in place at a manufacturing entity may need to exchange data with the platform and the different partners, and future potential users, will have different systems already in place. The purpose of the platform is not to replace existing processes and systems, but to serve as a glue between existing processes and systems to enable remanufacturing. A more standardized circular value information management solution will need to define the core business models and objects to support retake as well as offer alternatives to end consumers, and offer traceability of actions and quality, and will span over a set of other standard solutions.

Within the DiCiM project, Idener will leverage the know-how generated during the development of AI-Core to support the implementation of the core data management platform led by Signifikant. In addition, and depending on the final project’s technical requirements, it could be explored to reuse some of the AI-Core modules for data management or machine learning development purposes.

Within the DiCiM project, Signifikant will investigate how extending the Signifikant Aftermarket platform with functionality for reverse logistic improves circular processes and business models.

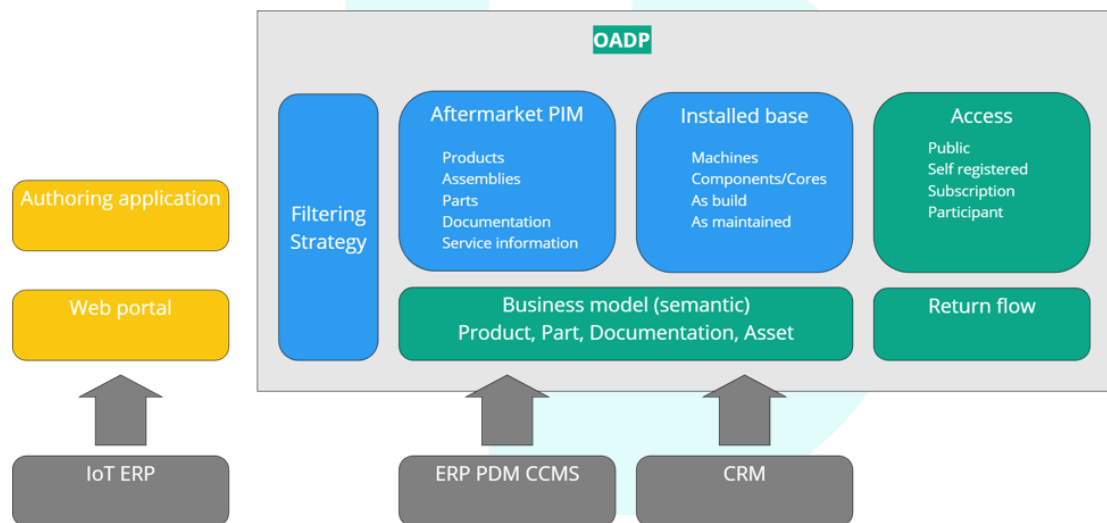


Figure 60: Open Access Digital platform overview

Figure 60 illustrates the various components of the Open Access Digital Platform. It is based on the current Signifikant Aftermarket Platform in blue (backend components) and yellow (client components) and extended with new functionality that will support the DiCiM goals in green:

- **Access**
The Open Access Digital Platform will not be proprietary for one OEM and their customers, service partners and end users. It will be open for multiple participants and for each piece of information a level of access can be chosen from public (open for everybody), free access for everybody, paid access for subscribers to Proprietary for one or more participant companies.

- Business model based APIs
Communication between the Open Access Digital Platform and third party systems need to be simplified and standardized to enable multiple participants to upload their data and connect their systems to the platform.
- Return flow
Functionality for return flow will be added to the OADP platform by integrating existing features of C-ECO's return options platform:
 - A ReturnOptionProvider that in a standardized manner can retrieve information about return options for a product, component or part. The provider can connect to a third party system (e.g. the C-ECO options platform) or a machine learning tool to retrieve the current and relevant return options and price offers.
 - An enhancement to the machine registry to not only keep track of produced and delivered machines, but also of returned machines, components and parts. Reusable parts and components can either be identified by themselves (in case they have their own identification) or through the machine they are part of.

5.4.2. C-ECO platform

The C-ECO platform currently mainly connects wholesalers from the automotive aftermarket. To fully exploit the potential of the concept of core-return-options and the ReCiPSS-platform, it is necessary to upscale the usage of the platform to increase the used spare parts return rate by a better allocation of core return-options to used products. This can only be achieved by connecting more users and new user groups to the platform, especially functions to better involve producer/remanufacturers are needed. The key to this is to provide relevant information and efficient user interaction tailored to the business domain and informational needs of the users. This should not be limited to the commercial situation, but also provide logistic information, product-condition-documentation, and decision-support to users. It should create transparency in value recovery business to enable them to control the value recovery chain without being burdened with its full complexity.

C-ECO is building on the foundation of the options-platform created within the Horizon2020 ReCiPSS project. The intention in line with the DiCiM-projects call is to provide a range of support solutions and innovative digital tools to help individuals in their business-domain in circular business processes. To achieve that C-ECO will develop the specified functions to support individuals' decision, integrate them into the platform and compile and adapt them to specific user-groups, especially remanufacturers. For that purpose, a portal will be developed compiling all relevant information for producers/remanufacturers to control the reverse value chain:

- Realtime Reporting-Cockpit on core-return-options-situation, returned products and condition, Supply-Chain- and warehouse situation
- Business-logic configurator for options-execution rules as decision-making support
- Underlying configurator: machine-readable core description based on a human-centred description
- Digital twin of core-stock: Machine learning powered supply-demand-planning and forecasting function for incentive-creation and real-time influence on sorting-decision

The extended ReCiPSS options-platform will connect to Signifikant's PIM-platform to propagate used parts demand basing on core-return options towards their users



6. Conclusions

This document is a result of Task 2.1 'Identify the key technology features for support solutions and define their current baseline'. This report defines a baseline of industry best practices in technologies (i.e., IoT for tracing, tracking and condition monitoring, ML for decision making, image processing and AR for value recovery) implemented for industrial value recovery processes in general and their adaptability for industrial sectors targeted in DiCiM. In general, the adaption of these technologies in industry is very heterogeneous. Especially, when looking on existing solutions for the white goods, printers and automotive spare parts industry in the context of circular economy there were no use case that were covering the objectives of DiCiM. However, certain solution on the market emerged that where principles will be considered in the implementation of the DiCiM solutions and open platforms. Next Steps include the detailed planning of the sketched solutions, integrating the gained knowledge form the industry applied State of the Art research.



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