Process Design for Robotic Unscrewing: Sensor-Based Anomaly Handling in Circular Production

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Abstract. Shorter product lifecycles increase raw-material consumption and intensify the need for effective end-of-life strategies to support a circular economy. While robotic assembly is well-established, automated end-of-life disassembly remains unresolved. Used products arrive in uncertain condition, introducing unpredictable anomalies, that current systems are unable to reliably handle. Unscrewing is a fundamental disassembly operation, yet highly susceptible to process anomalies. Conventional torque-based detection methods fail to reliably handle cases such as detached screw heads or occluded fasteners. This work contributes towards autonomous disassembly through a systematic redesign of anomaly detection for the robotic unscrewing process. Eight typical wear scenarios were identified from the fleet data of a power-tool manufacturer. Based on these scenarios, the unscrewing process was redesigned and a multimodal sensing system with calibrated accuracy requirements was developed. Anomaly detection is implemented using parameterised decision-tree models operating on torque, axial-force, and TCP-position streams. The system was validated on 3D-printed test specimens and on screws of a Fein CG15 angle grinder, achieving 100 % sensitivity and accuracy on 410 trials across eight failure-mode classes. Detected parameters can be persisted in an ontology-driven knowledge graph to enable cross-station parameter reuse.

Keywords: Disassembly · Adaptive Robotics · Unscrewing · Anomaly Detection · Circular Production

1 Introduction

Remanufacturing is the highest-value end-of-life strategy available at factory scale, yet its economic viability depends on cost-effective disassembly [11, 12].

Automated disassembly remains largely unsolved: real end-of-life (EoL) products deviate from their nominal design through wear, corrosion, and undocumented repairs, introducing a broad spectrum of unforeseen anomalies, that current robotic systems cannot reliably handle. Until robots can detect and respond to such anomalies autonomously, fully automated, end-of-life disassembly is out of reach. This work lays the groundwork by addressing how screw conditions affect the disassembly decision and designing a robotic unscrewing process that detects these conditions reliably, making it a critical step towards robust automated disassembly in circular production. This decision-oriented perspective frames the core research questions:

- How do EoL conditions manifest as disassembly-relevant anomalies, and which response decisions do they necessitate?
- Which sensor modalities and measurement precisions are required to detect these anomalies?
- How reliably and robustly can detection be implemented?

Following these questions, this work makes three contributions: First, a systematically derived failure-mode catalog of eight scenarios derived from fleet data and industry interviews. This catalog covers a broader range than prior work. Second, a redesigned unscrewing process with four phases that exposes discriminative signals for each failure mode, making previously undetectable anomalies observable for the first time. Third, a parameterized decision-tree anomaly detection system validated at 100 % sensitivity and accuracy across 410 trials and eight failure-mode classes on a Fein CG15 angle grinder.

2 State of the Art

The field of robotic unscrewing for EoL disassembly is nascent, but rapidly growing. While there are many works that focus on the detection of the screw head and the engagement of the screwdriver [4], fewer address the process itself. First of all recent work addressed that optical detection is often not precise enough to immediately find the screw head, which is why works such as [7],[1] or [3] use a spiral search strategy to find the screw head based on a rough initial position. While later works such as [10] further improved the search strategy by using deep reinforcement learning, these works assume that once the screw head is found, the unscrewing process can be executed without any anomaly. This is a strong assumption giving that screws can be damaged, occluded, or otherwise degraded in EoL conditions, which is why the detection of anomalies during the unscrewing process is crucial for a reliable and robust disassembly. Here works such as [9] and [8] established torque sensing as the dominant approach to supervise the unscrewing approach. However, current works such as [13] or [2] typically only use this information to detect expected anomalies such as positional errors or jammed screws on specific product families, while the detection of unseen anomaly classes such as occluded heads or loose anchors is not provided. Often these works also rely on manually tuned thresholds and human fallback such as

in [6], which is not a scalable solution for the wide variety of EoL conditions. To summarize while there are works that address anomaly detection during the unscrewing process, they typically focus on a closed set of expected anomalies designed for specific product families. A practitioner looking to build his own robotic unscrewing system for EoL disassembly of totally different products would have to start from scratch, which is not a scalable solution for the circular economy. Instead one needs a systematic design approach that starts from the failure modes observed in the field, derives the process and sensing architecture from these modes, and then validates the system on real EoL devices.

