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Optimizing quality and cost in remanufacturing under uncertainty

A novel optimization framework utilizing quality and process modelling

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Abstract
In the context of growing sustainability demands, businesses are increasingly adapting their production practices by integrating remanufacturing. However, companies often face challenges in profitably implementing remanufacturing due to complexities arising from uncertainties in processes, product quality, and market conditions. This highlights the need for effective decision support in remanufacturing processes. Addressing this challenge, our research introduces an algorithm designed to identify cost-efficient process plans that optimize order fulfillment while considering a company's specific capabilities and inventory levels. By modeling the remanufacturing planning process as a Markov process, our algorithm comprehensively accounts for both process-related and quality-related uncertainties. This approach enables the evaluation of all Pareto optimal process plans in terms of cost efficiency and reliability. We validate our methodology through a real-world application in the automation industry, specifically focusing on the remanufacturing of variable speed drives. This case study demonstrates the practical relevance of our approach and a potential for significant cost reductions, enhanced process efficiency, and improved labor productivity. Overall, businesses gain critical insights into the financial prospects of their remanufacturing efforts, identifying opportunities for optimization and expansion into new product quality categories. This enhances their economic potential and aligns with consumer preferences for distinct product qualities.

Keywords Remanufacturing · Optimization · Markov model · Order management

1 Introduction

The concept of the circular economy has gained prominence as a sustainable alternative to the traditional linear economic model of "take, make, dispose." The Circular economy concept emphasize the importance of resource efficiency, waste minimization, and the continuous use of materials through practices such as recycling, remanufacturing, and product life extension [1, 2]. Adopting circular economy practices can lead to significant environmental benefits, including reduced greenhouse gas emissions, lower energy consumption, and minimized waste generation [1]. Economically, circular economy practices can enhance cost efficiency, create new business opportunities, and improve resilience against resource scarcity [3]. However, implementing circular economy practices in manufacturing presents challenges, such as optimizing remanufacturing processes to balance environmental and financial objectives [1, 4]. With the sharp rise in global resource consumption, remanufacturing is becoming increasingly important [5, 6]. Remanufacturing involves restoring used products to like-new conditions, offering significant environmental and economic benefits by decoupling production from resource use and achieving substantial cost savings [7]. Unlike repair, which focuses on fixing specific faults to make a product functional again, remanufacturing includes complete disassembly, inspection, refurbishment, and replacement of worn components, resulting in a product that meets or exceeds the original performance specifications [8].

Despite these advantages, businesses encounter significant challenges in adopting remanufacturing due to the pressures of competitive markets and the uncertainties inherent in remanufacturing processes. These challenges are further compounded by the need to integrate circular economy into existing manufacturing systems, which requires innovative

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process planning and decision-making frameworks to optimize both environmental and financial outcomes [9].

Therefore, the aim of this work is to develop a systematic approach that addresses these challenges by providing effective decision support in remanufacturing process planning. We introduce an algorithm designed to identify cost-efficient process plans that optimize order fulfillment, considering the specific capabilities and inventory levels of a company while accounting for uncertainties in processes and product quality.

Our research introduces several key innovations. First, we develop a comprehensive approach to quality data modeling, enabling more accurate assessments of returned products. Next, we propose an algorithm for automated process planning that minimizes the need for manual intervention, reducing errors and increasing efficiency. Finally, we implement an optimization framework that carefully balances quality, reliability, and cost factors, ensuring that remanufacturing operations are not only sustainable but also profitable given a specific demand. This research is validated through a real-world application in the automation industry, specifically focusing on the remanufacturing of speed drives. The validation demonstrates the practical relevance of our approach, showcasing its potential.

The manuscript is organized as follows: Sect. 2 presents a detailed review of existing literature on quality data modeling and remanufacturing process planning (RPP), highlighting the current gaps in research. Section 3 outlines our methodological approach, including the modeling of product quality, the formulation of RPP as a Markov problem, and the development of optimized process plans. Section 4 presents an application of our approach in the automation industry. Section 5 discusses these results. Finally, Sect. 6 concludes with a summary of key findings, contributions, and potential directions for future research.

