# Data-Driven Decision-Making: Leveraging Digital Twins for Reprocessing in the Circular Factory

*Nehal Afifi*,*
*Victor Mas,*
*Jonas Hemmerich,*
*Felix Leitenberger,*
*Luisa Hoffmann,*
*Ali Darijani,*
*Patric Grauberger,*
*Michael Heizmann,*
*Jürgen Beyerer and*
*Sven Matthiesen*

Circular factories must ensure the functionality and reliability of used components for recombination with other components or subsystems from the same or different product generations. This paper presents a data-driven decision-making framework integrating the Functional Behavior Model and System Reliability Model within a Digital Twin. Data from physical testing is continuously incorporated, simulating recombination scenarios and guiding decision-making on component reprocessing. An angle grinder is used as a case study for demonstration. The proposed framework enhances sustainability and supports the use of reprocessed components in products designed for primary markets.

## Introduction

Modern manufacturing systems are increasingly complex, particularly in non-linear, interdependent production lines. This complexity raises the likelihood of downtime and maintenance, challenges that redundancy measures or stricter quality standards cannot fully mitigate. Circular factories (CFs), which aim to promote sustainability by reprocessing components, face additional challenges due to the variable quality of returned inputs [1]. Addressing these issues requires advanced frameworks capable of managing uncertainty and optimizing decision-making in dynamic environments. DDDM in manufacturing involves the continuous acquisition, processing, and analysis of data to optimize strategies across a product's lifecycle, from design to end-of-life decisions.

Within the CF [2], DDDM enables resource optimization, extended product lifespans, and sustainable practices by integrating machine learning to develop functional and reliability models that guide predictive and prescriptive decisions [3]. The FBM provides actionable insights to assess a product's operational performance based on its current condition. Using the relations between the embodiment and the functional behavior of a product, the FBM links the two domains and allows for the evaluation of used products. The operational performance can be derived [4] and expressed as a metric by comparing the functional behavior with the product's requirements. To gain insights into the performance over time, the System Reliability Model (SRM) complements this metric by addressing potential failure modes, including fatigue, corrosion, and wear, estimating the impact of failures, and predicting the product's performance under various conditions [5]. Together, these models enable monitoring and predicting product health and support DDDM in the CF. DTs serve as the core of this data integration

* Corresponding Author
*Nehal Afifi, M. Sc.;* Karlsruhe Institute of Technology (KIT), Institute of Production Engineering (IPEK), Kaiserstr. 10, 76131 Karlsruhe; Phone: +49 (0) 721 608-48060, E-Mail: nehal.afifi@kit.edu

Co-authors
*Victor Mas, M. Sc.;* Institute of Production Engineering (KIT IPEK)
*Jonas Hemmerich, M. Sc.;* Institute of Production Engineering (KIT IPEK)
*Felix Leiterberger, M. Sc.;* Institute of Production Engineering (KIT IPEK)
*Luisa Hoffmann, M. Sc.;* Institute of Industrial Information Technology (KIT IIIT)
*Ali Darijani, M. Sc.;* Institute of Anthropomatics and Robotics (KIT IAR)
*Dr.-Ing. Patric Grauberger;* Institute of Industrial Information Technology (KIT IIIT)
*Prof. Dr.-Ing. Michael Heizmann;* Institute of Industrial Information Technology (KIT IIIT)
*Jürgen Beyerer, M. Sc.;* Institute of Anthropomatics and Robotics (KIT IAR)
*Prof. Dr.-Ing. Sven Matthiesen;* Institute of Production Engineering (KIT IPEK)

Note
This article is peer reviewed by the members of the ZWF Special Issue Advisory Board.

process. A DT is a virtual representation of a physical asset [1], continuously updated with real-time product data throughout the processes within the CF. Data from the FBM and SRM is integrated and dynamically updated to inform reprocessing decisions. DTs ensure that data-driven insights provided by product conditions guide decisions.

## Background

DTs, FBMs, and SRMs form the foundation of modern manufacturing systems. They are particularly relevant in the context of CF, which faces significant challenges due to the variability in the quality of returned parts. DTs represent physical systems virtually and enable real-time, bidirectional data flow between physical and digital domains. Their characteristics have been defined across various authoritative implementations [6–10]. DTs have evolved significantly [11], driven by advancements in high-performance computing [12], Moore's Law [13], IoT technologies [14], chip design [15], and deep learning [16]. These advancements have expanded DT applications from predictive maintenance to real-time system simulations, enabling complex decision-making scenarios. The issue of R-strategies lies in their optimal choice [17]. To make informed decisions about reprocessing strategies, it is essential to have quantitative knowledge about the relations between a product's embodiment and functional behavior [3]. Understanding these embodiment-function relations (EFRs) provides insight into the product's current condition and creates a cornerstone for targeted and effective reprocessing. In the vision of the CF, this step is carried out by the FBM. Behavior investigation is carried out using behavioral models [18] of physical systems. They include qualitative approaches such as Characteristics Properties Modeling [19] and quantitative approaches like experimental studies or numerical simulations [20]. Behavioral models investigate how the product's functional behavior is derived from its embodiment [4]. However, the inversion of this investigation, needed for reprocessing decisions in the CF, requires implicit expert knowledge. In the CF, the FBM integrates this implicit expert knowledge to form real-time computational models, enabling bidirectional evaluation of the EFRs. Therefore, the FBM helps to assess product functionality based on the current condition but does not include degradation over time. SRMs address this gap by focusing on the performance of systems and components over time. Reliability is the probability of a system or component performing its required function at varying performance levels over a specified period under stated conditions [5]. Tools like Ishikawa diagrams [21] and Design Structure Matrices [22] identify key failure causes and subsystem interactions, while Reliability Block Diagrams (RBDs) [23] provide a graphical representation of the system's reliability.