3 Failure Mode Analysis

Before we can design a process and sensing system for anomaly detection during robotic unscrewing, we need to know which anomalies we have to detect. In other words, we need to know which failure modes are relevant for EoL disassembly, how they are characterized, and finally find a general criterion to screen the sensors. We achieve this by looking into the literature presented above, first, then conducting an interview with the remanufacturing department at Würth Masterservice, and finally consolidating the findings into a catalogue of eight failure modes covering both geometric and mechanical failure modes. Each failure mode maps to a characteristic combination of torque, axial force and TCP position signals, which drives both process design and sensor selection. The main results of the interview are that it's impossible to generalize wear due to a high variation of the location where Powertools are used, that the notion of rusty screws are outdated due to professional coatings, and that eight wear scenarios covering both geometric and mechanical failure modes can be consolidated to give a typical overview. These failure modes are shown in table 1. With those combinations, the robotic unscrewing System has to be able to categorize the dismantled product into three Categories: (green) Proceed normally, (yellow) Disassembly possible with additional tools, and (red) Destructive disassembly necessary. Assuming that each failure mode produces a characteristic combination of torque (M_y), axial force (F_y) and TCP position (P_y) signals, which can be used to design a process and sensing system that detects these modes reliably. For example, a missing screw would produce no rise in axial force during approach, while a rounded head would produce no form-fit torque during the form-fit phase. By mapping each failure mode to its characteristic signal pattern, we can derive the necessary sensor modalities and process steps to detect them effectively. However, matching product failure modes onto signals requires first a model of the unscrewing process, which is the topic of the next section.

4 Reference Screwing Process

Mapping Failure modes to signals requires a reference screwing process to identify which signals are available at which point in time, and how they can be used to discriminate between the failure modes. The existing unscrewing process can

Table 1: Failure modes discovered from literature and industry interviews, and their characteristic signal patterns in terms of counter moment (G), loosening moment (K_L) and dynamic moment (M_{dyn}).

Failure mode	**Description**	**G**	K_L	**D**
Screw intact	Nominal reference case.			
Missing screw	Screw absent from bore.	✓		
Missing head	Threaded shaft present, head detached.	✓	✓	✓
Rounded head	Drive recess worn, form-fit not achievable.	✓		
Head occluded	Foreign material or corrosion blocking access to head.			
Wrong type	Different drive geometry than expected (e.g., Torx vs. Phillips).	✓		✓
Loose anchor	Thread inserts or nut loose in base material.			
Stuck screw	Adhesion preventing rotation.		✓	

be divided into three parts: (1) Approach, (2) Form-fit and (3) Disassembly [8]. In each of these three parts, it is possible to measure the counter moment (G), the loosening moment (K_L) and the dynamic moment (M_{dyn}) around the screw axis via an integrated torque sensor in the screwdriver. However, the existing process does not allow to reliably detect all failure modes, which is why we propose to add a fourth phase (Preparation) between the Form-fit and Disassembly phase. In this phase, the screwdriver-internal spring is pre-tensioned fully to have a stiff axial connection, and then the Screwdriver executes half a turn counterclockwise. This allows to measure the loosening moment. This new four step process is shown in figure 1, where the signals that are measured in each phase are also shown. The process design and signal mapping are derived from the failure mode analysis, which is why the signals that are measured in each phase are chosen to discriminate between the failure modes as effectively as possible. For example, the axial force during the approach phase can be used to detect a missing screw, while the form-fit torque during the form-fit phase can be used to detect a rounded head or wrong type. The loosening moment during the preparation phase can be used to detect a loose anchor, while the dynamic moment during the disassembly phase can be used to detect a stuck screw. This is also captured in the signal-to-failure-mode mapping shown in table 2.

Table 2: Advanced–Signal–phase–failure-mode mapping.

