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Leveraging Digital Product Passports to Derive Circular Strategies

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Abstract

The circular economy is a key enabler to overcome the negative environmental consequences of value creation. By maintaining materials, components, and products in closed-loop systems, companies minimize their resource consumption. However, circular strategies differ in terms of their contribution to preserving resources and reducing environmental pollution. Therefore, manufacturing companies must identify suitable circular strategies for managing returned products to ensure sustainable end-of-life management. This paper proposes an iterative logic to assist decision-makers in deriving optimal circular strategy complexes for returned products. The approach is based on a technical assessment of the product's end-of-life condition, utilizing production and usage data provided by digital product passports. It quantifies the effects of the derived circular strategy complex in terms of costs as well as emissions and thus enables an efficient end-of-life management for returned products. The developed approach is tested using a company that manufactures and remanufactures water meters.

Keywords: Circular Economy, Digital Product Passports, Remanufacturing

1. Introduction

In the context of the aggravating climate crisis, manufacturing companies are increasingly responsible for rethinking their current form of value creation. Stricter legislative requirements are forcing companies to reduce their greenhouse gas emissions and resource consumption significantly. [1,2] Thus, the conventional linear economic system, which follows a "take-make-dispose" approach, has reached its operational limits [3]. In response, the circular economy (CE) has gained increasing attention as an alternative economic model. By decoupling economic value creation from resource consumption, closed material loops reduce waste and lower resource expenditure. Closed-loop systems promote the sustainable utilization of materials, components and products by employing circular strategies such as reuse, remanufacture and recycling [4,5].

However, the transition from linear to circular economic systems presents a significant challenge, particularly for manufacturing companies that must establish sustainable end-of-life (EOL) management for their products. A core issue lies in the uncertain condition of returned products, complicating the selection of viable circular strategies [6]. This uncertainty is primarily due to the limited availability and accessibility of product life cycle data, which is essential for an accurate assessment of the product's EOL condition and informed decision-making [7]. Emerging digital technologies, such as the Digital Product Passport (DPP), promise to bridge this information gap [8]. Nevertheless, the effective integration of such data into decision-making processes for EOL strategies remains an unresolved challenge [9].

To overcome this challenge, this paper introduces an iterative decision logic that leverages DPP data to improve the accuracy and increase the efficiency of the assessment of the condition of returned products. Based on this assessment, the optimal circular strategy complex for the product and its components is derived. Furthermore, the circular strategy complex is evaluated in terms of costs and environmental impact to support the effective and sustainable implementation in the manufacturing sector. The remainder of this paper is structured as follows: Section 2 discusses related approaches from the literature. Section 3 proposes the approach for deriving circular strategies based on DPP data. The approach is validated using a water

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meter as an exemplary product in Section 4. Section 5 discusses relevant insights and potential future research directions.

2. Related Work

To ensure the reliable assessment of a product's EOL status, comprehensive lifecycle data must be collected and analyzed. This chapter therefore first outlines lifecycle data as a foundation, then discusses technological enablers for data integration, and finally reviews decision-support approaches. High-level CE assessments that do not leverage lifecycle data are deliberately excluded.

To ensure the reliable assessment of a product's EOL status, it is essential to collect and analyse comprehensive product lifecycle data. Product Lifecycle Management (PLM) systems provide structured information, including bills of materials (BOMs), design specifications, and revision histories [10]. Usage data can be gathered through monitoring systems that track operational conditions over time [11]. Additionally, maintenance and service records contribute insights into the actual usage and condition of products [2]. [12] and [13] identify specific data types that enable the selection of circular strategies, including material composition, component reuse potential, and repair or refurbishment history.

Building on these lifecycle data sources, the technical realization of collecting and storing these data poses significant challenges for the industry. In this context, Digital Twin (DT) approaches such as [14] and [15] demonstrate, how product and usage data across the lifecycle may be integrated and analyzed in order to optimize processes and support circular strategies. DPPs extend DTs by providing a regulated and systematic framework to ensure transparency, traceability, and sustainability across the entire product life cycle and emphasize standardized and legally anchored data provision at the product-instance level [16,17].