Furthermore, probabilistic approaches, such as Bayesian inference [24] and Markov models [25], are used to evaluate gradual degradation and multi-state system reliability. This allows for more nuanced assessments of components that may not fail outright but experience performance declines. Multi-state system reliability models (MSSRMs) are effective for systems where performance degradation occurs gradually or in multiple modes and represent a special case of SRMs [26, 27]. Although DTs, FBMs, and SRMs are powerful individually, current methodologies cannot dynamically synchronize functional and reliability data. This limitation restricts their applicability in CFs, where real-time decision-making is essential. To address this gap, the paper proposes a unified framework that integrates DTs, FBMs, and SRMs to enhance strategies for component reprocessing.

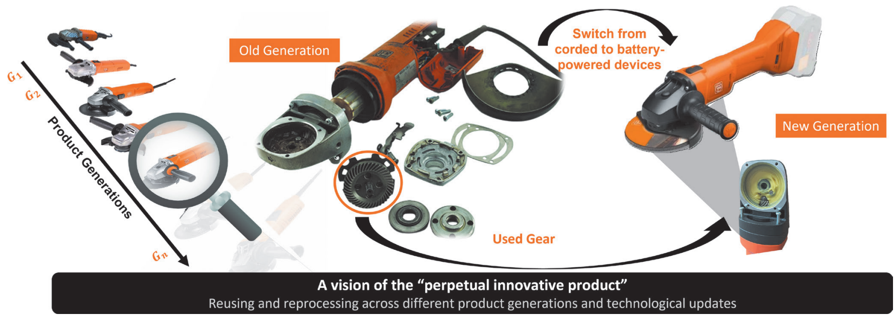


*Figure 1. A vision of the "perpetual innovative product" for reprocessing products in CFs using an angle grinder as a case study*

## Framework

The proposed framework integrates DTs, FBMs, and SRMs into a unified framework to enable precise DDDM in CFs. By dynamically synchronizing functional and reliability data within the DTs, the framework supports real-time decisions on component reprocessing. Angle grinder is used as the case study, as seen in Figure 1, to support the vision of the perpetual innovative product for reprocessing products in CFs.

**Digital Twin (DT) as the Decision Core**
The DT serves as the central component of the framework, providing a platform for real-time data aggregation, synchronization, and simulation. DTs enable hierarchical decision-making by dynamically updating system states and evaluating whether components require disassembly or a refit for reprocessing, as illustrated in Figure 2. Compared to linear production factories where there is more uniformity, the CF needs a more flexible DT because of the high variability of the products. When a product enters the CF, an instance is created in the DT and dynamically updated accordingly for new measurements and remanufacturing. This process makes the DT instance-specific in the CF context. For example, decisions regarding an angle grinder, such as determining if it retains 95 percent of its performance, rely on iterative updates from the DT [1]. In the case of decision-making on the bevel gear, for example, these updates are invoked by measurements of its parameters, such as circular pitch, shaft angle, and elasticity, represented as distributions that are refined

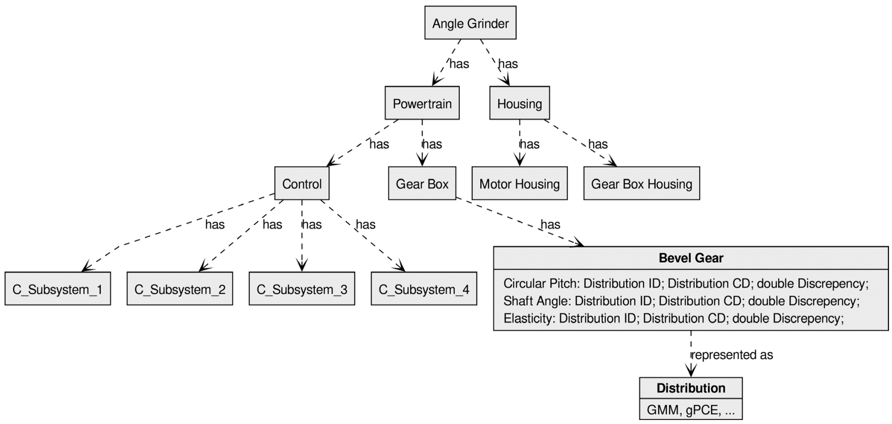


*Figure 2. Hierarchical disassembly of an angle grinder, using the data from the FBMs, the SRMs and other different stations in the CF, and replicating it digitally in the DT – Features are stored as probability distributions*

