**Robust digitalisation of manufacturing applications - RoDi**

**Public report**

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FFI Fordonsstrategisk Forskning och Innovation

## Content

FFI in short

FFI, Strategic Vehicle Research and Innovation, is a joint program between the state and the automotive industry running since 2009. FFI promotes and finances research and innovation to sustainable road transport.

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## 1. Summary


**Background**
Traditional responses to highly competitive markets have often focused on increasing production capacity through investments in new equipment and expanded facilities. While such strategies may improve short-term output, they are less aligned with current ambitions for sustainable and resource-efficient manufacturing. Future industrial competitiveness will increasingly depend on the ability to utilize existing assets more effectively, improve operational efficiency, and unlock unused production potential with limited additional resources. In this context, digitalization represents an important enabler.

The rapid introduction of sensors, connectivity, automation systems, and digital tools has significantly changed industrial production environments. Data is today generated at component, machine, line, and enterprise level, creating new opportunities eg., for process monitoring, manufacturing optimization and quality assurance [1]. International forecasts indicate substantial economic value from the implementation of Industrial Internet of Things (IIoT) technologies in manufacturing [10].

**Problem Addressed**
Despite technological progress, industrial equipment is often utilized well below its installed capacity. Average Overall Equipment Effectiveness (OEE) is commonly reported at around 55%, indicating significant losses related to downtime, reduced speed, disturbances, and operational inefficiencies [11]. Considerable potential therefore remains in improving the performance of existing production systems rather than expanding capacity. At the same time, large volumes of production data are already collected throughout industry. However, the usefulness of these data sets depends on their quality, relevance, and reliability. In many cases, data are incomplete, inconsistent, poorly structured, or difficult to validate, which limits their value for decision-making and advanced analytics. A central challenge is therefore how to identify the most relevant data, ensure sufficient quality, and establish confidence in the information used.

Digitalization also introduces environmental challenges. Increased use of sensors, computers, communication equipment, and storage infrastructure leads to higher material consumption, energy use, and future electronic waste. Furthermore, storage and processing of unnecessary or low-quality data contributes to the growing energy demand of digital infrastructures. Efficient and selective data management is therefore important from both an industrial and sustainability perspective.

**Project Activities**
The RoDi project applied a resource-efficiency perspective, focusing on maximizing the use of existing data resources. Priority was given to utilizing current sensors, machine signals, and default information already available in industrial equipment before considering new hardware. Methods were developed to identify which data sources are

most relevant for monitoring and decision support, enabling more targeted data collection and avoiding unnecessary investments.
A methodology was developed to identify critical functions that should be monitored at component, machine, and production-line level, and to assess whether the available data is sufficient for this purpose. The methodology provides a structured tool for evaluating monitoring readiness and improving industrial data quality. Another important activity was the development of approaches for identifying data quality issues before storage and further processing. By moving validation and monitoring earlier in the data pipeline, the project aimed to reduce unnecessary storage of low-value data and improve the quality of information used in later analysis stages.

**Results**

The developed methodology was applied in several case studies representing different levels of advanced manufacturing systems, including both synthetic demonstration cases and industrial applications. The work combined functional analysis, describing how systems are intended to operate, with dysfunctional analysis, identifying failure modes, disturbances, and performance losses. This provided a broader system understanding and enabled targeted recommendations for improvement. Industrial validation was carried out in collaboration with companies through case studies at component level (gearbox test rig), machine level (power skiving process), and line level (emulsion system). The project was conducted according to a triple-helix model involving academia, students, and industrial partners, which contributed positively to relevance, knowledge transfer, and competence development.

Some activities were affected by delayed access to industrial data, as several data-collection solutions were introduced during the project period. This required adjustments to the schedule, but the overall objectives and planned deliverables were successfully achieved. The results demonstrate how improved data selection, data-quality assessment, and structured monitoring can support estimation of remaining useful life, earlier detection of bottlenecks, increased productivity, and improved operational reliability.

**Future Impact**

In the longer term, the project results are expected to support earlier identification of wear, deviations, and emerging disturbances, and more proactive maintenance planning and reduced downtime. More efficient data management can reduce storage and processing needs, thereby lowering energy consumption and environmental impact.

The project also provides an important foundation for future industrial use of AI-based methods by ensuring access to relevant, trustworthy, and structured data. This can contribute to faster analysis, improved decision support, reduced bias, and more robust monitoring solutions.

## 2. Sammanfattning

Industriföretag har länge stärkt sin konkurrenskraft genom investeringar i ny utrustning och ökad produktionskapacitet. I dag är detta dock svårare att förena med krav på hållbarhet och resurseffektivitet. Framtidens konkurrenskraft väntas därför i högre grad bero på hur väl befintliga system utnyttjas och hur dolda förbättringsmöjligheter kan frigöras utan att resursförbrukningen ökar. Digitalisering och utvecklingen inom Industrie 4.0 och IIoT spelar en central roll i denna omställning genom att möjliggöra omfattande datainsamling, analys och optimering [10].

Trots tekniska framsteg ligger OEE-nivåer ofta runt 55 %, vilket visar att stora delar av kapaciteten fortfarande är outnyttjade [11]. Samtidigt växer datamängderna snabbare än förmågan att använda dem, och kvalitetsproblem som brus, saknade värden och sensordrift är vanliga. För att säkerställa tillförlitlig drift krävs därför robust övervakning och en djup förståelse för både systemens funktion och hur fel uppstår. Genom att kombinera funktionella analyser med fel- och konsekvensanalys kan kritiska svagheter identifieras och åtgärdas. Digitaliseringens expansion innebär samtidigt ökade hållbarhetsutmaningar, bland annat genom större materialåtgång och energikrävande datalagring.

Mot denna bakgrund utgår projektet från ett resurseffektivt angreppssätt där befintliga datakällor utnyttjas bättre i stället för att fler sensorer installeras. Genom att identifiera relevant information, förbättra urvalet av datakällor och upptäcka kvalitetsproblem tidigt kan beslutsfattandet stärkas och onödigt resursutnyttjande minskas, både digitalt och fysiskt. En central princip är att flytta datakvalitetskontrollen tidigare i datakedjan, så att brister i datan upptäcks innan den lagras och bearbetas. Detta minskar datamängder, ökar analysers tillförlitlighet och reducerar energi- och beräkningskostnader.

Projektets metodik bygger på att kombinera funktionell och dysfunktionell systemförståelse. Funktionell analys beskriver hur systemet ska fungera under normala förhållanden, medan dysfunktionell analys identifierar felmoder, degradering och prestandaförluster. Genom att integrera dessa perspektiv kan projektet systematiskt peka ut kritiska funktioner och komponenter där förbättrad övervakning eller datakvalitet är särskilt viktig.

Arbetet utgår från tre forskningsfrågor: hur kritiska systemfunktioner och deras felmekanismer kan identifieras metodiskt; hur datakvalitet och tillförlitlighet i industriella datastreams kan bedömas och förbättras; samt hur fysikbaserade modeller kan kombineras med datadrivna metoder för att stärka robusthet och beslutsstöd.

Projektet är organiserat i sex arbetspaket som sträcker sig från metodutveckling och systemanalys till experimentell validering och industriell implementering. Den övergripande metodiken följer är: först definieras informationsbehov och robusthetskriterier, därefter utvecklas metoder för dataförberedelse och systemanalys, följt av integrering av fysikbaserade och datadrivna modeller. Dessa testas i syntetiska fall innan de tillämpas i verkliga industrimiljöer. Löpande aktiviteter som litteraturstudier, examensarbeten och industrisamarbeten säkerställer praktisk relevans.

Projektets mål är att stärka robustheten och nyttan av industriella datastreams genom att integrera fysikbaserad domänkunskap i dataflöden. Genom att kombinera traditionell modellering och simulering med moderna datadrivna algoritmer skapas mer tillförlitliga och fysiskt korrekta data som förbättrar beslut kring drift och underhåll. Ambitionen är att öka värdet från befintliga system och data samtidigt som onödig datainsamling och bearbetning minimeras. Projektets övergripande ambition är att förbättra resursutnyttjandet i industriella system och överbrygga gapet mellan avancerad maskininlärning och praktiska fysiska tillämpningar.

## Sammanfattning av arbetspaketen

Arbetspaket 1 – Identifiering av kritiska funktioner och databehov
Arbetet inleddes med att utveckla en metod som kombinerar förbättrad funktionell analys (FAST) med fuzzy-baserad dysfunktionell analys (Fuzzy FMSA). Genom tre industriella fallstudier på komponent-, maskin- och linjenivå identifierades kritiska funktioner, felmoder och områden där övervakningen var otillräcklig eller resurser användes ineffektivt. Arbetspaketet resulterade i en översikt över befintliga metoder för datadrivet beslutsstöd, en kartläggning av datatillgång och use cases samt en skalbar metodik för tidig upptäckt av dataproblem. Dessa resultat lade grunden för projektets fortsatta arbete genom att tydligt definiera vilka funktioner som är mest kritiska och vilka datakällor som är mest relevanta.

Arbetspaket 2 – Fysikbaserad modellering och felinjicering
Utifrån de kritiska funktioner som identifierades i arbetspaket 1 utvecklades fysikbaserade modeller i MATLAB Simscape/SimMechanics. Modellerna representerade mekaniska strukturer och drivsystem och användes för att analysera systemens beteende och känslighet för störningar. Ett systematiskt ramverk för felinjicering togs fram, där olika typer av avvikelser, såsom geometriska fel.

Arbetspaket 3 – Data ‘curation’ och fysikinformerad analys
Arbetspaket 3 stärkte projektets datadrivna grund genom att utveckla verktyg och metoder för datacuration, datarensning och avvikelsedetektering. Ett generellt verktyg för tidsseriebaserad datarensning utvecklades och visade tydliga förbättringar i prediktionsnoggrannhet när maskininlärningsmodeller tränades på rensade dataset. Flera algoritmer för avvikelsedetektering utvärderades, och nya funktioner och klassificeringsmodeller utvecklades för att öka robustheten. Arbetspaketet levererade mjukvarumoduler för datacuration och maskininlärning samt ett öppet källkodspaket som möjliggör fortsatt användning och vidareutveckling. Detta arbetspaket utgjorde därmed en central länk mellan modellering, dataförberedelse och analys.