Phase	Signal	Condition	Detected failure mode
Approach	F_y (axial force)	No rise	Missing screw
Approach	P_y (position)	Early stop	Head occluded / missing head
Form-fit	G (form-fit torque)	Absent	Rounded head, wrong type
Preparation	K_L (loose torque)	Absent	Loose anchor
Disassembly	M_{dyn} (dyn. torque)	High	Stuck screw
All	—	All pass	Screw intact

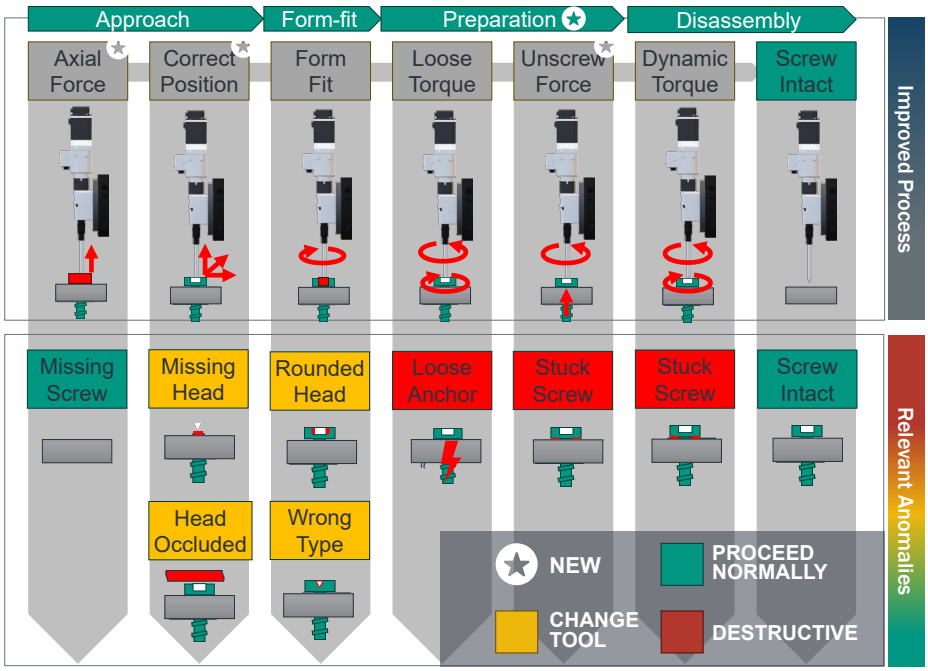


Fig. 1: The four phase reference unscrewing process with the corresponding signals that are measured in each phase. Each anomaly is mapped to a signal during the process. Each anomaly is assigned a decision: proceed normally - destructive methods required.

5 Anomaly Detection

Based on the four phases of the unscrewing process and the corresponding signals, one can already gleam a structure for the anomaly detection logic. The idea is to evaluate the signals in a sequential decision tree, where each node evaluates a boolean condition on the signal of a given phase, and the first failing condition terminates the sequence and returns the corresponding failure class. For example, if there is no rise in axial force during the approach phase, we can immediately classify the case as a missing screw without needing to evaluate any further conditions. If there is a rise in axial force but no form-fit torque during the form-fit phase, we can classify it as a rounded head or wrong type. If there is form-fit torque but no loosening torque during the preparation phase, we can classify it as a loose anchor. If there is loosening torque but high dynamic torque during disassembly, we can classify it as a stuck screw. If all conditions pass, we classify it as screw intact. The full decision tree is shown in figure 2, where the conditions and the corresponding failure modes are also shown. The decision tree is parameterized by the thresholds for each condition, which can be tuned per screw type and persisted in an ontology-driven knowledge graph

(specifically the KAPPS architecture [5], see 7) to support cross-station reuse and regression-based parameter learning.

The specific parameters per screw type are the lower tightening torque threshold ($M_{y,lower}$), the upper dynamic loosening torque threshold ($M_{y,upper}$), the lower axial-force threshold on approach ($F_{y,lower}$), the axial-force rise criterion during approach ($F_{y,\text{approach}}$), and the expected TCP position at end of approach ($P_{y,\text{approach}}$). These parameters are derived from the failure mode analysis and the process design, and they determine how the decision tree classifies each case based on the measured signals.