throughout the CF. DTs in the context of the CFs also simulate recombination scenarios to assess the cross-generational compatibility of components, which is also part of CF DTs being instance-specific. They integrate real-time data from FBMs and SRMs, enabling reprocessing decisions such as disassembling, remanufacturing, or reusing parts. By synchronizing these inputs, DTs lay the foundation for precise and efficient decision-making in CFs, optimizing resource use while maintaining high-reliability standards.

## Functional Behavior and System Reliability Models as Decision Inputs

*Functional Behavior Model (FBM)*

The functional behavior based on its current condition must be considered to decide how a used product should be reprocessed in a CF. This is done by the FBM, which expands behavioral models to evaluate the EFRs in both directions automatically. The FBM is developed in a controlled laboratory environment before the runtime of the CF. To incorporate the previously described implicit expert knowledge into the FBM, comprehensive system insights are created by using qualitative product models. The main emphasis of these models is to identify relevant EFRs and their interactions in the system. Afterward, this qualitative knowledge is embedded in a quantitative approach, such as a physics-informed neural network. As a result, the quantified EFRs and their interactions are not pure black box models inside the FBM, but conclusions can be drawn between the two domains.

Furthermore, the approach enables the combination of specific key performance indicators (KPIs) in the form of a performance metric to evaluate functional behavior. In the CF, the FBM supports the inspection of used products entering the CF and guides their disassembly and reprocessing. Figure 3 shows the different inputs of the FBM and their corresponding domains.

Functional tests at the inspection station provide information about the current performance. If the functional requirements of the target condition are fulfilled, the system or subsystem is fit to be reused. If not, further disassembly and measurements are required. To guide this iterative disassembly, the FBM identifies structural areas of interest. These areas include the subsystems or components that are most likely to cause degradation in performance. For example, the gearbox's condition is most likely to cause a change in the vibration emissions of an angle grinder. After each step, geometric measurements are carried out to verify the assumptions. This way, a minimal degree of disassembly can be achieved. The FBM also defines how the structural parameters must be adjusted to meet the functional requirements. This is possible due to the bidirectional assessment of the EFRs and references in the form of historical data. The derived Instance-Specific Tolerance Scheme (ITS) is shown in Figure 3. The exemplary three-dimensional space's boundaries represent the target condition's functional requirements. Everything inside exceeds the requirements, and everything outside falls short. Based on the geometric measurements and their corresponding uncertainty, the instances of used products are mapped as points or areas in the ITS. As indicated by the different colors, an initial statement regarding the end-of-life strategies and manufacturing processes can be derived. The FBM, therefore, facilitates runtime decisions during the inspection of used products and links functional evaluation to long-

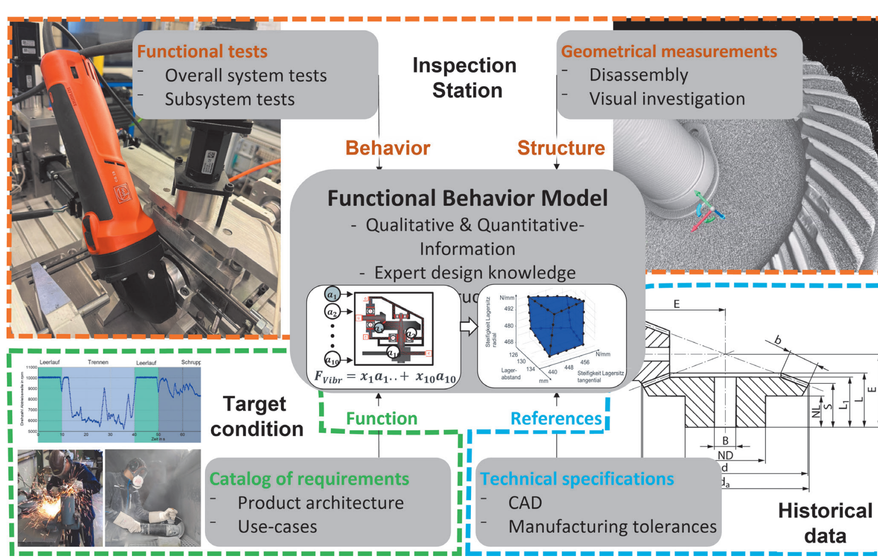


*Figure 3. Inputs of the functional behavior model (FBM) spanning the domains of design*