Based on the collected data, circular strategies for EOL products may be selected. Existing approaches primarily differ in the factors considered for decision-making. Some approaches adopt a holistic, multi-criteria decision-making perspective, integrating the perspectives and interests of diverse stakeholders. [18] and [19] present multi-criteria decision problems that include various decision-making factors across ecological (environmental), legislative, market, social, business, economic, and technical dimensions. Conversely, other approaches are characterised by the selective inclusion of decision factors from discrete categories (cf. [6,7,20–27]). [21] propose a diagnostic tool to assess the health status of individual product components at the end of their life cycle. The condition assessment incorporates various features, such as wear and tear as well as electronic ageing, characterised by a high number of parameters. [25] present a condition-based optimization model that evaluates damage and remaining useful life. Similarly, [6] evaluate wear-out life, dimensional deviation, and cleanliness level. Lastly, it is essential to assess the viability of the respective CE strategy complex for implementing the respective circular strategies effectively in practice. [28] provides a comparative literature analysis of micro-level indicators that systematically assess the implementation of circular strategies at the micro level. [29] focus on an economic assessment by undertaking a cost comparison between remanufacturing and new part production. In contrast, [30–32] each use eco-efficiency to integrate both economic and environmental assessments.

Despite these advancements, the reviewed literature does not reveal any papers that present a decision-making approach for deriving circular strategies based on the EOL condition of products, considering digitally available product data and simultaneously considering the viability assessment of the resulting circular strategies. This paper aims to close this research gap by leveraging standardized, instance-specific DPP data to derive dedicated circular strategy complexes.

3. Methodology

A structured decision-making approach enables the derivation of suitable circular strategies based on the EOL condition of products. Central to this approach is a decision logic that relies on product-specific life cycle data, accessed through a DPP. Building upon the DPP introduced by [2], the focus of the present paper lies on leveraging the respective data for lifecycle analysis and circularity assessment, rather than addressing the challenges of DPP implementation or data completeness. The aim is not only to identify the most technically appropriate circular strategy at the product, component, or subcomponent level but also to evaluate the environmental and economic feasibility of these strategies. The approach unfolds in three main stages: establishing the respective foundations (Section 3.1), detailing the iterative decision logic (Section 3.2), and evaluating the viability of the derived circular strategies through an integrated economic and environmental analysis (Section 3.3).

3.1. Fundamentals

The development of the decision logic requires a systematic understanding of the product's hierarchical structure (Section 3.1.1) and quality assessment (Section 3.1.2), supported by relevant data from the DPP (Section 3.1.3).

3.1.1. Hierarchical Representation of Product Structure

The first foundational element involves representing a product's structural hierarchy. Since the circular strategy selection depends heavily on the condition of individual functional units, it is critical to model the structural composition of a product in a way that reflects its hierarchical (dis-)assembly. To accomplish this, Hierarchical Attributed Liaison Graph (HALG), originally developed by [33] and refined by [34] for EOL products, is applied (cf. Figure 1). HALG synthesizes the traditional

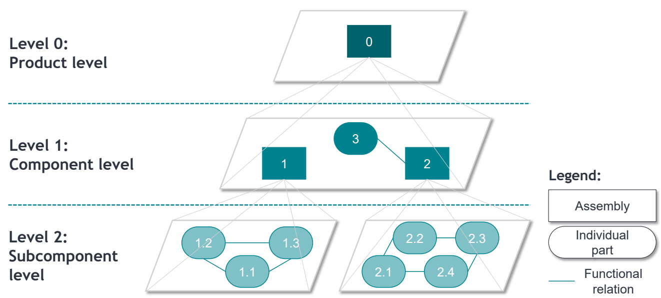

Figure 1. Exemplary Hierarchical Attributed Liaison Graph (HALG)

bill-of-material (BOM) representation and connection diagrams to visualize both, the structural and functional interrelations among components [34]. Constructed in a bottom-up manner, the HALG begins with the smallest elements at the base level of the BOM and builds up to the entire system, mapping physical and functional connections between components at each stage [33]. This representation is instrumental in enabling detailed disassembly planning and product evaluation at various structural depths, which is particularly valuable in the context of deriving the appropriate circular strategy. Although deriving a HALG requires an initial, product-specific effort, the process can be substantially supported by standardized BOM formats. Once defined, the approach can be consistently applied to all cores of the respective product.