Arbetspaket 4 – Experimentell validering i testbädd
För att validera metodiken i praktiken genomfördes experiment på en tvåaxlig testbädd för precisionsmaskiner. Testerna visade att den ursprungliga lösningen med endast roterande encoders inte kunde upptäcka viktiga positioneringsfel. Genom att integrera högupplösta linjära skalor ökade systemets observabilitet avsevärt, vilket möjliggjorde mätning av både linjära och vinklade avvikelser. Arbetspaketet bekräftade metodikens funktion i laboratoriemiljö, visade tydliga prestandaförbättringar och utvecklade ett ramverk för syntetisk datagenerering. Resultaten stärkte projektets slutsats att förbättrad datakvalitet och direkt mätning är avgörande för robust övervakning.

Arbetspaket 5 – Industriella demonstrationer
I arbetspaket 5 tillämpades projektets metodik i tre industriella fallstudier för att demonstrera dess praktiska användbarhet. På komponentnivå förbättrades övervakningen av en växellåda genom installation av nya sensorer. På maskinnivå utvecklades en vibrationsbaserad metod för att följa verktygsslitage och processstabilitet i power-skiving-operationer. På linjenivå analyserades ett komplext emulsionssystem där metodiken identifierade funktioner som krävde förbättrad övervakning. Arbetspaketet levererade demonstrationer av robust digitalisering och visade hur förbättrad datakvalitet leder till mer tillförlitliga analyser och bättre operativa beslut. Workshops med industripartners bidrog till att förfina metodiken ytterligare.

Arbetspaket 6 – Projektledning och genomförande
Det avslutande arbetspaketet hanterade projektledning och koordinering. Trots personalförändringar och varierande tillgång till industridata kunde projektet anpassas till förändrade förutsättningar och genomföras enligt planens övergripande mål. Samarbetet inom konsortiet förblev starkt och säkerställde att resultaten från de olika arbetspaketen integrerades till en sammanhållen helhet.

Summering
Tillsammans visar arbetspaketen hur en kombination av funktionell och dysfunktionell systemanalys, fysikbaserad modellering, datacuration, experimentell validering och industriell tillämpning kan skapa en robust metodik för att förbättra datakvalitet, övervakning och beslutsstöd i industrin. Projektet demonstrerar att betydande förbättringar kan uppnås genom att bättre utnyttja befintliga datakällor, integrera fysikbaserad kunskap i dataflöden och stärka analyskedjan från sensor till beslut.

## 3. Background

Conventional strategies for operating in highly competitive markets have largely relied on expanding production capacity through new investments in machinery and facilities. While such measures may increase output in the short term, they are increasingly difficult to reconcile with the demands of sustainable and resource-efficient manufacturing. Future competitiveness is instead expected to depend on how well existing production assets are utilized, how efficiently systems are operated, and how hidden performance potential can be extracted without significant additional resource use. In this context, digitalization is a key enabling factor.

During the past decade, manufacturing has undergone a substantial transformation driven by digitalization, commonly referred to as *Industrie 4.0* in Europe and the *Industrial Internet of Things (IIoT)* in the United States. This development has enabled extensive data collection and analysis across industrial systems, from individual components and machines to full production lines and factory networks. The resulting data streams support new opportunities for performance monitoring, process optimization, maintenance strategies, logistics, and supply chain coordination. At the same time, global estimates indicate that IoT-based manufacturing could contribute trillions of dollars in added economic value in the coming years.

Despite these advances, a significant gap remains between installed production capacity and actual performance. Overall Equipment Effectiveness (OEE) is typically reported at approximately 55%, indicating that a substantial portion of production resources is not effectively utilized [10]. The primary losses are associated with reduced availability, operational inefficiencies, and process disturbances. This suggests that considerable improvements can still be achieved by optimizing existing systems rather than increasing capacity. At the same time, industry is facing an increasing imbalance between data availability and data usability. Large amounts of production data are collected continuously, yet their value is strongly dependent on accuracy, consistency, and relevance [1]. In practice, industrial data may be affected by measurement noise, missing or corrupted values, calibration deviations, and sensor drift. These issues are further amplified by demanding operating conditions and the growing complexity of interconnected digital systems. Consequently, ensuring reliable and meaningful data for decision support remains a central challenge.

Modern manufacturing systems rely on effective monitoring and measurement capabilities to enable fault detection, diagnosis, prognosis, and maintenance planning, as well as to maintain overall system reliability. Functional descriptions of systems provide insight into intended behaviour and interactions between subsystems, but they do not capture how and where performance degradation occurs. By integrating functional views with failure-oriented analysis, a more complete understanding of system behaviour can be achieved, enabling identification of critical functions and weak points in the system [2].

In parallel, the expansion of digitalization introduces additional sustainability considerations. The widespread deployment of sensors, computing hardware, communication infrastructure, and storage systems increases material demand and contributes to the generation of electronic waste. Moreover, the continuous storage and processing of large-scale data requires substantial energy consumption through computational infrastructure and data centres. As data volumes grow, the environmental impact of data handling becomes an increasingly relevant aspect of industrial digitalization. Within this context, the project applies a resource-oriented approach aimed at making more effective use of existing data sources rather than increasing the number of sensors and systems. The focus is on identifying the most relevant information already available in industrial environments, improving the selection of data sources, and introducing methods for early detection of data quality issues before storage and processing. By linking system-level functional understanding with structured assessment of data quality and relevance, the objective is to improve reliability, support better decision-making, and reduce unnecessary use of computational and physical resources in industrial applications.

## 4. Purpose, research questions and method

Against this background, the project adopts a resource-efficiency perspective aimed at maximizing the value of existing industrial data sources while minimizing unnecessary data collection and processing. The approach prioritizes the use of already installed sensors and available machine signals, focusing on identifying the most relevant information for monitoring, diagnostics, and decision support. A central principle is to shift data-quality assessment and validation earlier in the data pipeline, enabling detection of issues before storage and downstream processing. This reduces unnecessary data handling, increases the reliability of subsequent analytics, and lowers computational and energy demands.

The methodological foundation combines functional and dysfunctional system understanding with structured data assessment. Functional analysis is used to describe how the system behaves under intended operating conditions, while dysfunctional analysis identifies failure modes, degradation mechanisms, and performance losses. Integrating these perspectives enables systematic identification of critical system functions and components where improved monitoring, robustness, or data quality is required, whether at the component, machine, or production-line level.

The work is structured around the following research questions:

RQ1: Which methodological approach can systematically identify critical system functions and their potential failure mechanisms in industrial production systems?
This question focuses on how functional and dysfunctional analysis can be used to understand system behaviour and pinpoint where robustness improvements are most needed. The outcome provides a structured basis for prioritizing monitoring efforts and improvement actions.

RQ2: How can the quality, reliability, and trustworthiness of industrial data streams be assessed and improved in manufacturing environments?
This includes developing methods for data evaluation, validation, and curation, with emphasis on identifying and mitigating issues such as sensor drift, noise, missing values, and inconsistencies. The goal is to ensure that only relevant and reliable data are used for analysis and decision-making.

RQ3: How can physics-based modelling be effectively combined with data-driven methods to improve robustness and decision support in manufacturing systems?

This question addresses hybrid modelling approaches that integrate domain knowledge with machine learning and advanced analytics. The aim is to generate physically consistent and reliable representations of system behaviour that enhance interpretability, robustness, and industrial applicability.

**Work Package Structure**

The project is implemented through six interconnected work packages (WPs): WP1: Robustness assessment and recommendation framework; WP2: Generalized systems perspective on robustness; WP3: Physics-based data curation for robust decision-making; WP4: Experimental validation using synthetic use cases; WP5: Robustification and industrial implementation; WP6: Project management and dissemination

**Overall Methodological Flow**

The overall methodology follows a structured progression from conceptual development to industrial validation:

1. Identification of information requirements and definition of robustness evaluation criteria (WP1)
2. Development of generalized methodologies for data preparation and system-level analysis (WP2)
3. Integration of physics-based modelling with data-driven methods, including machine learning approaches (WP2–WP3)
4. Verification of data robustness and hybrid algorithm performance using synthetic use cases, with iterative feedback to model development (WP4–WP3 loop)
5. Implementation and validation in industrial case studies at component, machine, and system level (WP5)

Supporting activities include literature studies, master thesis projects, and industrial engagement through workshops, interviews, and site visits. These activities ensure continuous alignment between methodological development and industrial relevance.

Figure 1 gives an overview on the project activities and approaches.

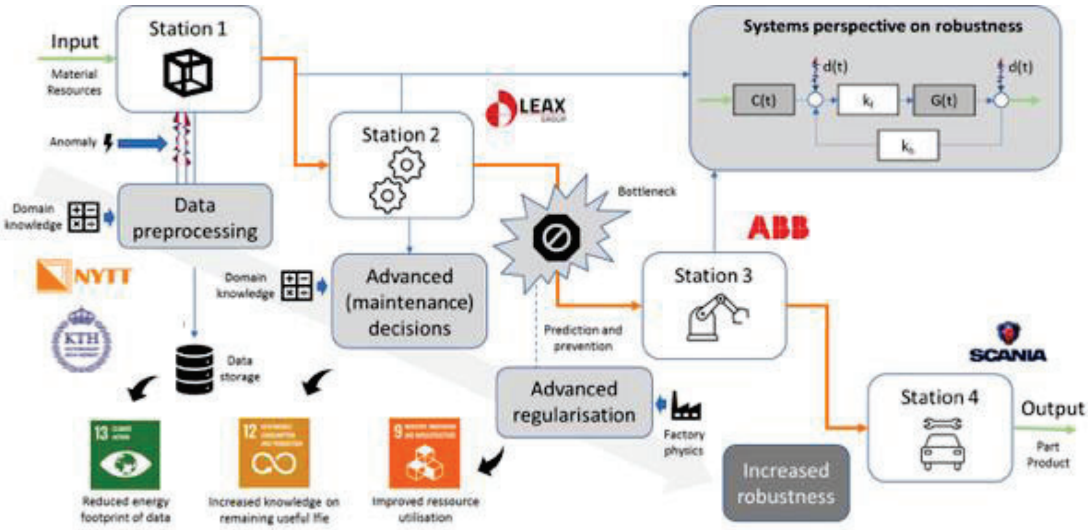



Figure 1: Overview of the RoDi project approaches for increasing the robustness of components, machines, and production lines in relation to sustainability goals.