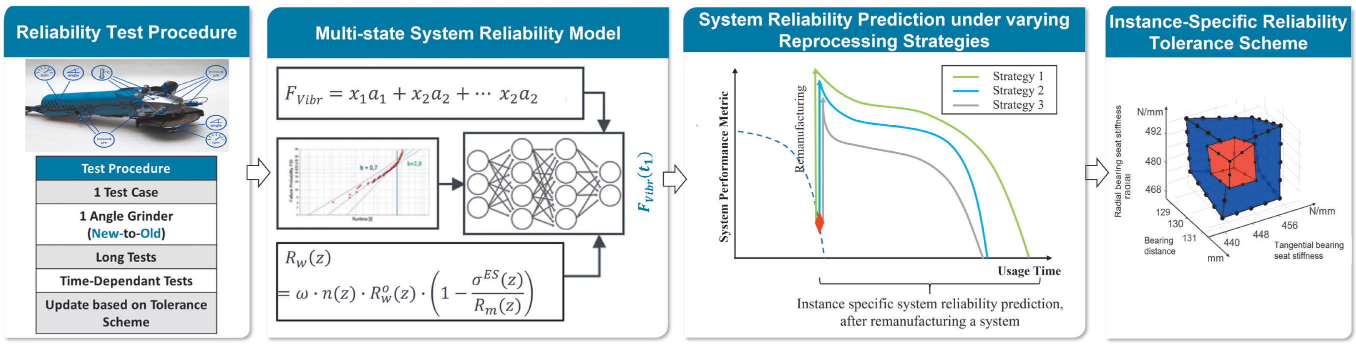


*Figure 4. Workflow of the Instance-specific SRM within the CF*

term dependability by providing a performance metric.

*System Reliability Model (SRM)*
To reprocess products in the CF, it is essential to know about the individual systems and subsystems' performance over time. The SBM complements the FBM by predicting the instance-specific reliability of components, subsystems, and systems under various conditions. The SRM used in this framework uses MSSRM, which provides a nuanced evaluation of performance degradation over time. The SRM development consists of two distinct phases Figure 4. In the first phase, the SRM is built and trained using lifetime test data and knowledge about the functional behavior of the FBM. This process occurs in a controlled laboratory environment, as described by *Leitenberger et al.* [25]. First, it defines the system's reliability structure by identifying key failure modes using Ishikawa diagrams, RBD, and Design Structure Matrices as described above. Next, it collects data through sensors and test-bench simulations, capturing operational loads and material behavior. The SRM is then parameterized with historical load curves and a system performance metric, enabling predictive capabilities. Bayesian approaches and Markov models are applied to analyze state transitions and handle model uncertainties.

*4SRM within the CF*
Once the SRM is developed and validated, it is implemented and applied directly on the shop floor of the CF and integrated into the DT. The data incorporated in the DT, combined with the FBM, which records the current state of the angle grinder, serves as input for the SRM during deployment. The SRM must account for the impact of varying reprocessing strategies on multi-state system and subsystem reliability, as different recombination or remanufacturing approaches for components affect their instance-specific functional behavior over time. Consequently, a key output of the SRM is the multi-state system and subsystem reliability prediction under diverse reprocessing strategies, as exemplified by three different strategies in Figure 4. The blue cube in Figure 4 part (d) is the ITS based on the current condition described by the FBM. As performance degrades over time, it is necessary to establish tolerance boundaries, as seen in Figure 4 (d), as the red cube, to ensure the tool continues to meet the required functional behavior throughout its lifecycle. This reliability-related ITS, aligned with the functional requirements defined by the FBM, is another critical output of the SRM. Figure 4, part (d) by the green dot, symbolizes an exemplary instance of fulfilling the requirements. Both outputs, the instance-specific reliability prediction, and the reliability-related ITS, inform the R-strategies for optimizing component reuse while maintaining functionality.

*Model integration for decision-making*
The decision-making process relies on the reliability-related ITS, which integrates FBM and SRM outputs within the DT to guide remanufacturing decisions. The process begins at the inspection station by evaluating whether components meet baseline functional requirements. If not, the FBM guides the disassembly and geometrical measurements on the subsystem and component levels. Therefore, the FBM guarantees that the SRM receives all relevant information to assess performance over time. All the gathered data is passed to the DT, feeding the DT representation in Figure 5. The DT dynamically updates component attributes using Bayesian techniques by combining prior knowledge and real-time evidence [24].

Furthermore, the FBM determines the system's performance based on its current condition and passes it on to the SRM. This performance can be expressed both in the form of a performance metric focusing on the behavior or in the form of an ITS, concentrating on the structure. An initial statement regarding the possible end-of-life strategies can be derived based on the comparison between the current performance and its target condition. Depending on the possible combinations and reprocessing strategies, the SRM predicts the instance-specific system reliability. The varying performance predictions enable the DT to dynamically decide on further reprocessing within the CF. Compared to the FBM, a reliability-related ITS further refined the manufacturing tolerances to incorporate the degradation over time. This ensures that decisions regarding reuse, repair, or disassembly are based on precise, data-driven insights.