2 Fundamentals and literature review

This section reviews the literature on remanufacturing process planning (RPP), focusing on three key criteria: quality data modeling, remanufacturing uncertainties, and optimization. Quality data modeling refers to how studies represent and manage the variability and characteristics of product quality in remanufacturing. This includes the methods used to assess, classify, and utilize quality information of returned products (cores) in the planning process. Remanufacturing uncertainties involve the inherent uncertainties in remanufacturing processes, such as the unpredictable condition of returned products, variability in processing times, and the probabilistic outcomes of remanufacturing tasks. Studies are evaluated based on how comprehensively they address these uncertainties in their models. Optimization criteria pertain to the extent to which studies incorporate optimization aspects-specifically, cost, quality, and reliability considerations-into their remanufacturing process planning models. This involves developing methods or algorithms that aim to optimize one or more of these factors, such as minimizing costs while ensuring product quality and process reliability.

2.1 Methodology of literature review

We used the term "remanufacturing process planning" and key criteria as keywords for our literature search, along with various combinations and synonyms. Additionally, we included the keyword "reinforcement learning," recognizing it as a key alternative method for solving remanufacturing process planning problems. A manual search in databases such as Web of Science, Google Scholar, and ScienceDirect yielded a preliminary list of 190 papers. These papers were selected based on a quick review of their titles, abstracts, and keywords to ensure they were within the scope of this work. We then applied inclusion criteria focusing on studies that addressed quality data modeling, remanufacturing uncertainties, and/or optimization. Papers not meeting these criteria-such as those focusing on carbon emission calculations or lacking empirical evidence-were excluded. This process resulted in 25 papers selected for in-depth review.

In Table 1, we evaluate each selected paper based on the three criteria, indicating the degree to which each study considers them. The level of consideration is represented using symbols ranging from not considered (◯) to fully considered (●), with intermediate levels at approximately 25% (◔), 50% (◑), and 75% (◕). For example, an article that only partially addresses cost optimization but does not consider quality or reliability would be indicated as partially considering the 'Optimization criteria,' representing approximately 25% consideration.

2.2 Analysis of the literature

Remanufacturing process planning involves designing and optimizing the sequence of operations required to restore used products to like-new conditions. This task is inherently complex due to the varying conditions of returned products and the need to balance multiple objectives such as cost, quality, and process reliability [26]. The quality of cores in remanufacturing, which is crucial for process planning, is

Table 1 State of the Art

References	Quality data modeling	Remanufacturing uncertainties	Optimization criteria
Fernández et al. (2008) [10]	◔	◑	◑
Wadhwa et al. (2009) [11]	◔	◑	◕
Jin et al. (2013) [12]	◔	◑	◕
Takahashi et al. (2014) [13]	○	◑	◑
Dehghanbaghi et al. (2016) [14]	◔	◑	◕
Yang et al. (2016) [15]	◔	◑	◕
Cui et al. (2017) [16]	◔	◑	◕
Wang et al. (2017) [17]	◑	◑	◕
Aydin et al. (2018) [18]	○	◑	◑
Ji and AbouRizk (2018a) [19]	◑	●	◔
Ji and AbouRizk (2018b) [20]	◑	●	○
Stavropoulos et al. (2019) [21]	◑	◑	◑
Jiang et al. (2019) [22]	◔	◑	◑
Meng et al. (2020) [23]	◔	◑	◕
Li et al. (2021) [24]	◔	◑	◑
Yanıkoğlu and Denizel (2021) [25]	◔	◑	○
Yanxiang Chen et al. (2021) [26]	◑	◑	◕
Stavropoulos et al. (2021) [27]	○	◑	◑
Liu et al. (2022) [28]	◑	●	◑
Allagui et al. (2023) [29]	○	◑	◕
Liu et al. (2023) [30]	◑	●	○
Paraschos et al. (2023) [31]	○	◑	◑
Paraschos et al. (2024) [32]	○	◑	●
Wang et al. (2024) [33]	○	◔	◕

not considered ○ ◔ ◑ ◕ ● fully considered

also complex, involving both inherent product characteristics and customer perceptions [34]. Therefore, quality data models must be flexible enough to account for product usage histories and uncertainties.