## 5. Objective

The RoDi project aims to improve the utilization and robustness of industrial data streams by integrating physical domain knowledge into manufacturing data workflows. By combining traditional physics-based modelling and simulation with modern data-driven algorithms, the project enables the creation of robust, physically consistent data that strengthens operational and maintenance-related decision-making. The overarching ambition is to increase the value extracted from existing industrial systems and their data, while minimizing unnecessary data collection and processing.

The project focuses on three complementary objectives:

1. Identifying opportunities for robust data acquisition and utilization in industrial environments → Robustification
2. Increasing the trustworthiness, reliability, and quality of in-situ production data → Curation
3. Improving decision-making related to machine operation and maintenance activities → Preparation

Together, these objectives support the development of a generalized methodology for embedding physical domain knowledge into manufacturing data streams. This methodology enables applications such as anomaly detection, wear prediction, extension of machine lifetime, and identification of production bottlenecks. The primary goal of RoDi is to enhance the resource utilization of industrial systems and machinery, both in terms of physical assets and the data they generate. The project bridges the gap between theoretical advances in machine learning and their practical application to physical systems.

To achieve this overarching goal, the project defines a set of secondary objectives, summarized in Table 1.

*Table 2. RoDi project secondary objectives with descriptions.*

| Objectives | Description |
|---|---|
| O1 | Quantify the gain in robustness from using proposed methodology (combining physics and data-drive models with ML). |
| O2 | Exploit synergies between domain experts, with experts in data and physics-based analytics |
| O3 | Positive impact on the United Nations Sustainability Goals in environmental and ecological dimensions. |
| O4 | Validate the developed methodology on known systems (test beds) and industrial use cases. |
| O5 | Publish guidelines for how to perform physics informed analytics with clear limits for safe usage. |
| O6 | Educate one PhD student funded by the project and 4-6 MSc candidates with MSc projects and theses. |

## 6. Results and deliverables

### 6.1 Robustness assessment and recommendation framework (WP 1)

Effective decision-making in manufacturing relies fundamentally on robust, high-quality data to support monitoring, diagnostics, and maintenance strategies. To achieve this, a systematic data robustification process is essential. A cost-effective robustification strategy should maximize the confidence of the monitoring system while minimizing both the number of sensors required and the overall volume of collected data. In this context, the present work introduces a methodology that combines functional and dysfunctional analysis approaches to enable a comprehensive assessment of detection and monitoring conditions in advanced manufacturing systems. The methodology supports the identification of critical system functions as well as potential deficiencies in existing monitoring architectures.

As illustrated in Figure 2, the proposed approach integrates an enhanced Functional Analysis System Technique (FAST) with a fuzzy-based Functional Mode and Effect Analysis (Fuzzy-FMSA) [3] [4]. The methodology provides a structured process for evaluating both functional performance and dysfunctional risk factors in monitoring systems. The approach was applied to three industrially relevant case studies representing different hierarchical levels of manufacturing systems: component, machine, and production line. For each case, system functions were systematically categorized. On one hand, the methodology identifies functions that would benefit most from improved monitoring coverage. On the other hand, it highlights functions where monitoring resources may be excessive or inefficiently allocated. These insights were subsequently used to formulate recommendations for optimizing monitoring strategies, thereby improving overall system reliability and decision-support capability.

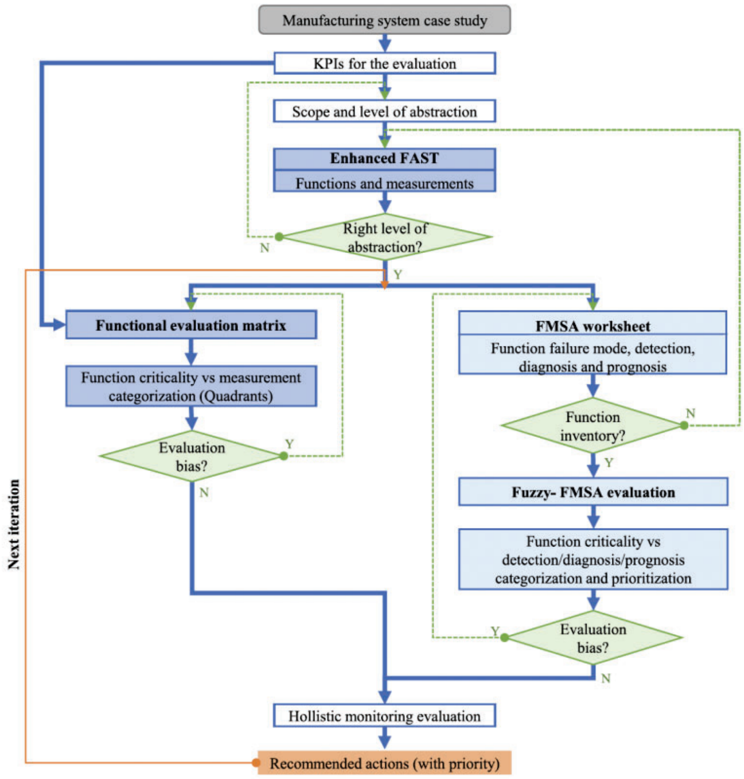



Figure 2: Process flow diagram of the proposed methodology combining functional (Enhanced FAST, dark blue blocks) and dysfunctional (Fuzzy-FMSA, light blue blocks) approaches for the assessment of detection and monitoring techniques in advanced manufacturing systems. [4]

**Functional analysis: FAST**

Feed-drive systems are common in industry. Figure 3 and Figure 4 illustrates an example of the enhanced FAST diagram applied to a single-degree-of-freedom feed-drive system, typically found in engineering and advanced manufacturing systems, e.g., machine tools, robots, additive manufacturing machines and semiconductor manufacturing equipment.

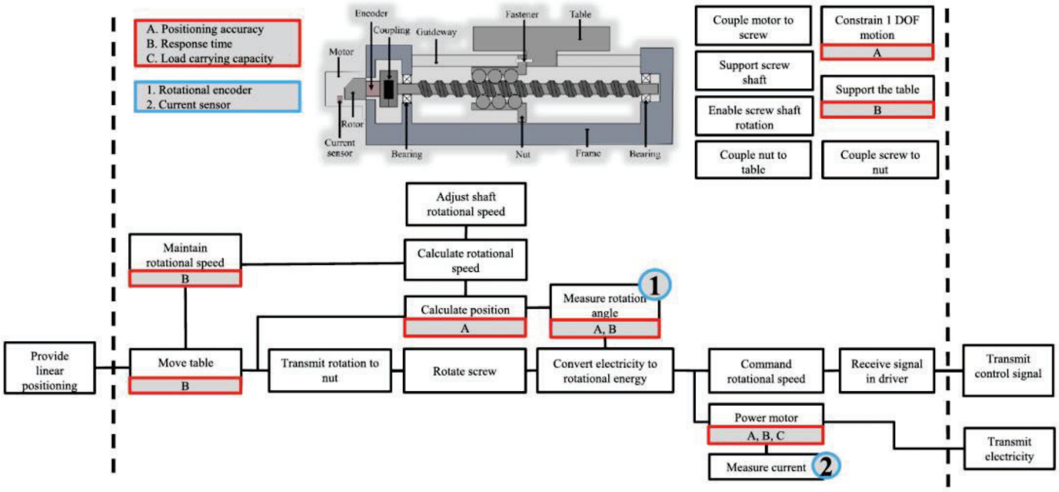



Figure 3: Example of the enhanced FAST applied to a feed-drive system [3].

The functional evaluation matrix enables the extraction of the expert knowledge about system's functions from the FAST diagram and provides a quantitative assessment of current monitoring coverage. Figure 4 illustrates how these values are then used to allocate functions and measurements to specific quadrants based on their criticality and current monitoring level. This allocation leads to general recommendations for improvement

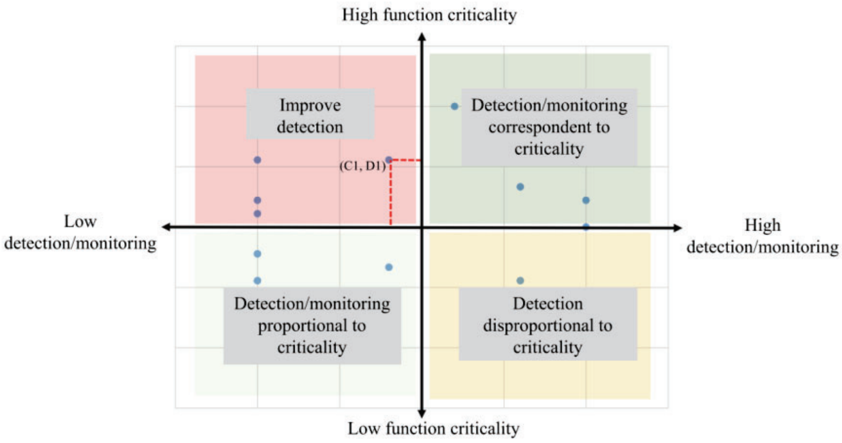



Figure 4: Function and monitoring evaluation quadrants [3].