Bayesian fusion methods on Gaussian Mixture Models (GMMs), which can represent complex uncertainties inherent to the products in the CFs, further refine these insights, enabling accurate decisions on component compatibility (Eq. 1). Where $P(a)$ represents the prior knowledge about the attributes, $P(a|I)$ is the

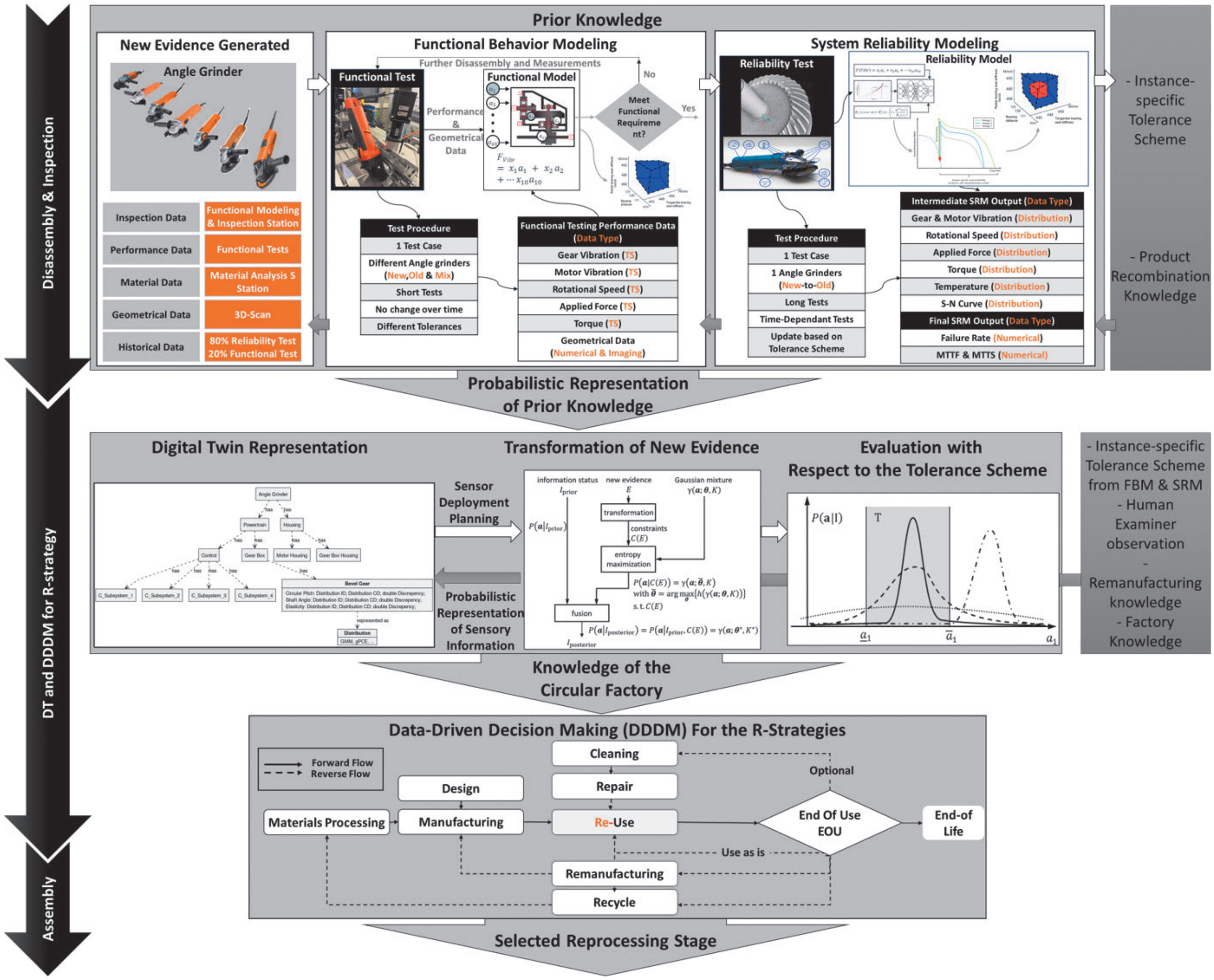


*Figure 5. Framework of the DDDM in the CF leveraging DT and the integration of FBM and SRM for the R-strategies*

likelihood function of the evidence, derived from measurements. The normalization factor $P(a)$ is negligible as it adds no information to $I$. Bayesian fusion updates prior knowledge by combining it with the likelihood function as new evidence is being updated in the DT. After this update, the ITS is used as a benchmark for decision-making regarding the actual posterior knowledge in the DT. Figure 5 illustrates how FBMs and SRMs interact within the DT to ensure reprocessed components meet functional and reliability standards.