3.1.2. Quality Assessment

The product quality assessment is guided by three key parameters: functional condition, remaining useful life, and physical condition [7]. These quality parameters collectively form the basis for evaluating the EOL condition. The quality assessment begins with verifying whether the product or component still performs its intended function. If functionality is confirmed, the remaining useful life is then determined by considering factors such as wear, fatigue, and obsolescence. The final assessment step addresses the product's physical condition by examining factors such as structural integrity or surface degradation. These parameters, assessed sequentially, provide a holistic view of the product's residual value. This, in turn, serves as the foundation for selecting a circular strategy that emphasizes technical feasibility.

3.1.3. Assignment of DPP Data

To ground the quality assessment in empirical data, the approach integrates DPP information. The DPP serves as a comprehensive repository of product life cycle data, capturing key operational, maintenance, and structural records. [35] present a classification framework for product data stored on a DPP to support circularity. Their approach categorizes 62 data points into 21 subcategories and four main categories. The four main categories are (i) product information, (ii) utilization information, (iii) value chain information and (iv) sustainability information and are adapted from [36]. Specifically relevant data points for the product condition assessment are included in the subcategories: application information, logistic information, standards, status information, service information, process information, and machine information.

This classification framework is used to map specific data points from the DPP to the respective quality parameters, as shown in Table 1. Here, the quality parameters comprise first the assessment of the physical condition, followed by the evaluation of the functional condition of the core, and finally an estimation of its remaining useful life, whereby this order particularly serves the purpose of determining whether further disassembly is required and potentially worthwhile.

The proposed mapping establishes a direct linkage between digital data and the EOL condition assessment. Noteworthy, this mapping is not a definitive allocation, but may need to be adapted to the specific product context and data availability and thus requires expert judgment.

Table 1. Assignment of DPP data to quality assessment parameters

Quality parameter	**DPP data**
Physical condition	- Logistic information - Process information
Functional condition	- Standards - Status information - Process information
Remaining useful life	- Application information - Service information - Status information - Process information

3.2. Iterative Decision Logic

At the core of the approach lies a structured and recursive decision-making tool in the form of a decision tree. This decision tree facilitates the systematic development of circular strategies by applying established quality parameters to each level of the product hierarchy. The iterative nature of the decision process enables it to progress gradually from the entire product to its primary components and, where necessary, to subcomponents, depending on the assessed condition.

As shown in Figure 2, the decision tree begins with a root node representing the product or component under analysis. It progresses through decision nodes that correspond to the inspection of functional condition, remaining useful life, and physical condition in the specified order. Expert judgment is applied when constructing the decision tree to ensure that only technically and economically meaningful disassembly steps are included, preventing unnecessary assessment of subcomponents that would be unfeasible or uneconomical. Based on the outcomes at each node, the process branches toward suitable circular strategies, thereby taking into consideration restrictions such as regulatory constraints or technical feasibility. Building on [37], the circular strategies considered are *reuse* (the use of a functional product in a similar application without significant alterations), *repurpose* (the use of a largely functional product in a different application), *remanufacture* (the restoration of a non-functional product while preserving existing functionality), and *recycle* (the destructive utilization of materials in a product for new products).

A distinctive feature of the logic is its adaptability. Not every product element requires assessment against all three quality parameters. For example, internal components may bypass physical condition checks if its functionality and remaining useful life are ensured. Consequently, the configuration of decision nodes within the decision tree remains tailored to the product's characteristics. If a product fails at certain assessment stages, further disassembly of the product is triggered, and the decision logic is reapplied at the next hierarchical level. This iterative disaggregation continues until either a feasible circular strategy is identified or the maximum disassembly depth is reached. Throughout this process, data from the DPP serve as the basis for every quality evaluation, reinforcing objectivity and accuracy. The final result is a CE strategy complex, which denotes an aggregate of optimal circular strategies for each evaluated product and (sub-)component as introduced by [22].