**Dysfunctional analysis: FMSA**

The FMSA takes a more nuanced approach to monitoring by focusing on failure symptoms FMSA analysis can be initiated using two primary approaches: top-down and bottom-up, see Figure 5. The top-down approach is employed during the early design stages, before the system design is finalized and focuses on identifying critical functions and the consequences of their failure to meet their intended purpose. In contrast, the bottom-up approach is used once the system design is complete and the focus shifts to analyzing the potential failure modes of individual components at a lower level and their cascading effects on the system.

| Number | Function | Part | Failure mode | Failure effect | Failure cause | Failure symptoms | Detection method | Monitoring location | Monitoring frequency | DET | SEV | DGN | PGN | MPN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | Ensure rotational speed | Motor | Incorrect rotational speed | Delay in positioning | Incorrect speed calculation | Response time not achieved | Operation time | Centralized in MC controller | Continuous\ every cycle | 5 | 2 | 2 | 1 | 20 |
| **2** | Move table | Table | Lack of movement | Positioning error | Insufficient power\torque to displace table | Commanded position not attained | Rails | Local | Continuous\ every cycle | 4 | 3 | 2 | 1 | 24 |
| **3** | Enable 1 DOF | Linear rails | Unconstrained motion in 2 or more DOF | Positioning error | Misplacement of the rails\ incorrect mounting | Commanded position not attained | Rails joint connection | Local | Continuous\ every cycle | 3 | 2 | 2 | 1 | 12 |
| **4** | Support the table | Linear rails | Excessive bending of table | Positioning error | Excessive load, incorrect mounting | - | - | - | Continuous\ every cycle | 3 | 2 | 2 | 1 | 12 |
| **5** | Calculate position | Motor controller | Incorrect position estimation | Positioning error | Faulty position data | Commanded position not attained | Visual inspection | Centralized in MC controller | Continuous\ every cycle | 5 | 3 | 3 | 3 | 135 |
| **6** | Transmit rotation to nut | Nut | Absence of rotation of the nut | Table cannot be displaced | Excessive vibrations, incorrect mounting | Commanded position not attained | Visual inspection | Nut\screw assy | Continuous\ every cycle | 5 | 4 | 2 | 1 | 40 |
| **7** | Couple screw to nut | Nut | Parts not coupled | Table cannot be displaced | Excessive vibrations, incorrect mounting | Noise\vibrations | - | Nut\screw assy | Continuous\ every cycle | 5 | 4 | 2 | 1 | 40 |
| **8** | Couple nut to table | Joints | Inexistent connection between nut and table | Table cannot be displaced | Excessive vibrations, incorrect mounting | Noise\vibrations | Visual inspection | Local | Continuous\ every cycle | 4 | 3 | 2 | 2 | 48 |
| **9** | Adjust shaft rotational speed | Motor controller | Unfeasibility to adjust the shaft speed | Shaft rotational speed remain unchanged | Control logic not working properly | Response time not achieved | Operation time | Local | Continuous\ every cycle | 3 | 2 | 1 | 3 | 18 |
| **10** | Calculate rotational speed | Motor controller | Incorrect rotational speed estimation | Rotational speed set to an incorrect value | - | - | Operation time | Local | Continuous\ every cycle | 3 | 2 | 2 | 3 | 36 |
| **11** | Measure rotation angle | Encoder | Incorrect angle measurement | Incorrect calculations based on rotation angle | Encoder not working properly | Response time not achieved\ commanded position not attained | Operation time | Local | Continuous\ every cycle | 3 | 3 | 3 | 4 | 108 |

Figure 5: Example of FMSA applied to the 2-axis feed-drive system [4].

Using the developed methodology, the system's functionality is decomposed into functional elements and associated criticality modes through a structured functional–dysfunctional analysis, as shown in Figure 6. This analysis identifies which system functions are essential for maintaining correct operation and which failure modes pose the highest risk to overall system performance.

For the functions classified as critical, physics-based models are developed to describe their behaviour under varying operating conditions. These models are then used to perform sensitivity analyses, evaluate criticality criteria, and determine how disturbances or parameter variations influence system performance. The results of these analyses form the basis for defining recommended actions and mitigation strategies. Further details on this process are provided in Section 6.2.

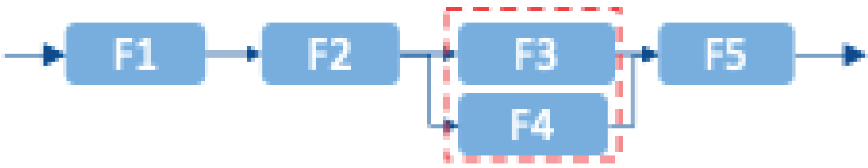



Figure 6: Critical functions identified.

**Results and deliverables and their relationship to the overall objectives**

All planned activities and associated deliverables were successfully completed. The results demonstrate clear progress toward the project's overarching objectives of robustification, data curation, and improved decision support in industrial environments. Additional details and scientific contributions are available in the published papers [3] and [4].

D1.1 State-of-the-Art Analysis and Gap Assessment
This deliverable provides a structured review of current approaches to data-driven decision support for maintenance at component, machine, and production-line levels. The analysis covers condition monitoring, prognostics, and industrial analytics with a focus on sustainable and resource-efficient production systems.

The review maps industrial practices, academic research, and enabling digital technologies relevant to FFI Sustainable Production goals, including reduced environmental impact through improved maintenance strategies and extended asset lifetime. Key challenges and knowledge gaps were identified, particularly regarding data quality, integration barriers, and the practical deployment of analytics in real production environments.
The outcome establishes a baseline for defining KPIs related to reliability and data usability directly supporting the project's objective of robustification.

D1.2 Industrial Data Availability Assessment and Use-Case Definition
This deliverable presents a pre-study of data availability, accessibility, and usability across participating companies. It includes mapping of existing sensor infrastructures, data interfaces, and industrial data ecosystems, as well as organizational and technical constraints affecting the implementation of data-driven strategies.

A central focus is how improved data utilization can support resource-efficient operation, reduced waste, and extended equipment lifetime, key principles of circular and sustainable production. Based on the assessment, representative industrial use cases were defined at system, process, component, and machine tool levels, ensuring relevance to real production conditions.
The results support KPI definition for data coverage, data quality, and predictive-maintenance capability, contributing directly to the project's objective of curation.

D1.3 Data Management and Analysis Methodology for Industrial Application
This deliverable introduces a structured and scalable methodology for industrial data management, covering acquisition, preprocessing, validation, quality assessment, and analysis. The methodology is designed to support robust and resource-efficient use of industrial data by enabling early detection of data-quality issues and reducing unnecessary data processing.

The framework integrates best practices for ensuring data reliability, traceability, and robustness in industrial environments. By shifting data-quality assessment earlier in the pipeline, the approach reduces computational load, minimizes storage requirements, and improves the reliability of downstream analytics. The deliverable defines implementation guidelines for industrial deployment and establishes KPI links to data quality, computational efficiency, decision-support performance, and sustainability indicators such as reduced resource usage, improved maintenance planning, and extended asset lifetime. These outcomes directly support the project's objective of preparation, improving decision-making based on trustworthy and physically meaningful data.

### 6.2 Generalized systems perspective on robustness (WP 2)

For each critical function identified through the methodology developed in WP1, a corresponding physics-based model was developed to analyse system behaviour, evaluate sensitivity to disturbances, and assess robustness under varying operating conditions. These models form the analytical base of the work package and provide a structured way to understand how deviations propagate through the system and affect functional performance.

The modelling framework was implemented in MATLAB Simscape/SimMechanics, enabling a high-fidelity representation of the mechanical structure, drive train, and control loops of the two-axis system. This environment allows component-level and system-level dynamics to be represented consistently, while also supporting modular extensions for additional functions or error sources.

A key feature of the modelling approach is the ability to inject controlled errors into the system. These injected deviations include geometric imperfections, thermal drift, backlash, compliance variations, sensor noise, and control-related disturbances. By systematically introducing these errors, the models make it possible to evaluate how each disturbance influences the system's ability to fulfil its intended function. This provides a quantitative basis for identifying critical modes, defining robustness criteria, and formulating recommended improvement actions.

The physics-based models also serve as a reference for defining the standard functional behaviour of the system. By comparing nominal performance with performance under injected disturbances, the methodology highlights which functions are most sensitive and where improvements, such as enhanced sensing, increased stiffness, or refined control strategies, are most effective.

In parallel with the modelling activities, the project explored physics-informed machine learning on the physical testbed. Although this was not fully implemented during the project period, it will form an important part of a future follow-up project. Synthetic data generated from the physics-based models is combined with real measurements from the upgraded testbed, which is equipped with multi-degree-of-freedom linear encoders. This hybrid approach strengthens the machine-learning models by ensuring consistency with physical laws while also capturing real-world variability. The result is a robust data-generation and validation pipeline that supports both model development and system-level robustness assessment. Together, the physics-based modelling, error-injection framework, and physics-informed machine learning form a comprehensive methodology for analysing and predicting system robustness, as illustrated in Figure 7. This integrated approach ensures that recommendations are grounded in both theoretical understanding and empirical evidence.

Matlab Simuling building functional blocks.

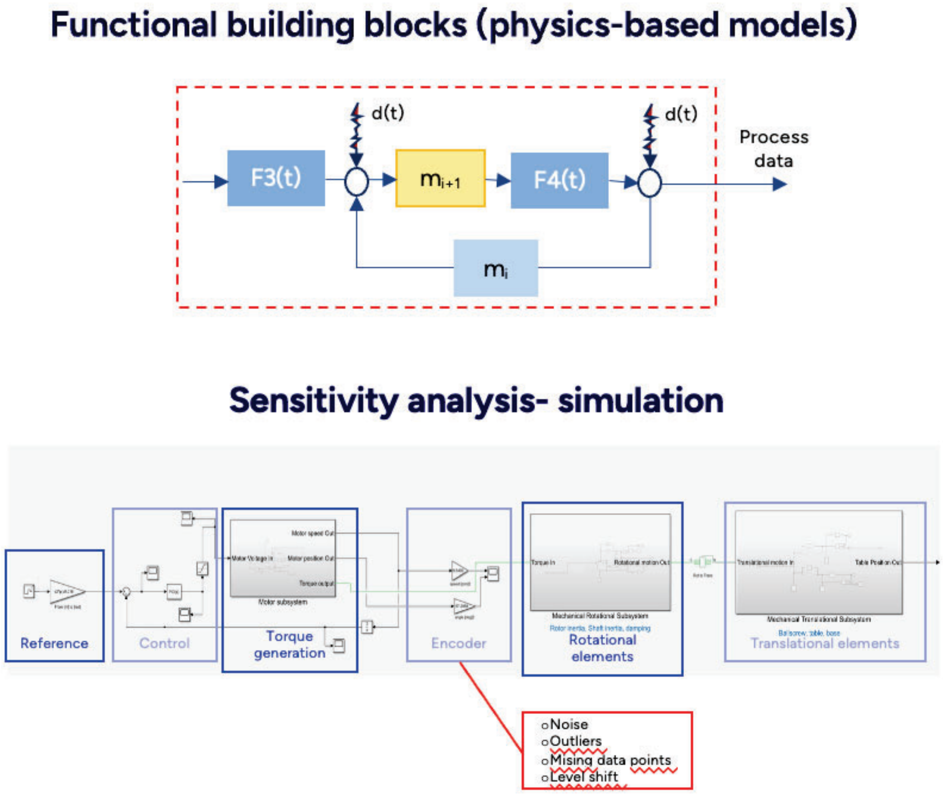



Figure 7: Generalized systems perspective on robustness: function buildings blocks of the critical functions and corresponding physics-based model.