$$P(I) = \frac{P(I)\,P(I)}{P(a)} \tag{1}$$

## Discussion

The proposed DDDM framework leverages DT technology, particularly instance-specific handling, to address the challenges of reprocessing used returned products with uncertainties, ensuring that each product‘s unique condition is thoroughly considered. By integrating FBMs and SRMs, the framework enables precise, data-driven recombination decisions aligned with market standards. The DT aggregates real-time data, supports scenario simulations, and optimizes resource utilization in CFs. The FBM evaluates the functional state of components, facilitating targeted disassembly and adjustments to meet performance metrics. It combines implicit expert knowledge with measurable parameters, and its bidirectional approach between EFRs and historical data allows iterative refinement of parameters, driving the development of ITS. The SRM complements this by providing predictive insights into system and subsystem reliability under varying conditions, with reliability-related ITS further refining decision-making by balancing structural tolerances against degradation over time. Additionally, Bayesian fusion techniques enhance the framework’s ability to address uncertainties, enabling the DT to update prior knowledge dynamically and improve decision accuracy, ensuring alignment with evolving performance and reliability conditions.

However, the framework faces several challenges and limitations. Experimental validation is lacking, which limits the demonstration of its real-world effectiveness. The methodology for setting ITS boundaries in the FBM and SRM remains unclear, as does selecting appropriate reliability metrics to evaluate performance for diverse components and recombination strategies. DT implementation is further constrained by the high data acquisition costs and computational demands for real-time integration, posing scalability and broader adoption challenges. Additionally, the focus on the three core components, FBM, SRM, and DT, overlooks other critical aspects of CFs, such as inspection processes, material considerations, manufacturing stations, and factory planning, which are essential for a fully integrated circular factory.

Future work should focus on experimental validation to establish the framework's practical effectiveness and refine methodologies for defining ITS boundaries and selecting reliability metrics for performance evaluation. Expanding the framework to incorporate additional elements of CFs, such as inspection and material handling processes, could enable a more comprehensive and holistic approach to sustainable manufacturing.

## Conclusion

This paper addresses the challenge of reprocessing returned products with unknown conditions within a CF, driven by the need for sustainable resource use aligning with circular economy principles. The proposed framework integrates FBM, SRM, and DT by leveraging DT to enable DDDM across product generations. The FBM quantifies performance metrics, while the SRM predicts reliability and informs tolerance schemes, both dynamically interacting with the DT to guide reprocessing decisions on component disassembly, reuse, repair, or recombination. The DT is a central data hub, aggregating various data to support scenario evaluations. The results demonstrated through an angle grinder case study highlight the framework's ability to ensure functionality and reliability standards for primary market applications and reduce waste. Despite its strengths, it faces challenges such as high-quality data acquisition, computational demands, and the need for experimental validation. Future work should address these limitations and explore integrating additional factory elements to enable a more comprehensive and scalable approach.