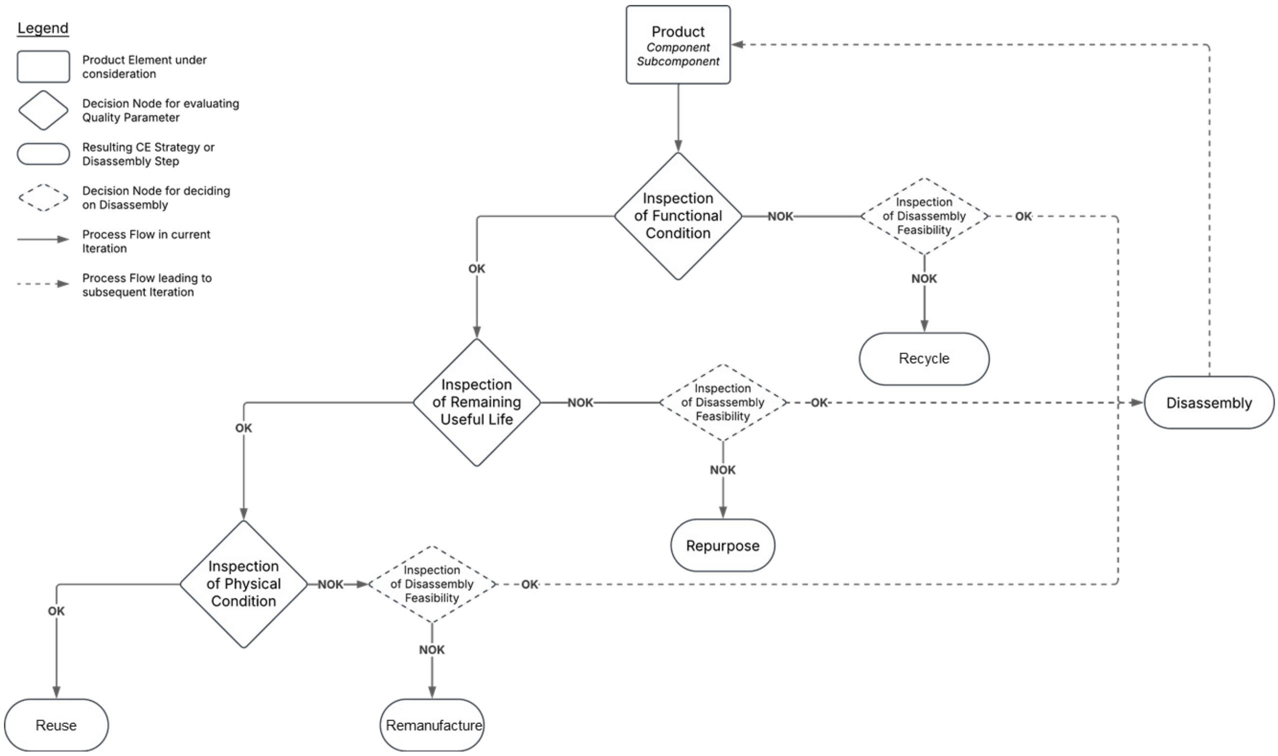

Figure 2. Iterative decision logic for deriving circular strategies

3.3. Economic and Environmental Evaluation

To ensure that the derived circular strategies are successfully implemented in industrial practice, it is essential to validate their feasibility based on economic and environmental criteria. The identified CE strategy complex will only be realized in practice if it proves to be both economically viable and environmentally beneficial for manufacturing companies. In addition to economic considerations, assessing the environmental sustainability of circular strategies is crucial, as companies face increasing regulatory and societal pressure to establish environmentally friendly production methods [38]. An integrated analysis of both dimensions in terms of eco-efficiency provides a profound decision-making basis for the sustainable implementation of circular strategies. Thus, the eco-efficiency does not only evaluate feasibility but also reveals potential trade-offs between economic and environmental objectives, supporting more balanced decision-making.