Studies often classify core quality with fixed values or ranges (cf. [16, 18, 25, 35, 36]), but these classifications can be ambiguous and fail to capture true quality differences. Some researchers address this by basing quality on specific fault features (cf. [17, 26]), while others use more neutral criteria (cf. [10, 11, 14, 22, 23]). Research on quantitatively evaluating the quality of remanufactured products is limited. Approaches like the Taguchi quality concept assess quality loss based on deviations from target values [30]. Other methods estimate quality as a fraction of non-conforming items, which can neglect significant quality differences [12, 15, 20]. It is crucial to consider product features that impact overall functionality, as emphasized in quality management studies [37, 38].

Integrating these nuanced quality assessments into remanufacturing process planning is therefore essential. Takahashi et al. [13] propose an adaptive strategy that balances manufacturing and remanufacturing rates to minimize inventory costs, integrating process planning with inventory management to respond to fluctuations in product returns and market demand. Similarly, Aydin et al. [18] develop a multi-period model addressing quality uncertainties in returned products, facilitating dynamic process planning by considering the probabilistic nature of product conditions. Yanıkoğlu and Denizel [25] explore the impact of variable core quality on remanufacturing costs and process times through a robust optimization framework, emphasizing the need for flexible process plans that accommodate variations in product quality. Stavropoulos et al. [27] introduce a two-stage decision support system aimed at integrating manufacturing processes in microfactories for electric vehicles, optimizing both feasibility and cost, and addressing economic and environmental benefits by evaluating technology integration from feasibility and ROI perspectives. Liu et al. [28] incorporate uncertain machining effects and quality losses into the process planning model, highlighting the importance of accounting for variability in remanufacturing operations. Ji and AbouRizk [19] present a Markov-chain model focusing on quality-induced rework, capturing probabilistic transitions between different quality states and enabling process plans that account for potential rework requirements. Stavropoulos et al. [21] developed a decision support system for the assembly/disassembly of multi-material components, facilitating efficient material flow management within the circular economy framework. Their system integrates considerations of material compatibility and disassembly sequences into process planning, improving remanufacturing effectiveness. Fernández et al. [10] utilize conditional rules to optimize recovery strategies based on product value and useful life, providing insights into prioritizing different recovery paths. Jiang et al. [22] employ case-based reasoning to match new cases with similar past scenarios, facilitating adaptive process planning leveraging historical data. Wang et al. [17] propose a hybrid method integrating genetic algorithms and neural networks to optimize process plans based on fault features, demonstrating the potential of combining evolutionary algorithms with machine learning techniques. Dehghanbaghi et al. [14] apply fuzzy inference systems to rank recovery options, providing a nuanced method for evaluating multiple criteria. Yanxiang Chen et al. [26] develop multi-objective optimization models simultaneously considering cost, quality, and assembly accuracy, underscoring the multifaceted nature of remanufacturing process planning.

Recently, reinforcement learning (RL) has emerged as a novel alternative to traditional optimization methods in remanufacturing process planning. Several studies have explored the application of RL to address complex decision-making problems.

Paraschos et al. [31] present a reinforcement learning framework combined with ad-hoc control policies to optimize manufacturing processes in a flexible, multi-stage system. The study highlights the importance of adaptive planning and scheduling in maintaining sustainability amidst frequent system failures. Through RL, the proposed framework enhances decision-making for material management and system maintenance, integrating lean manufacturing practices such as CONWIP and opportunistic maintenance. The approach assumes steady operational conditions, limiting adaptability where product conditions fluctuate.

Furthermore, Allagui et al. [29] focus on optimizing disassembly sequence planning (DSP) using a Q-network RL algorithm to reduce disassembly costs and time in both partial and full disassembly processes. The approach addresses key optimization parameters such as minimizing tool and direction changes, optimizing time, and prioritizing critical wear parts. A demonstrative example validates the approach, showing improvements in DSP generation and execution. While RL effectively optimizes DSP, the study does not fully address product quality and uncertainties.

Wang et al. [33] focus on integrating remanufacturing process planning and scheduling to optimize energy consumption and enhance production efficiency. Their proposed method, Energy-aware Remanufacturing Process Planning and Scheduling (ERPPS), incorporates flexibility in machine operations and sequence planning. A novel RL-based particle swarm optimization (RL-PSO) algorithm is applied, incorporating energy-saving techniques such as machine speed-switching rather than turn on/off strategies. The study demonstrates the superiority of this approach in optimizing both energy consumption and production flow. While the paper strongly integrates energy awareness and scheduling with process planning, it primarily focuses on operational efficiency, leaving aspects like product quality uncertainties underexplored.