## Literature


1. Asch, M.: A Toolbox For Digital Twins. SIAM, 2022 DOI:10.1137/1.9781611976977
2. Lanza, G.; Deml, B.; Matthiesen, S. et al: The Vision of the Circular Factory for the Perpetual Innovative Product. at – Automatisierungstechnik 72 (2024) 9, pp. 774–788 DOI:10.1515/auto-2024-0012
3. Grauberger, P.; Dörr, M.; Lanza, G. et al.: Enabling the Vision of a Perpetual Innovative Product – Predicting Function Fulfillment of New Product Generations in a Circular Factory. at – Automatisierungstechnik 72 (2024) 9, pp. 815–828 DOI:10.1515/auto-2024-0010
4. Gero, J. S.; Kannengiesser, U.: The Function-behaviour-structure Ontology of Design. In: Chakrabarti, A.; Blessing, L. T. M. (Eds.): An Anthology of Theories and Models of Design. Springer, London 2014, pp. 263–283 DOI:10.1007/978-1-4471-6338-1_13
5. Naresky, J. J.: Reliability Definitions. IEEE Transactions on Reliability R-19 (1970) 4, pp. 198–200 DOI:10.1109/TR.1970.5216447
6. Glaessgen; E.; Stargel, D.: The Digital Twin Paradigm for Future Nasa and U. S. Air Force Vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference and 20th AIAA/ASME/AHS Adaptive Structures Conference, AIAA 2012 DOI:10.2514/6.2012-1818
7. Chen, Y.: Integrated and Intelligent Manufacturing: Perspectives and Enablers. Engineering 3 (2017) 5, pp. 588–595 DOI:10.1016/J.ENG.2017.04.009
8. Liu, Z.; Meyendorf, N.; Mrad, N.: The Role of Data Fusion in Predictive Maintenance Using Digital Twin. In: AIP Conference Proceedings 1949 (2018) DOI:10.1063/1.5031520
9. Vrabič, R.; Erkoyuncu, J. A.; Butala, P.; Roy, R.: Digital Twins: Understanding the Added Value of Integrated Models for Through-life Engineering Services. Procedia Manufacturing 16 (2018) 10, pp. 139–146 DOI:10.1016/j.promfg.2018.10.167
10. Madni, A. M.; Madni, C. C.; Lucero, S. D: Leveraging Digital Twin Technology in Model-based Systems Engineering. Systems 7 (2019) 1 DOI:10.3390/systems7010007
11. Allen, B. D.: Digital Twins and Living Models at Nasa. ASME Digital Twin Summit Presentation, 2021 (https://ntrs.nasa.gov/api/citations/20210023699/downloads/ASME%20Digital%20Twin%20Summit%20Keynote_final.pdf [Accessed on Jan. 25th, 2025])
12. Asanovic, K.; Bodik, R.; Demmel, J. et al.: A View of the Parallel Computing Landscape. Communications of the ACM 52 (2009) 10, pp. 56–67 DOI:10.1145/1562764.1562783
13. Moore, G.: Cramming More Components onto Integrated Circuits. In: Proceedings of the IEEE 86 (1998) 1, pp. 82–85 DOI:10.1109/JPROC.1998.658762
14. Hassan, R.; Qamar, F.; Hasan, M. K. et al.: Internet of Things and its Applications: a Comprehensive Survey. Symmetry 12 (2020) 10 DOI:10.3390/sym12101674
15. Hennessy, J.; Patterson, D.: Computer Architecture: A Quantitative Approach. Morgan Kaufmann, 2017
16. LeCun, Y.; Bengio, Y.; Hinton, G.: Deep Learning. Nature 521 (2015), pp. 436–444 DOI:10.1038/nature14539
17. Bakker, C.; Wang, F.; Huisman, J.; Den Hollander, M.: Products that Go Round: Exploring Product Life Extension through Design. Journal of Cleaner Production 69 (2014), pp. 10–16 DOI:10.1016/j.jclepro.2014.01.028
18. Lee, E. A.; Seshia, S. A.: Introduction to Embedded Systems: A Cyber-physical Systems Approach. MIT Press, 2017
19. Weber, C.: Modelling Products and Product Development Based on Characteristics and Properties. In: Chakrabarti, A.; Blessing, L. T. M. (Eds.): An Anthology of Theories and Models of Design. Springer, London 2014 DOI:10.1007/978-1-4471-6338-1_16
20. Vajna, S.; Weber, C.; Zeman, K. et al.: CAx für Ingenieure: Eine praxisbezogene Einführung. Springer, Berlin Heidelberg 2018 DOI:10.1007/978-3-662-54624-6
21. Liliana, L.: A New Model of Ishikawa Diagram for Quality Assessment. In: IOP Conference Series Materials Science and Engineering 161 (2016) DOI:10.1088/1757-899X/161/1/012099
22. Browning, T. R.: Applying the Design Structure Matrix to System Decomposition and Integration Problems: a Review and New Directions. IEEE Transactions on Engineering Management 48 (2001) 3, pp. 292–306 DOI:10.1109/17.946528
23. Modarres, M.; Kaminskiy, M. P.; Krivtsov, V.: Reliability Engineering and Risk Analysis. Taylor & Francis, Boca Raton 2016 DOI:10.1201/9781315382425
24. Sander, J.; Beyerer, J.: Bayesian Fusion: Modeling and Application. In: 2013 Workshop on Sensor Data Fusion: Trends, Solutions, Applications (SDF), 2013, pp. 1–6 DOI:10.1109/SDF.2013.6698254

25. Leitenberger, F.; Dörr, M.; Gwosch, T.; Matthiesen, S.: Methodical Approach to Instance-specific Reliability Modeling for the Perpetual Innovative Product in the Circular Factory. In: Proceedings of the ASME 2024 International Mechanical Engineering Congress and Exposition (IMECE2024), Portland, Oregon, November 17-21 2024 DOI:10.1115/IMECE2024-144013
26. Yingkui, G.; Jing, L.: Multi-state System Reliability: a New and Systematic Review. Procedia Engineering 29 (2012), pp. 531–536 DOI:10.1016/j.proeng.2011.12.756
27. Liu, Y.; Xiahou, T.; Zhang, Q. et al.: Multi-state System Reliability: an Emerging Paradigm for Sophisticated Engineered Systems. Frontiers of Engineering Management 11 (2024) 3, pp. 568–575 DOI:10.1007/s42524-024-0140-8

## Authors

Nehal Afifi is a researcher at IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements at Karlsruhe Institute of Technology (KIT). Her research focuses on the data-driven validation of machine elements, with a particular emphasis on statistical learning, machine learning, and deep learning techniques for testing and reliability assessment. As part of the research group “Mechatronic Machine Elements and System Reliability”, she contributes to sustainability, connectivity, and individualization by developing innovative data-driven approaches for the testing and validation of mechatronic systems. Her work also supports the vision of a Circular Factory, focusing on reliability modeling.