The economic feasibility is captured through a cost index (CI) that compares the life cycle costs of realizing the CE strategy complex (C_{CE}) with those of manufacturing a new product (C_{NP}) as shown in Equation (1). The lower the ratio, the more economically favorable the application of the CE strategy complex is. The corresponding cost values are collected within the framework of Life Cycle Costing (LCC). The approach by [29] regarding the evaluation of the cost-effectiveness of remanufacturing versus demanufacturing at the product level thus constitutes the foundation for the cost index.

$$CI = \frac{C_{CE}}{C_{NP}} \leq 1 \tag{1}$$

Likewise, the environmental performance is evaluated via an emissions index (EI) (see Equation (2)). This index quantifies the emissions resulting from the respective CE strategy complex (E_{CE}) relative to the emissions of new production (E_{NP}) based on data obtained, e.g., through Life Cycle Assessment (LCA).

$$EI = \frac{E_{CE}}{E_{NP}} \leq 1 \tag{2}$$

For both, CI and EI, a value below one indicates that the circular process results in a lower economic/environmental burden than new production. However, this threshold only serves as a benchmark rather than a strict cut-off, providing a reference for interpretation while allowing flexibility according to company-specific criteria. To assess the feasibility of the CE strategy complex holistically, both indices are integrated into an eco-efficiency assessment using an eco-efficiency graph, as outlined by [30]. As shown in Figure 3, the graph visualizes the environmental performance of the evaluated CE strategy complex relative to its economic performance. The x-axis represents the economic impact based on the cost index, while the y-axis illustrates the environmental impact using the emissions index. Finally, the derived CE strategy complex is assigned to one of four quadrants: high eco-efficiency (both economically

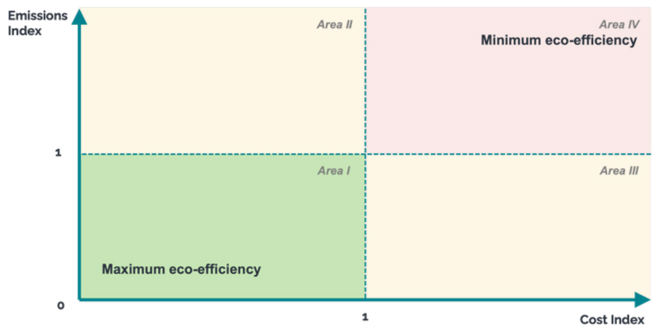

Figure 3. Eco-efficiency graph (based on [20])

and environmentally favorable), economically advantageous but environmentally burdensome, environmentally beneficial but economically unviable, and low eco-efficiency (unfavorable on both fronts).

4. Case Study

To validate the applicability of the proposed approach, it is applied to the use case of a digital water meter produced by a German manufacturer. This product presents a suitable test case due to two key attributes: a regulatory framework that requires the periodic return of used meters for calibration intervals, and an inherently modular design that supports disassembly and reprocessing.

Against this background, the manufacturer seeks to implement a CE business model that facilitates an efficient circular production process and the reintegration of water meters into the market. The manufacturer's circular processes revolve around the systematic collection, assessment, and reprocessing of decommissioned water meters. Upon return, each unit undergoes an EOL assessment applying the developed decision logic that determines the optimal CE strategy complex.

The analysis begins with modelling the water meter using HALG. The product is divided into three hierarchical levels: the complete product, five main components, and their respective subcomponents. This hierarchical mapping enables a structured disassembly sequence, which is crucial for deriving iterative strategies.

Each returned water meter is accompanied by a DPP containing life cycle data. This data is processed during registration at the manufacturer to assess the product's EOL condition based on the three core quality parameters. Table 2 demonstrates how specific DPP data points are allocated to product elements and linked to the respective quality parameters based on expert knowledge. For the purpose of this case study, the evaluation requires each data point to be mapped to a binary decision: "OK" (meets the requirement) or "NOK" (does not meet the requirement). Only when all associated data points for a given parameter are marked "OK" is that parameter deemed fulfilled. For transparency, the complete iterative decision tree of the case study is provided in the supplementary materials, ensuring full traceability of the decision process.