**Results and deliverables and their relationship to the overall objectives**

Work Package 2 focused on establishing a generalized systems perspective on robustness, with emphasis on physics-based modelling, error propagation, data-quality requirements, and methodological best practices. The activities in WP2 directly support the project's overarching objectives of robustification, curation, and preparation by providing the analytical and methodological foundations needed for reliable, resource-efficient, and physically consistent data use in industrial environments. Activities related to Deliverables D2.1–D2.3 were completed as planned. Deliverable D2.4 was initiated but not fully finalized within the project period due to limited time and the need for additional case studies to validate and refine the proposed best-practice framework.

D2.1 Physics-based modelling framework

This deliverable established physics-based models for two representative synthetic use cases at both component and system level. The models were complemented by physics-informed data-preprocessing methods to ensure consistency, interpretability, and usability across different analysis stages. The modelling framework provides a foundation for understanding system behaviour under nominal and disturbed conditions, supporting the project's objective of robustification by enabling early identification of critical functions and potential failure mechanisms. It also contributes to curation by defining how physical knowledge can guide data preparation and validation.

D2.2 Error propagation and criticality assessment tools
This deliverable developed tools for analysing how disturbances and uncertainties propagate through a system and how they affect functional performance. The work includes error-propagation models, criticality-assessment matrices, and integrated data-processing pipelines supported by software tools and methodological guidelines. These tools enable systematic evaluation of robustness at component, machine, and system levels, directly supporting the project's objective of preparation by improving the reliability of decision-making based on quantified system sensitivities and failure risks.

D2.3 Data quality requirements and preprocessing guidelines
This deliverable defined a structured understanding of data-quality requirements for robust modelling and analytics. It identifies critical stages in data preparation and provides guidelines for filtering, augmentation, and removal of data depending on use-case characteristics. The results contribute directly to the project's objective of curation, ensuring that industrial data streams are reliable, consistent, and suitable for downstream analysis. The guidelines also support resource-efficient data handling by promoting early detection of quality issues and reducing unnecessary processing.

D2.4 Best-practice framework and recommendations
This deliverable aimed to consolidate insights from WP2 into a set of best practices and actionable recommendations for data-driven modelling workflows, including data preparation, model development, and application-specific adaptation strategies. Although significant progress was made, the deliverable was not fully completed within the project period. Additional case studies are required to validate the framework across a broader range of industrial conditions. The work initiated under D2.4 provides a strong foundation for future refinement and aligns with all three project objectives by supporting robust, trustworthy, and physically informed data use.

### 6.3 Physics-based data curing for robust decision making (WP 3)

Within Work Package 3, several activities were carried out to strengthen the data-driven aspects of the methodology and improve the robustness of the case-study analyses. A key focus was the optimization of data quality and model performance. This included applying advanced data-cleaning techniques, such as interpolation for missing values and systematic outlier detection, to enhance the reliability of the available datasets beyond the initial preprocessing steps [5].

As prediction models for automated decision-making in manufacturing become more widespread, enhancing their reliability is increasingly critical. One effective approach is improving the quality of training data through data curing or cleaning. However, most existing data curing methods rely on domain-specific expertise in data science, limiting their accessibility. To address this challenge, a general-purpose timeseries data curing toolbox with a user-friendly interface was developed, Figure 8. Designed to minimize user input while maintaining traceability, the toolbox was tested on various publicly available time-series datasets. Its performance was evaluated by comparing the prediction accuracy of machine learning models trained on original versus cleaned data. The results demonstrate the significant potential of the general-purpose toolbox enhancing data quality and model performance across a range of applications.

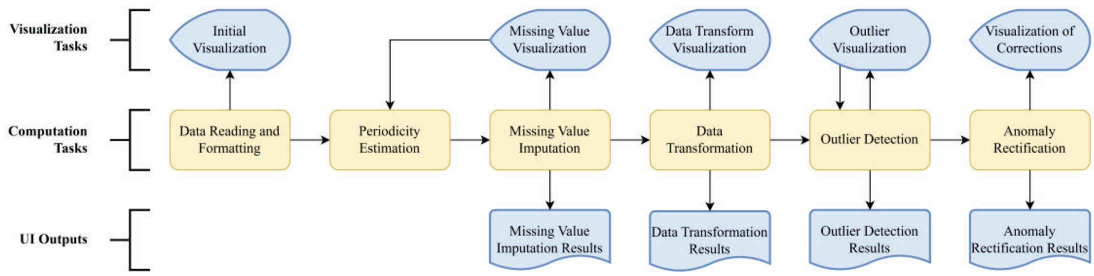
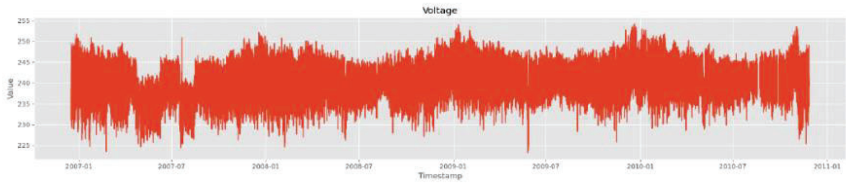
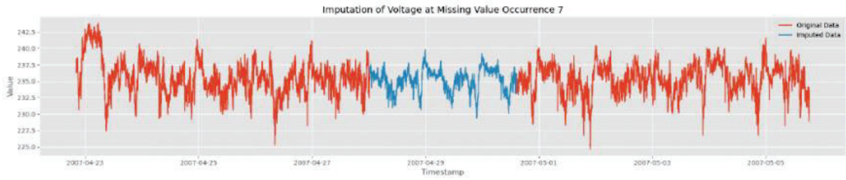



Figure 8: Workflow: Time-Series Data Curing: Design, Implementation, and Performance Evaluation of a General-Purpose Toolbox [5]

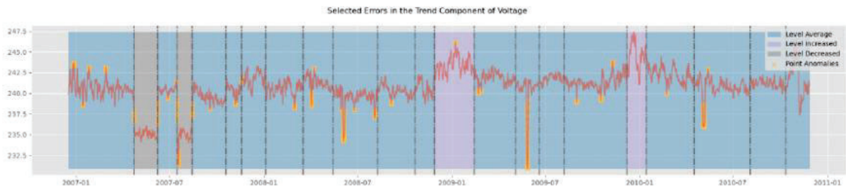
Figure 9 illustrates how the interface supports the handling of missing values after the initial data input and periodicity analysis. Before imputation is performed, the user can explore several visualizations, such as cumulative-sum plots, spanwise-proportion plots, and nullity-correlation heatmaps, to understand how missing data is distributed and to assess whether sufficient information is available for reliable imputation.



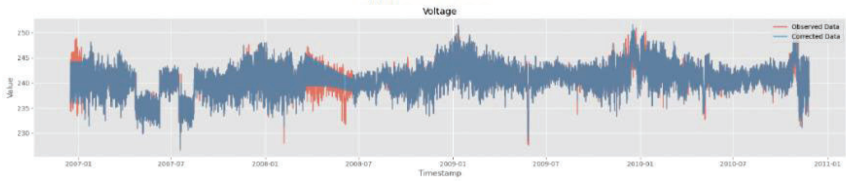

(a) Initial visualization




(b) Missing value imputation




(c) Outlier detection




(d) Anomaly rectification

Figure 9: Evolution of the voltage signal from the individual electric power consumption dataset throughout the different processing stages of the toolbox [5]

To improve the detection of abnormal behaviour in the studied systems, additional anomaly-detection methods were explored. Algorithms such as DeepAnt, One-Class SVM, and DBSCAN were evaluated to compare their performance and identify opportunities for more accurate and sensitive detection.

Further work was carried out on training optimization through feature engineering. New features were created to capture richer information about system behaviour, including moving averages, rolling standard deviations, and interaction-based variables. These enhanced the models' ability to learn meaningful patterns from limited or noisy data.
Finally, prediction performance was strengthened by testing alternative classification algorithms. Gradient Boosting Machines, XGBoost, and Neural Networks were explored as complementary approaches to improve accuracy and robustness in the predictive tasks.
Together, these activities contributed to refining the analytical workflow in WP5 and demonstrated how data-centric improvements can enhance diagnostics and monitoring across the case studies.

**Results and deliverables and their relationship to the overall objectives**

Work Package 3 focused on developing software-based tools for data curation and physics-informed analytics. The activities in WP3 translate the methodological foundations established in WP1 and WP2 into practical, implementable solutions that enable structured, reliable, and physically consistent data workflows in industrial environments.

Deliverable D3.1 was fully completed and resulted in a set of software modules supporting data curation, preprocessing, and the integration of machine-learning approaches. These modules form the core of the project's capability to ensure high-quality, trustworthy data streams and contribute directly to the project's objectives of curation and robustification.
Deliverable D3.2 was initiated and partially implemented. While key dashboard functionalities were developed, the deliverable could not be fully finalized within the project period due to time constraints and the need for additional refinement and validation.

In addition to the formal deliverables, WP3 produced an open-source software package that consolidates the main functionalities developed throughout the work package. The software is freely available on GitHub (see Section 7), enabling continued use, testing, and extension by both industrial and academic partners.

## 6.4 Experimental validation of data curing in synthetic use-case (WP 4)

Precision machine tools depend on feed-drive systems to generate linear and rotational motion, and the accuracy of these systems directly determines the achievable positioning performance. Geometric errors within the drive train propagate through the structural loop and result in deviations at the tool center point. The two-axis testbed (see figure 10), developed in earlier KTH projects, provides a controlled and repeatable platform for evaluating how the proposed methodology identifies and compensates these errors.

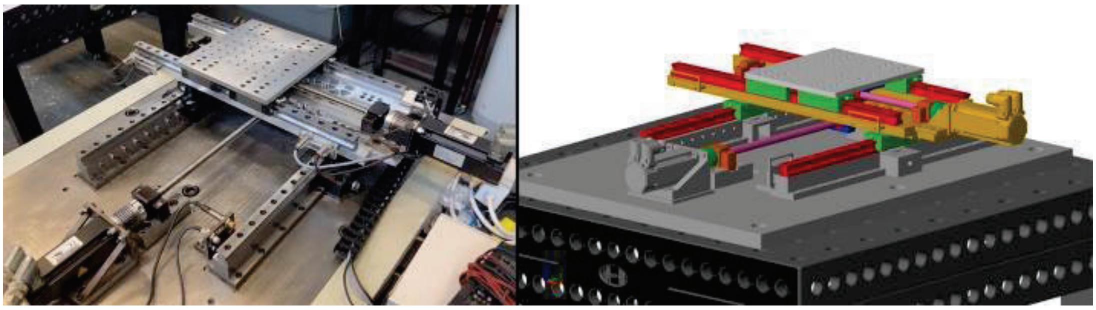


Figure 10: Physical two-axis feed-drive testbed in a stacked-axis configuration, with out linear encoder integrated (left) and its corresponding physics-based virtual model (right).