Paraschos et al. [32] address production sustainability within the framework of Industry 4.0, focusing on remanufacturing systems. They propose an RL-based decision-making system designed to optimize multi-stage manufacturing and remanufacturing processes while maintaining lean and green principles. The system optimizes operations like predictive maintenance and material reuse, contributing to lowering operational costs and reducing environmental impact. Experimental analysis validates the method, demonstrating improvements in system sustainability and material reuse efficiency. However, the paper's approach is limited in addressing uncertainties in remanufactured product quality.

2.3 Summary of literature findings

The reviewed studies collectively highlight diverse approaches to remanufacturing process planning, ranging from adaptive strategies and robust optimization to probabilistic models, advanced decision support systems, and emerging reinforcement learning methods. These contributions emphasize the necessity of integrating quality assessment, uncertainty management, and multi-criteria optimization to develop effective and efficient remanufacturing processes within the circular economy.

Despite significant advancements, gaps remain in fully integrating quality data modeling, remanufacturing uncertainties, and optimization criteria into a unified framework. Many studies address these aspects partially, as shown in Table 1, indicating the need for comprehensive approaches that simultaneously consider all three criteria to enhance remanufacturing process planning.

While reinforcement learning approaches offer novel solutions, they often lack transparency and may not be suitable for companies with high manual labor, which is dominant in current remanufacturing practices. The complexity and interpretability of RL models can pose challenges for adoption in environments where human operators play a significant role, underscoring the importance of developing methods that are both effective and practical for industry implementation. As a result, there are companies that specifically demand solutions that are easy to understand, transparent, and seamlessly integrate with their existing manual processes, as it is the case in the use case later on.

3 Methodical approach for remanufacturing planning

To fill the research gap, we start by modeling the RPP problem as a Markov process. Each state in the model thereby represents a specific quality class and each action describes a feasible remanufacturing process. As the RPP problem is a sequential process, we need to derive an optimal policy that specifies the remanufacturing tasks that are to be chosen, given that a certain quality state is reached at a certain stage. The intention is thereby to maximize the aggregated amount of expected rewards, i.e., to minimize the associated costs and simultaneously maximize the corresponding transition probabilities. The corresponding quality data model that we considered in our model is specified in the first subsection of this chapter (see Sect. 3.1). Subsequently, a detailed description of the developed process model for RPP and order management is provided in the Sects. 3.2, 3.3 and 3.4. Given that remanufacturing currently relies heavily on human expertise and manual processes, our approach aims to support human decision-making by providing a comprehensive overview of alternative process plans. This comprehensive view is essential for human workers to make informed decisions during the transition to higher levels of automation. Our method serves as an intermediate solution that facilitates semi-automated support, bridging the gap between manual labor and fully automated systems.

3.1 Quality data modeling

Quality data modeling comprises the specification of suitable quality parameters and their admissible value ranges as well as the formation of the respective quality classes.

3.1.1 Quality parameter and quality class definition

Each product can be described as a composition of multiple quality parameters $\{QP_1, ..., QP_N\}$. In terms of the quality parameter selection process, it is essential to capture the specific quality characteristics of the product at focus. The identified set of quality parameters should therefore include all the relevantcharacteristic product features that can be differently affected, depending on the respective product usage history. This is important to enable the representation of varying core quality conditions. From a market perspective, additional criteria like the product age or functionality can be relevant. Thus, to enable a suitable reflection of distinct customer preferences, these parameters should be identified and integrated in the quality data model.

For example, a remanufactured hydraulic motor may have quality parameters that include:

- QP_1: Seal Condition (e.g., 'New', 'Worn', 'Damaged')
- QP_2: Housing Integrity (e.g., 'Intact', 'Minor Wear', 'Cracked')
- QP_3: Shaft Wear Level (measured in mm, e.g., 0.01 mm, 0.05 mm, 0.10 mm)
- QP_4: Bearing Status (e.g., 'Good', 'Fair', 'Needs Replacement')
- QP_5: Cleanliness Level (measured in particle concentration, e.g., 50 ppm, 100 ppm)
- QP_6: Functional Test Result (e.g., 'Pass', 'Fail')

Each selected quality parameter thereby has to be defined in terms of its admissible parameter value range. Depending on the specification of the permissible parameter value range, parameter values can be categorical (e.g., 'Pass' or 'Fail'), ordinal (e.g., 'Good', 'Fair', 'Needs Replacement'), or numerical (e.g., wear in mm, particle concentration in ppm).