Victor Mas is a researcher at IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements at Karlsruhe Institute of Technology (KIT). His research focuses on reliability testing, with an emphasis on gaining knowledge about subsystems, their interactions with other subsystems, and how these influence overall system reliability and functional behavior over time. As part of the research group “Mechatronic Machine Elements and System Reliability”, he contributes to sustainability, connectivity, and individualization by developing new analysis methods for the collection and interpretation of load curves at the subsystem level, as well as a test method to efficiently collect reference reliability data. His work also supports the vision of a Circular Factory, focusing on reliability testing.

Jonas Hemmerich is a researcher at IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements at Karlsruhe Institute of Technology (KIT). His research focuses on the quantification process of relations between embodiment parameters and functional behavior, with particular emphasis on the integration of implicit design knowledge. As part of the research group “Design Methods”, his research contributes to the development and evaluation of needs-based design support for building and storing design knowledge.

Felix Leitenberger is a researcher and team manager at IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements. His research focuses on the validation of mechatronic systems, with particular emphasis on system reliability, cross-domain simulation modeling, and testing. As team manager of the research group “Mechatronic Machine Elements and System Reliability”, he and his team drive sustainability, connectivity, and individualization by developing innovative solutions for mechatronic systems. Their work also supports the vision of a Circular Factory, focusing on testing for reliability.

Luisa Hoffmann is a PhD student at the Institute for Industrial Information Technology at the Karlsruhe Institute of Technology, specializing in information fusion under the supervision of Professor Michael Heizmann.

Ali Darijani is a researcher working with Prof. Dr.-Ing. habil. Jürgen Beyerer on the SFB1574.

Patric Grauberger is an academic advisor at the IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements. He conducts research in the field of data-driven design research and functional modeling for the circular economy. From his career through vocational training, studies and doctorate to his currently aspired habilitation, the implementation of the models and methods developed in design research into practice is close to his heart.

Michael Heizmann is Professor of Mechatronic Measurement Systems at the Institute of Industrial Information Technology at the Karlsruhe Institute of Technology (KIT). His research interests include measurement science, machine vision, signal and image processing, image and information fusion and their applications.

Jürgen Beyerer has been a full professor for informatics at the Institute for Anthropomatics and Robotics at the Karlsruhe Institute of Technology (KIT) since March 2004 and director of the Fraunhofer Institute of Optronics, System Technologies and Image Exploitation IOSB in Ettlingen, Karlsruhe, Ilmenau, Görlitz, Lemgo, Oberkochen and Rostock. Research interests include automated visual inspection, signal and image processing, variable image acquisition and processing, active vision, metrology, information theory, fusion of data and information from heterogeneous sources, system theory, autonomous systems and automation.

Sven Matthiesen is Professor and Head of Institute at IPEK – Institute of Product Engineering – Chair of Power Tools and Machine Elements. His research focuses on design methods, human-machine systems, mechatronic machine elements and system reliability. He is a DFG review board member, member of several scientific societies, former board member of WiGeP (Scientific Society of Product Development), author of over 200 scientific publications and as inventor involved in 18 patents from his time at HILTI Corporation and his current research on power tools.

## Abstract

**Datengestützte Entscheidungsfindung: Nutzung von digitalen Zwillingen für Wiederaufbereitung in der Kreislauffabrik.** Kreislauffabriken müssen die Funktionalität und Zuverlässigkeit gebrauchter Komponenten für die Rekombination mit anderen Komponenten oder Subsystemen der gleichen oder anderer Produktgenerationen sicherstellen. In diesem Beitrag wird ein Framework zur datengetriebener Entscheidungsfindung vorgestellt, welches das funktionale Verhaltensmodell und das Systemzuverlässigkeitsmodell in einem digitalen Zwilling integriert. Es werden kontinuierlich Daten aus physischen Tests eingebunden, um Szenarien für die Rekombination zu simulieren und bei der Entscheidungsfindung für die Wiederaufbereitung von Komponenten zu unterstützen. Ein Winkelschleifer wird als Fallstudie zur Demonstration verwendet. Das vorgestellte Framework fördert die Nachhaltigkeit und unterstützt die Verwendung von wiederaufbereiteten Komponenten in Produkten, die für den Primärmarkt bestimmt sind.

## Acknowledgment

This research was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) in the collaborative research center (CRC) 1574 “Circular Factory for the Perpetual Product” with the project ID 471687386. While preparing this work, the authors used AI tools such as deepl.com and grammarly.com to improve readability and language. After utilizing these tools, the authors reviewed and edited the content as necessary. The authors take full responsibility for the publication’s content. All authors have read and agreed to the published version of the manuscript.

## Keywords

Circular Factory, Data-Driven Decision-Making, Digital Twin, Functional Behavior Model, System Reliability Model

## Schlüsselwörter

Kreislauffabrik, Datengetriebene Entscheidungsfindung, Digitaler Zwilling, Funktionales Verhaltensmodell, Systemzuverlässigkeitsmodell

## Bibliography

DOI:10.1515/zwf-2024-0160
ZWF 120 (2025) Special Issue; page 170 – 176

ISSN 0947-0085 · e-ISSN 2511-0896