Applying the methodology from the earlier work packages showed that reliable detection of loss-of-function in axis positioning requires direct measurement of axis motion. For this reason, linear encoders were added to both stacked axes of the testbed.

The original testbed relied solely on indirect position measurements using motor-side rotary encoders. Through the methodology developed in the earlier work packages, it became clear that this configuration posed a high risk of failing to detect a loss of positioning function, the primary function of the system, see Figure 11. It was also highly sensitive to disturbances such as thermal variation, mechanical play, and limited control stiffness. To reduce these risks and improve detectability, it was recommended to introduce direct measurement of the table position. Consequently, linear encoders were integrated into both axes of the testbed.

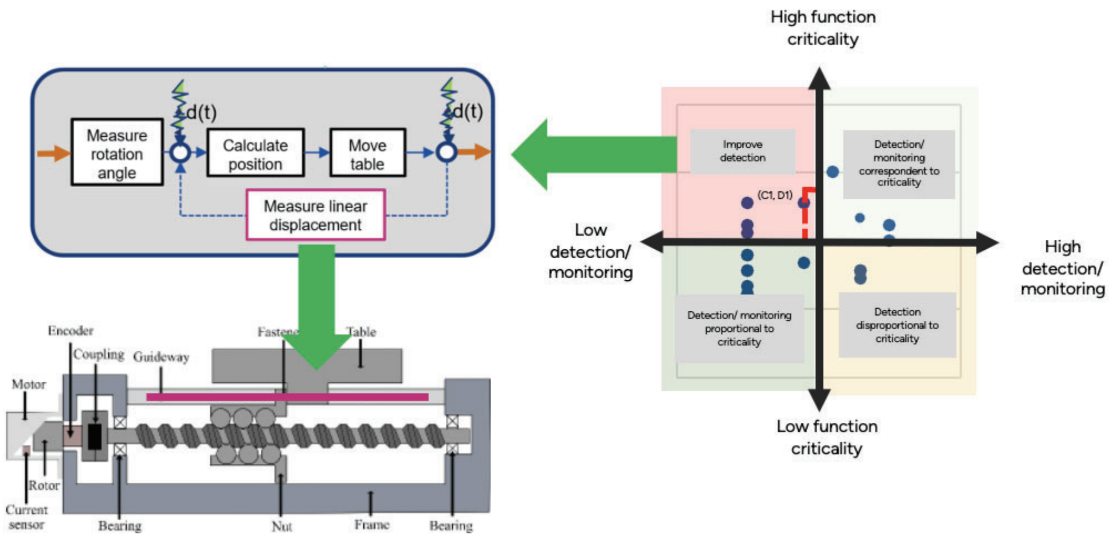



Figure 11: Methodology used to improve the detectability of errors in the feed-drive system.

Direct-measuring linear encoders reduce several error sources typical of ball-screw-driven systems, including thermal drift, reversal errors, and pitch-related kinematic deviations. In this project, advanced multi-degree-of-freedom (multi-DoF) linear encoders are used, Figure 12. These sensors operate on an interferential principle, generating signals through light diffraction and interference on a finely divided grating. This allows simultaneous measurement of linear displacement and angular deviations along a single axis, enabling cross-axis error detection and compensation.

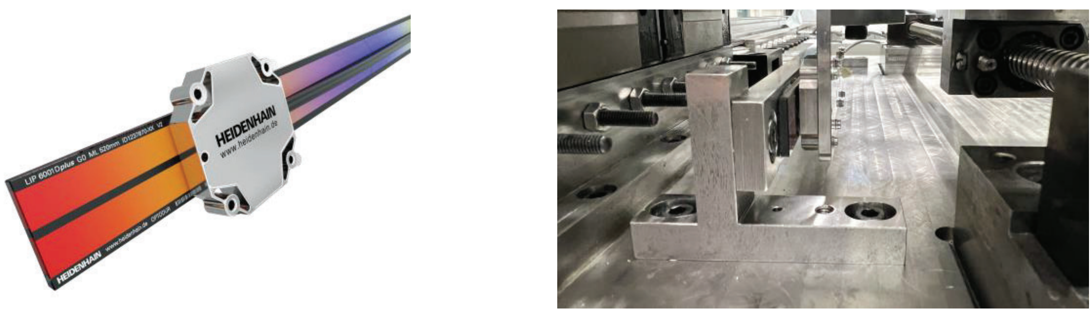



Figure 12: The Heidenhain Dplus encoder family measures multiple degrees of freedom relative to a single axis, enabling detection and compensation of deviations across neighboring axes (left). The installed encoder on the testbed (right). The encoder was provided by Heidenhain.

The upgraded testbed now enables direct measurement of table position, replacing the traditional indirect sensing approach. This direct feedback makes it possible to detect and compensate positioning deviations that would otherwise remain hidden when relying only on motor-side measurements.

**Deliverables and their relationship to the overall objectives**

Work Package 4 focused on validating the developed methodologies through controlled experiments and synthetic data generation. Deliverable D4.1 was fully completed. Deliverables D4.2 and D4.3 were initiated and are ongoing, with preliminary results indicating promising performance improvements.

D4.1 Experimental validation in laboratory environment
This deliverable involved validating the RoDi methodology using a two-axis stacked linear-motion testbed equipped with bearings, linear guideways, ball screws, encoders, and a control system. The main system function, axis positioning, was analysed using the functional and dysfunctional framework developed in WP1 and WP2.

The analysis revealed that, in the event of positioning errors, the motor-side encoder alone is insufficient for detecting loss of function. As a result, the methodology recommended enhancing the measurement system by integrating direct-position sensors. A high-precision linear scale (Heidenhain LIP 6001Dplus) was installed and is currently undergoing functional testing. This improvement directly supports the project's objective of robustification by increasing system observability and enabling earlier detection of anomalies.

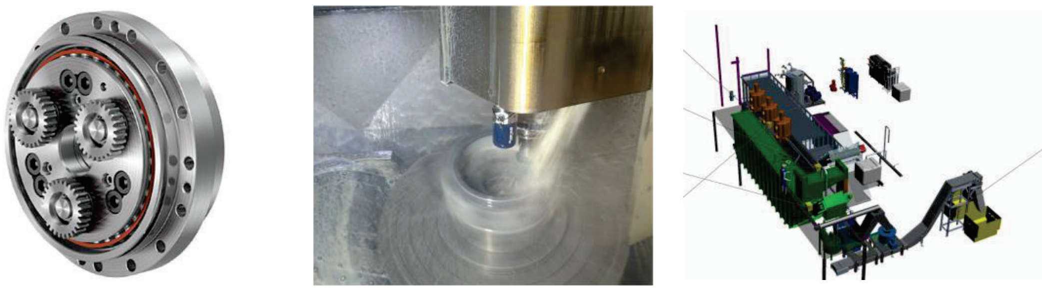
D4.2 Benchmarking of achievable performance improvements
This deliverable focuses on benchmarking the performance gains resulting from the developed methods, using the criteria defined in WP1. The assessment includes comparisons against baseline configurations and quantifies improvements in robustness, accuracy, and decision-support capability. Deliverable 4.2 is ongoing. Preliminary screening tests show promising improvements in system sensitivity and anomaly detection.

D4.3 Optimized simulation framework for synthetic case data generation
This deliverable aims to develop an optimized methodology for generating and managing simulation data for synthetic use-case scenarios. Deliverable 4.3 is ongoing.

### 6.5 Robustification of industrial systems (WP 5)

Work package 5 focused on applying and refining the project's methodology through a set of industrial case studies. These case studies were selected to represent different levels of manufacturing systems: component, machine, and line level. Together, they provided a broad and realistic basis for testing the methodology and evaluating its ability to support diagnostics, monitoring, and improvement work in real industrial environments. The chosen cases covered several industrial sectors and offered different levels of technical complexity. The gearbox test rig (component level) and the power skiving process (machine level) were selected because power-transmission systems are widely used in manufacturing equipment such as machine tools, industrial robots, pumps, and fans. The emulsion system (line level) was included to demonstrate how the methodology performs in a more complex, multi-stage support process involving pumps, valves, sensors, and filtration stages.

By working with these diverse scenarios, WP5 demonstrated that the methodology can be applied across different system levels and can support the evaluation of detection and monitoring conditions. The case studies also showed how expert knowledge can be integrated into the prioritization of improvement actions and the formulation of recommendations. For more information see published papers in references 4.



(a) (b) (c)

Figure 13: Case studies: (a) Component level (gearbox test rigg). (b) Machine level (power skiving). (c) Line level (emulsion system) [4]

**Component level (gearbox test rigg)**
The component-level case study examined a gearbox undergoing endurance testing in a dedicated test rig. The gearbox is a key transmission component in a robot manipulator, responsible for transferring power and controlling joint movement.

The test rig includes the mechanical components (gearbox, loading mass, support structure, and couplings) as well as a drive system with motion control and angular position feedback via a resolver. Endurance testing is used to determine component lifetime and typically includes both stationary and dynamic operating cycles to reproduce realistic wear patterns. This setup provided a controlled environment for analysing failure modes, monitoring conditions, and evaluating how data scarcity affects diagnostics at component level.

Overall, Figure 14a indicates a weak correlation between the identified functions and the available measurement data, independent of the function's criticality. This suggests either a substantial need to improve the monitoring setup or a potential bias among stakeholders toward underestimating the current monitoring capability.

Further analysis showed that the gearbox testbed would benefit from additional measurement points to improve anomaly detection during test procedures. These sensors were subsequently integrated into the setup, and preliminary results demonstrate a clear improvement in the ability to detect anomalies.

**Machine level (power skiving)**

The machine-level case study focused on a power-skiving machining centre (Figure 14b) used to produce internal and external gears for planetary gear systems in electric-vehicle powertrains. Power skiving is a gear-manufacturing process in which a pinion-shaped cutter machines the gear teeth. The industrial partner sought support in addressing both production-related and quality-related challenges. Based on stakeholder input, two key performance indicators (KPIs) were defined: tool life, measured as the number of parts produced per tool, and workpiece quality, assessed through GD&T conformance. Operating in highly specialized markets such as heavy commercial vehicles and passenger cars, the partner requires both high precision and stable process performance.