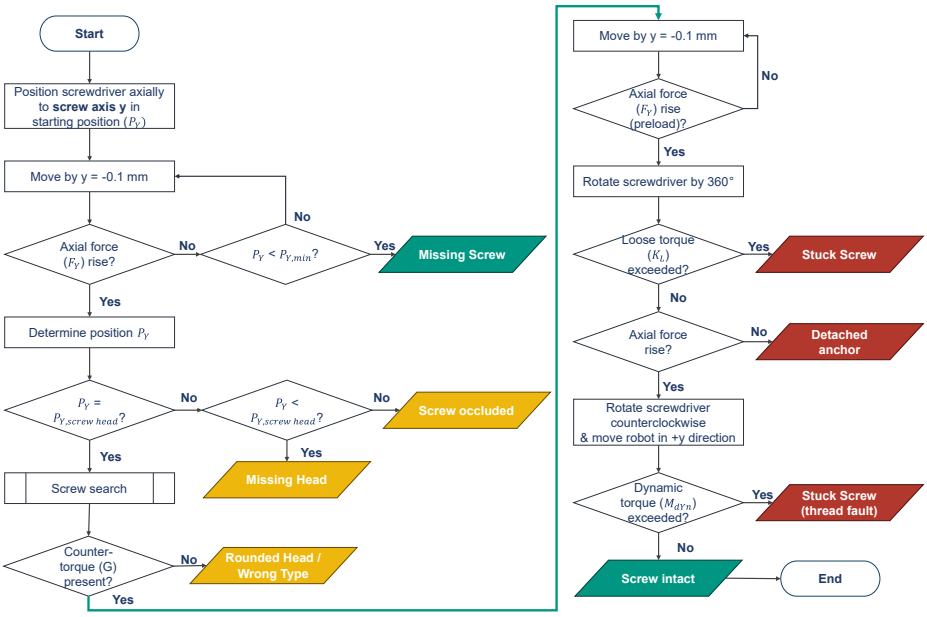


Fig. 2: Parameterized decision tree for anomaly detection during robotic unscrewing. Each node evaluates a boolean condition on the corresponding signal, and the first failing condition determines the classified failure mode.

6 Validation and Results

The validation of the anomaly detection system follows the right side of VDI/-VDE 2206 and consists of two stages: (1) domain-specific validation of the individual failure modes and (2) system-level validation on a complete product.

6.1 Validation of the Eight Failure Modes

To evaluate the individual sensor and process capabilities, each failure mode was reproduced on 3D-printed test specimens with threaded inserts and tested

Table 3: Confusion matrices of the system-level validation before and after adapting the turning angle for loose-anchor detection.

(a) Initial system-level validation.

		Actual	
		Intact	Wear
Predicted	Intact	58	6
	Wear	2	38

(b) Validation after increasing the Preparation-phase turning angle by 180°.

		Actual	
		Intact	Wear
Predicted	Intact	65	0
	Wear	0	35

35 times. Four misclassifications were observed. Two occluded-head cases were incorrectly classified because material was removed from the screw head during repeated engagement attempts. In addition, two intact screws were incorrectly classified due to insufficient axial-force transmission caused by the low stiffness of the printed specimens. These observations indicated that the loose-anchor detection criterion required further refinement before system-level testing.

6.2 System-Level Validation

The complete anomaly-detection system was evaluated on a Fein CG15 angle grinder using Torx 15 and Torx 20 screws representing all eight failure-mode classes. The initial system-level validation achieved an overall classification accuracy of 97.3 % (399/410), as shown in Fig. 3a. Most misclassifications occurred in the loose-anchor class, where several samples were classified as intact screws. To investigate these outliers, the axial-force signal during the Preparation phase was analysed. As shown in Fig. 3, the limited stiffness of the test setup reduced the axial-force increase generated by screw extraction, making the loose-anchor signal difficult to distinguish from the nominal case. The highlighted region corresponds to the rotational movement used for loose-anchor detection.

Based on this observation, the turning angle in the Preparation phase was increased by 180° to amplify the force response. The updated parameterization produced a clearer separation between nominal and loose-anchor cases and eliminated the remaining classification errors. The resulting confusion matrix is shown in Tab. 3b, yielding a classification accuracy of 100.0 % (410/410) across all eight failure-mode classes.