Table 2. Extract of DPP data points for water meter EOL assessment

DPP data point	Affected product element	Quality parameter
Data point #1	1.1	Functional condition
Data point #2	1.2	Physical condition
Data point #3	1.3	Functional condition
Data point #4	1.3	Functional condition
Data point #5	1.4	Functional condition
Data point #6	2.1	Physical condition
Data point #7	2.2	Functional condition
Data point #8	2.2	Functional condition
Data point #9	2.3	Remaining useful life
Data point #10	2.3	Remaining useful life
Data point #11	2.4	Functional condition
Data point #12	3	Functional condition
…	…	…

The first iteration of the decision logic evaluates the water meter as a whole. If it passes all quality checks, it is directly reassigned for reuse. If not, a root cause analysis identifies which data points led to a NOK result. In case critical failures are identified (e.g., via data point #8), the unit is diverted directly to recycling. If no such terminal failure is identified, the product is disassembled, and each of the five main components undergoes a separate iteration of the decision logic. Components that still do not meet the criteria may be further disassembled into subcomponents, initiating a third iteration. This structured evaluation yields individual decision trees for each product level, enabling a comprehensive CE strategy complex to be derived, as shown in Figure 4.

In the final step, the derived CE strategy complex is subjected to eco-efficiency analysis. The respective results are then visualised on an eco-efficiency graph. The outcome indicates that the exemplary CE strategy complex for the water meter achieves a favourable position in the high eco-efficiency quadrant. This confirms the economic and environmental viability of implementing the proposed circular strategies, reinforcing the practicality of the developed decision logic in real-world manufacturing contexts.

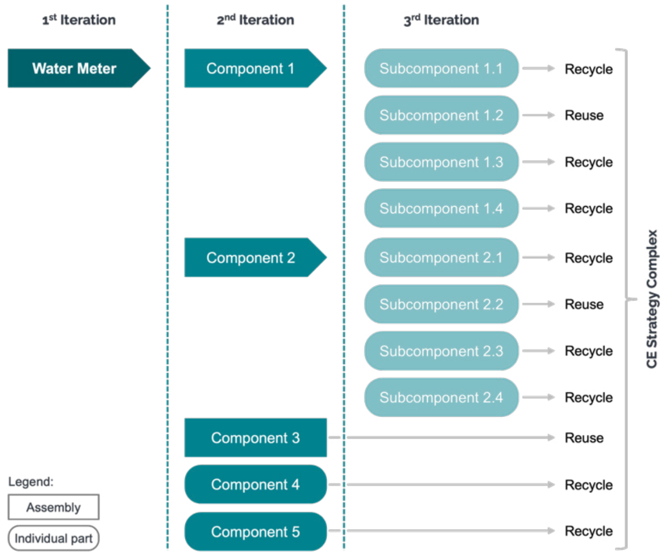

Figure 4. Exemplary CE strategy complex of water meter

5. Discussion and Outlook

The presented solution approach addresses the challenge of deriving appropriate circular strategies for used products based on their EOL condition. Even though DPPs are currently implemented primarily on an application-specific basis and industry-wide standards are still under development, they are considered as key enabler for standardizing cross-industry traceability, seamlessly integrating all life-cycle phases, and thus overcoming missing life cycle information for products at their EOL [2]. The present approach leverages these holistic data and integrates them into an iterative decision logic, fostering a structured and transparent method for circular decision-making at the product and component level leveraging DPP data. The integration of a viability assessment further enhances the practical relevance by considering the economic and environmental implications of strategy implementation.

Despite its strengths, the approach is bounded by several limitations. These include its initial setup effort, exclusive focus on technical criteria, reliance on expert-based data assignment and simplified binary data evaluation. The lack of comprehensive life cycle and environmental data, especially among SMEs, further constrains its application and accuracy. Additionally, the adaptability of the decision logic is influenced by product complexity and the granularity of available information.

Looking ahead, the automation of DPP data integration represents a promising field of research to enhance both efficiency and scalability. However, the correlation between lifecycle data and actual product condition at its EOL is not yet fully understood, which highlights the need for further research. Furthermore, advances in data analytics, including machine learning, could refine quality assessments by introducing error tolerances and uncovering hidden patterns in historical product data. Furthermore, broader validation across diverse product types would offer insights into the approach's generalizability and robustness.

In summary, this contribution lays a foundation for a data-driven, technically grounded approach for EOL decision-making in the context of the CE. Future research should focus on enhancing data integration and refining the approach to incorporate additional dimensions, thereby strengthening the strategic deployment of circular practices in industry.

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