Figure 14b presents the results of the functional analysis for the power-skiving machine. A total of 23 out of 30 functions fall into quadrant III, indicating low monitoring for functions perceived as low priority. This distribution reveals a clear stakeholder bias toward classifying most functions as low criticality and therefore not requiring extensive monitoring. Of the remaining seven functions, two are placed in quadrant I—high monitoring and high criticality—reflecting an appropriate focus on functions essential to process stability and product quality.

This case study provided an opportunity to apply and evaluate the project's methodology in a high-precision machining environment where even small deviations can have significant impact. As part of the analysis, a comprehensive vibration-monitoring framework was developed to address the specific challenges of the power-skiving process. Twelve health indicators were introduced to capture different aspects of process behaviour, including synchronization accuracy, early detection of regenerative chatter using the Modified Energy Ratio, and tracking of tool-wear progression and mechanical degradation through harmonic analysis. Statistical moment tracking was used to monitor changes in signal characteristics over time, and insights from cutting-force simulations supported the interpretation of vibration patterns. Together, these elements enhanced the diagnostic capability of the methodology and provided a deeper understanding of the machining process.

## Line level (emulsion system)

The line-level case study examined a complete emulsion system used alongside machining centres that produce cylinder heads. The system is installed at a company providing transport solutions.

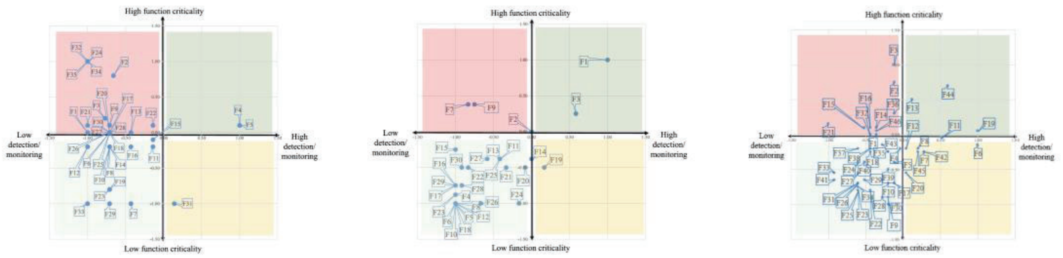
The emulsion system receives process fluid contaminated with metal chips from several machining centres. Its main function is to recover and clean the emulsion by separating chips and filtering the fluid through multiple stages. The chips are dried and sent for re-melting at the foundry, while the filtered fluid is reused in the cutting process.

Two KPIs were identified for this case:

- Quality of the process fluid after filtration
- System availability

This case demonstrated how the methodology can be applied to a complex, multi-stage support process with several interacting components and varying operating conditions.

The results of the functional analysis applied to the emulsion system, using the FAST method and evaluation matrix, are shown in Figure 14c. The output evidences the functions that need either review or improvement of their monitoring condition. An equal number of functions fall into quadrants II (improvement needed) and IV (review monitoring) of the figure. However, it is important to note that several functions lie close to the quadrant borders. Their membership to a certain quadrant is highly dependent on the grading numbers assigned during the system evaluation. For example, function F3 has high criticality and is classified for monitoring improvement. A slightly different grading in function/measurement correlation could have placed it in quadrant I (satisfactory monitoring). This highlights the sensitivity of the evaluation matrix and the need for careful review of functions near quadrant boundaries.




(a) (b) (c)

Figure 14: (a) Evaluation quadrants and functional matrix for the component-level case (gearbox test rig). (b) Evaluation quadrants and functional matrix for the machine-level case (hard-skiving center). (c) Evaluation quadrants and functional matrix for the line-level case (emulsion system) [4].

Improvements were also identified in this case study. In the existing system, the chip conveyor relied on limited monitoring to detect errors in the feed-screw system. To address this gap, an additional monitoring channel was introduced by measuring the feed-motor current. This enhancement strengthens the system's ability to detect anomalies during operation and provides earlier indications of mechanical issues.

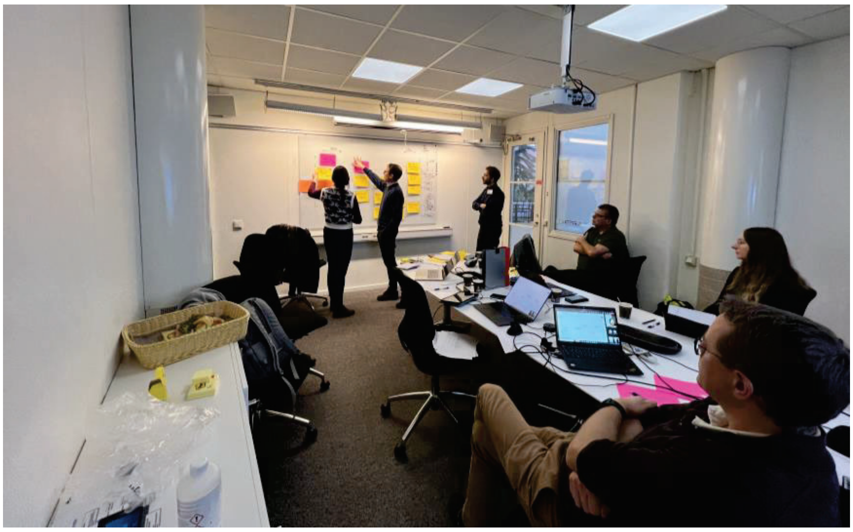
**Deliverables and their relationship to the overall objectives:**

The first objective, addressed in deliverable D5.1, was to showcase robust digitization capabilities in real industrial applications. This included integrating physics-based modelling, advanced data-processing pipelines, and machine-learning approaches into existing industrial workflows. The demonstrations confirmed that the developed methods can be effectively applied to complex processes and systems, enabling more reliable monitoring, analysis, and interpretation of operational behaviour.

The second objective, covered in deliverable D5.2, focused on demonstrating improvements in data reliability and the resulting impact on decision-making. The results showed that higher data quality, structured preprocessing, and robustness-aware analytics significantly strengthen both operational and engineering decisions. By ensuring that data is consistent, trustworthy, and contextually meaningful, the methodology supports more confident and informed actions in industrial settings.

All demonstration activities were successfully completed, and the results confirm that the project's methodologies are applicable, scalable, and beneficial across a range of industrial use cases.

Workshops in which functional and dysfunctional aspects of the studied systems were discussed and outlined, contributing to the development of the methodology, Figure 15.



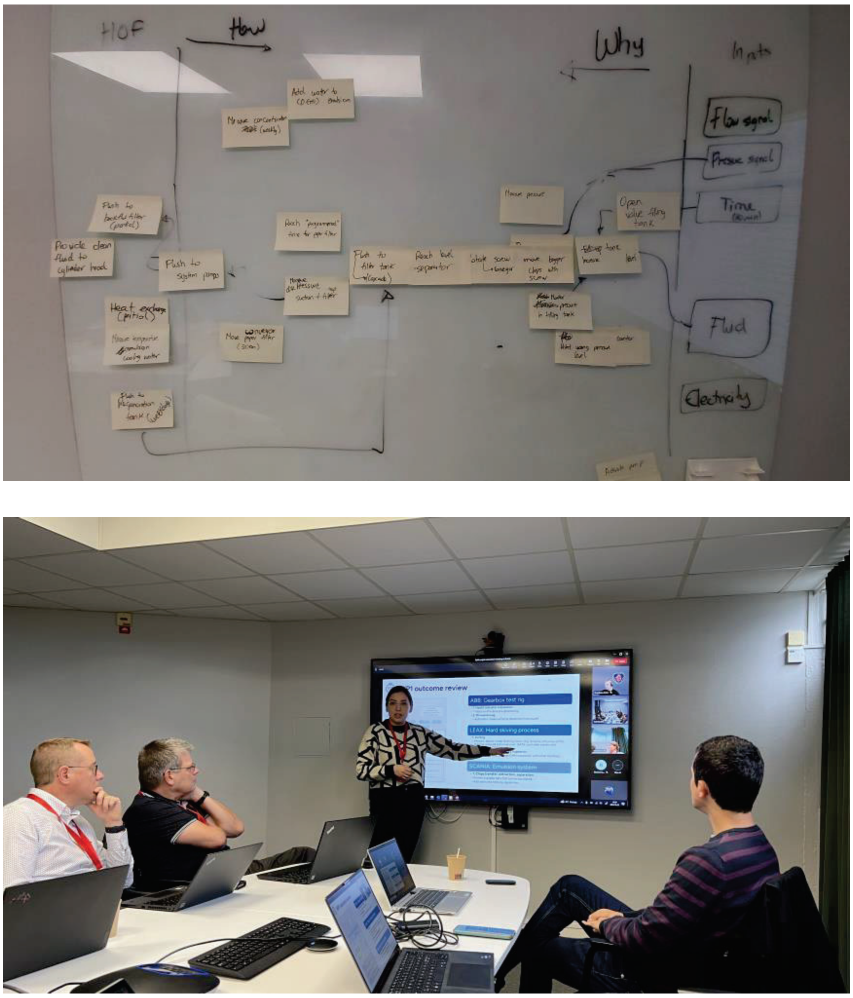



Figure 15. Workshops in which functional and dysfunctional aspects of the studied systems where investigated.

### 6.6 Project management and dissemination (WP 6)

A structured management model was used to support collaboration and communication across the consortium. The steering committee consisted of the work package leaders and the industrial case leaders. This group, chaired by the project coordinator KTH, met regularly at the general meetings to review progress, align activities between work packages, and prepare updates for the steering committee. These meetings served as an important forum for identifying risks, adjusting timelines, and ensuring that results from the technical work were integrated into the WP4 case demonstrations. The steering committee, consisting of one representative from each project partner, provided strategic oversight and ensured that the project remained aligned with the intended outcomes and the targets of the FFI program. The committee met twice per year and was chaired by ABB. The steering committee also reviewed and approved any proposed changes to the project plan, including adjustments related to timelines, resource allocation, or scope.

In addition to the general project meetings, each work package held its own regular meetings and workshops. These were closely linked to the ongoing research and development activities and allowed the teams to coordinate tasks, share results, and resolve technical challenges. The work package leaders were responsible for ensuring that the goals and deliverables of their respective work packages were achieved.