7 Process integration into the Circular Factory's data infrastructure

Section 6 shows that the anomaly detection system detects the eight failure modes reliably, on the condition that the five screw-type parameters derived in Section 4 are present and correctly set. This condition does not hold by default:

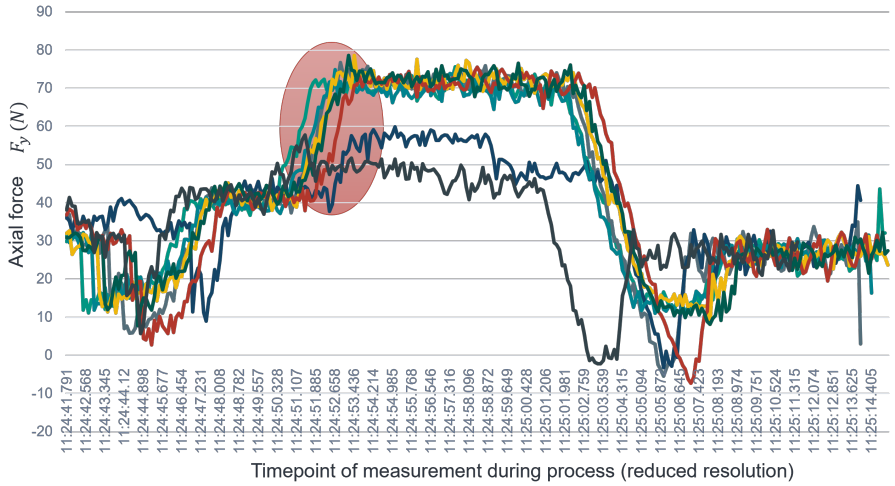


Fig. 3: Axial-force signal during loose-anchor detection, shown across six repetitions of the process. The highlighted region corresponds to the rotational movement in the Preparation phase. In some cases the screw did not produce a sufficient increase in F_y, which required retuning of the process.

a station must know which object is under its tool and which screws that object should contain before the parameters can be retrieved. The anomaly detection system is therefore integrated into the runtime system of the Circular Factory, which follows the KAPPS architecture [5]. KAPPS relies on a knowledge graph that records each workpiece as an instance linked to its product type, and the product type links to the screw type expected at each screw position. The graph additionally links the five unscrewing parameters to the screw type and makes them discoverable by any unscrewing resource in the factory. The anomaly detection system is integrated as a service that fetches this information from the graph and uses it to detect anomalies during unscrewing. The graph supplies the screw type expected at a given position, while the sensing system classifies the screw actually encountered. Detection runs against the nominal screw that the product type specifies, and any failure mode is considered a case in where the encountered screw departs from it. Because the parameters reside on one shared type-level individual, every station unscrewing that screw type reads the same values, and a screw type characterized once becomes available factory-wide. Additionally, each unscrewing attempt is persisted as an operation individual that records the classification outcome, references the recorded sensor signals, and holds a snapshot of the five parameters active at the decision. The operation individual links the screw instance, the unscrewing process, and the screwing resource, so the parameter set behind any past classification remains recoverable. These persisted operations allow the screw-type parameters to be refined. Persisting a completed operation triggers a learning service, which re-

trieves the operations accumulated for a given screw type, applies regression to the referenced signals, and derives refined estimates of the five parameters. By updating the parameters on the screw type in the knowledge graph, the refinement reaches every station that draws on that screw type. This write path also extends to screw types that have yet to be characterized. Such a type can be parameterized incrementally from the operations accumulated against it, extending detection coverage as further angle grinder variants enter the factory.

8 Discussion and Outlook

The results demonstrate that torque-limit monitoring alone is insufficient for reliable end-of-life (EoL) disassembly, as comprehensive failure detection requires the combination of torque, force, and position sensing. In particular, the introduction of the Preparation phase enables the detection of the two most common wear-related failure modes, rounded screw heads and loose anchors—which are not addressed by conventional unscrewing processes. While optical sensing may improve localisation during the approach phase, it does not provide the classification accuracy required for robust anomaly detection. Future research will focus on integrating the identified detection parameters into the KAPPS knowledge graph to enable automated parameter learning and cross-station deployment [5]. In addition, the proposed sensor-design methodology will be extended to other disassembly operations, such as milling and gripping, while increasing data availability may enable more advanced data-driven classification approaches.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process During the preparation of this work the authors used Claude in order to improve language and readability of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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