Project general assemblies and steering committee meetings: 2022-04-07 at KTH, 2022-10-16 at ABB, 2023-03-23 at Leax, 2024-03-20 at Nytt, 2024-10-10 at KTH, 2025-05-16 at ABB, 2025-10-21 at KTH, Project Kick-off: 2022-04-07 at KTH, Project End: 2025-10-21 at KTH.

Overall, the project progressed well, and the work developed steadily over time. However, several challenges influenced the project's activities and timeline. The most significant factor leading to a prolongation of the project was the change in project personnel. Some team members who were initially responsible for project management and research activities left their roles during the project period, which created delays and required redistribution of responsibilities. In addition, shifting priorities among the industrial partners affected the availability and continuity of the planned case studies. As a result, it became difficult to obtain the necessary data for early development work and initial screening tests. Data scarcity is a well-known challenge in research projects of this nature, and it must be considered when planning and executing project activities, particularly when industrial case studies form a central part of the methodology. Despite these challenges, the project adapted to the evolving conditions, and the consortium maintained good collaboration throughout the project period.

For further dissemination activities, see Section 7.

## 7. Dissemination and publications

### 7.1 Dissemination

| How are the project results planned to be used and disseminated? | Mark with X | Comment |
|---|---|---|
| Increase knowledge in the field | X | • Systematic process: How to assess what to measure, how to measure it, and when to measure it for manufacturing equipment, processes, and products.<br>• Improved understanding of how physics-informed machine learning can be combined with industrial data for system-level diagnostics.<br>• New insights into error propagation mechanisms in multi-sensor industrial systems.<br>• Enhanced knowledge of how data quality affects robustness in predictive maintenance models. |
| Be passed on to other advanced technological development projects | X | • Use of the developed data curation pipeline in other AI-driven manufacturing research initiatives.<br>• Adoption of the robustness assessment framework in follow-up projects on digital twins and smart production systems.<br>• Transfer of simulation and modelling methodology to projects focusing on autonomous production systems and adaptive control. |
| Be passed on to product development projects | X | • Integration of validated sensor fusion and diagnostics methods into next-generation machine tool and industrial robot monitoring systems.<br>• Application of robustness dashboard concepts in commercial industrial software for condition monitoring.<br>• Use of physics-informed ML models to improve predictive maintenance |

| | | |
|---|---|---|
| | | functionality in industrial equipment platforms. |
| Introduced on the market | - | Not planned at the moment |
| Used in investigations / regulatory / licensing / political decisions | - | No plans now |

**Phd thesis related to the project**

Gonzalez Bassante, Monica Katherine, On the Accuracy of Articulated Robots: A Comprehensive Approach to Evaluate and Improve Robot Accuracy for Contact Applications, TRITA-ITM-AVL; 2025:6, ISBN: 978-91-8106-224-3
Dissertation held 2025-04-02 at KTH in Stockholm.

Eleonora Iunusova, Towards reliable diagnostics under data scaracity: machine learning for manufacturing equipment, TRITA-ITM-AVL 2026:12, ISBN 978-91-8106-625-8
Dissertation planned 5$^{th}$ of June, 2026 at KTH in Stockholm

**GitHub Software Repository**

M. Kovács, Time-Series Data Cleaning User Interface. 2024. doi: 10.5281/zenodo.11057684

As part of the RoDi research project, a GitHub software repository has been established to disseminate the developed results in an accessible and reusable form. The repository contains a Python-based user interface for time-series data cleaning, designed to support users without extensive domain knowledge or prior experience in data science.
The software addresses a common bottleneck in machine learning workflows, where data cleaning is often omitted due to complexity and the wide range of available methods. By providing an intuitive interface, the tool enables more efficient preprocessing of time-series datasets and supports improved data quality prior to model training.

The GitHub repository serves as an important project deliverable, ensuring open access to the developed methods and enabling continued use, validation, and further development by researchers and industry practitioners.

### 7.2 Publications

[1] Andreas Archenti, Wei Gao, Alkan Donmez, Enrico Savio, Naruhiro Irino, Integrated metrology for advanced manufacturing, CIRP Annals, Volume 73, Issue 2, 2024, Pages 639-665, ISSN 0007-8506, https://doi.org/10.1016/j.cirp.2024.05.003.

[2] Iunusova, E., Gonzalez, M.K., Szipka, K. et al. Early fault diagnosis in rolling element bearings: comparative analysis of a knowledge-based and a data-driven approach. J Intell Manuf 35, 2327–2347 (2024). https://doi.org/10.1007/s10845-023-02151-y

[3] Monica Katherine Gonzalez, Bernd Peukert, Andreas Archenti, Assessment of fault detection and monitoring techniques for effective digitalization, Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023) ©2023 ESREL2023 Organizers. Published by Research Publishing, Singapore. doi: 10.3850/978-981-18-8071-1_P430-cd.

[4] Monica Katherine Gonzalez, Mariano Jose Coll-Araoz, Andreas Archenti, Enhancing reliability in advanced manufacturing systems: A methodology for the assessment of detection and monitoring techniques, Journal of Manufacturing Systems, Volume 79, 2025, Pages 318-333, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2025.01.015.

[5] M. Kovács, M. K. Gonzalez and A. Archenti, "Time-Series Data Curation: Design, Implementation, and Performance Evaluation of a General-Purpose Toolbox," in IEEE Access, vol. 13, pp. 193937-193955, 2025, doi: 10.1109/ACCESS.2025.3628941

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[8] Mariano Jose Coll-Araoz, Pu Sun, Farzad Ghadam, Andreas Archenti, Evaluating Spindle Degradation and Machining Quality using an Exchangeable Spindle Unit and Vibration-Based Monitoring, euspen's 25th International Conference & Exhibition, Zaragoza, ES, June 2025.

To be published:
[9] Vibration Analysis for Enhanced Tool Wear and Defect Detection in Power Skiving of Gears: The Challenges, Authors: Jerzy Mikler, Robert Tomkowski, Oskar Johansson

### 7.3 Invited presentations

XXXVI CIRP Sponsored Conferenceon Supervising and Diagnostics of Machining Systems, 2025, Karpacz, Poland
A comprehensive vibration-analysis framework was developed to address the specific challenges of the power-skiving process.
Presenter: Dr Jerzy Mikler

Swedish R&D Cluster, 2024, Skövde
The project was invited to be presented at the Swedish R&D Cluster conference held in Skövde in 2024. The audience showed interest in the work, and the presentation generated many questions and engaging discussions among the participants.

Presenters: Dr. Monica Gonzales, Mariano Coll, and Prof. Andreas Archenti

CIRP General Assembly, 2024, Thessaloniki
The project was invited to be presented at the CIRP General Assembly at the STC P meeting in Thessaloniki in 2024. Robust digitalisation by process monitoring improvement in industry.
Presenter: Mariano Coll

## 8. Conclusions and future research

The RoDi project builds on a long tradition of research in precision manufacturing, industrial analytics, and machine-tool and robot characterization. Many of the participating partners have collaborated in earlier initiatives, creating a strong technical and methodological foundation that RoDi could extend.

Several previous projects contributed directly to this foundation. The IAM project (Vinnova 2018-05033) advanced industrial analytics through sensor data, signal processing, and metrology. The Fritext project (Vinnova 2017-05540) deepened understanding of functional surfaces and their characterization. The McGuide project (Vinnova 2016-05397) improved knowledge of machine-tool behaviour and cutting-process interactions, essential for modelling and testing. In parallel, the Eureka SMART COMACH project (Vinnova 2018-03330) strengthened calibration and compensation methods for industrial robots. Additional contributions came from the CHARMS and Sensor-Based Metrology projects within the Powertrain Manufacturing for Heavy Vehicles Application Lab, a collaboration between KTH, Fraunhofer, and RISE. Together, these initiatives provided a solid platform for RoDi's development.

Building on this background, RoDi combined data-driven methods, physics-based insights, and industrial case studies into a coherent framework for reliable diagnostics under limited and imperfect data conditions. Throughout the project, new challenges and opportunities were identified, pointing toward future research on scalable diagnostic methods, improved sensor integration, and more advanced modelling of industrial equipment.

**Addressing the Research Questions**
RQ1 Identifying critical functions and failure mechanisms
Addressed through the functional and dysfunctional analysis framework, applied across all case studies to identify critical functions, failure modes, and monitoring gaps.

RQ 2 Ensuring data quality and reliability
Addressed by defining data-quality requirements, developing curation and preprocessing guidelines, and implementing software tools for early data validation to ensure that only reliable and relevant data enter the analysis pipeline.

RQ 3 Combining physics-based and data-driven methods
Addressed through hybrid modelling approaches that integrate physics-based models with machine-learning methods, validated through synthetic and laboratory testbeds to improve robustness and decision support.

Through this continuous line of research, RoDi has both benefited from and contributed to a broader scientific and industrial ecosystem. The results strengthen the foundation for future work in intelligent manufacturing systems. In the longer term, the project's outcomes are expected to support earlier detection of wear, deviations, and disturbances, enabling more proactive maintenance and reduced downtime. More efficient data handling can also reduce storage and processing demands, lowering energy use and environmental impact.
Finally, the project provides an important basis for future industrial use of AI-based methods by ensuring access to relevant, trustworthy, and well-structured data. This supports faster analysis, better decision-making, reduced bias, and more robust monitoring solutions.

## 9. Participating parties and contact persons

Members of the consortium.

Partner companies and institutions and members involved in the project.

| | Partner | Role | Kontact persons |
|---|---|---|---|
| ABB | ABB Robotics | Industrial partner | Dr Björn Lundén, Dr Mikael Norrlöf, Jens Andersson, Amandine-Heqing Sun |
| LEAX | Leax | Industrial partner | Oskar Johansson, Elias Häggström |
| SCANIA | Scania | Industrial partner | Dr Gopalakrishnan Maheshwaran, Mariano Coll, Sanjabi Yoones |
| NYTT | Nytt AB | Research partner | Praveen Natarajan, Sture Wikman, Praveen P. |
| KTH VETENSKAP OCH KONST | KTH Royal Institute of Technology | Project leader and research partner | Jonny Gustafsson Prof. Andreas Archenti, Dr Monica Katherine Gonzales, Dr Robert Tomkowski, Dr Jerzy Mikler, Dr Bita Daemi, Dr Bernd Peukert, |

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