A product quality class is a unique combination of specific quality parameter values. Hence, it can be defined by assigning particular values to each of the predefined quality parameters $QP_1 - QP_N$.

For instance, a specific quality class of the hydraulic motor might be:

- Quality Class QC Example:
  - QP_1: Seal Condition = 'New'
  - QP_2: Housing Integrity = 'Intact'
  - QP_3: Shaft Wear Level = 'Low'
  - QP_4: Bearing Status = 'Good'
  - QP_5: Cleanliness Level = 'Clean'
  - QP_6: Functional Test Result = 'Pass'

The set of potential quality classes $QC_1, ..., QC_M$ can thus be determined by creating all possible combinations of

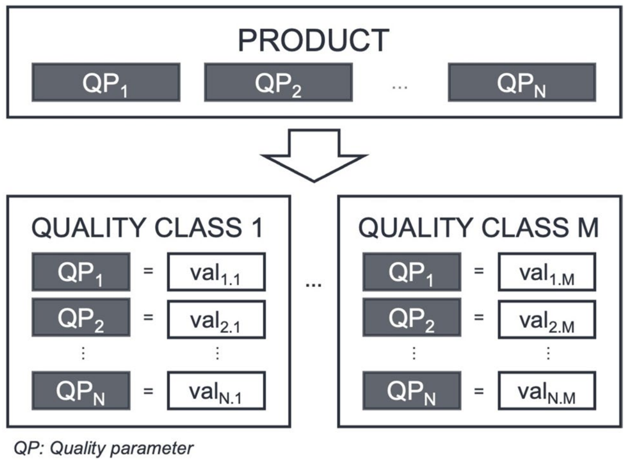


Fig. 1 Quality parameter and quality classes

quality parameter values (see Fig. 1). For example, if we have 3 options for QP_1, 3 options for QP_2, 3 options for QP_3, 3 options for QP_4, 2 options for QP_5, and 2 options for QP_6, the total number of potential quality classes would be $3 \times 3 \times 3 \times 3 \times 2 \times 2 = 324$. Theoretically, the number of potential combinations increases exponentially with the number of quality parameters and quality parameter values.

However, in practice, not all of these combinations are feasible or relevant. To manage this problem, we classify and handle infeasible combinations using the following approaches:

- **Logical Constraints:** Some combinations are logically inconsistent and can be excluded. For example, a product cannot simultaneously have a 'new' and a 'worn' condition for the same parameter. By defining logical rules that specify incompatible parameter values, we eliminate such combinations from consideration.
- **Manufacturing Capability Constraints:** Certain quality classes may not be achievable due to limitations in the manufacturing or remanufacturing processes. For instance, a facility may lack the equipment or technology to upgrade a parameter to a certain value. By considering the company's capabilities, we exclude quality classes that are unattainable.
- **Market Relevance:** Some combinations may not be relevant or desirable from a market perspective. If customers do not demand products with certain combinations of quality parameters, those quality classes can be disregarded. Market analysis helps identify and focus on quality classes with commercial viability.
- **Regulatory and Compliance Constraints:** Regulations may prohibit certain combinations of parameter values. For example, safety standards may require that certain components meet minimum quality levels. Combinations violating these standards are excluded.

The definition and application of these rules are carried out manually by engineers or trained personnel. The experts analyze the product characteristics, manufacturing processes, market demands, and regulatory requirements to establish the relevant constraints. It is possible to support this task computationally, e.g. checking logical rules. This systematic elimination of infeasible combinations addresses the problem of exponential growth in the number of potential quality classes, making the approach practical for real-world applications.

The introduction of different quality classes as combinations of specific parameter values enables the quantification of quality differences between products based on the corresponding parameter value differences. It is therefore a suitable approach to account for the prevailing quality uncertainties induced by varying usage histories of cores or machine failures. Moreover, it enables distinctions between varying customer preferences at a suitable level of detail.

3.2 Process modeling—fundamental definitions

In this section, the foundations of the developed RPP model are outlined. This includes further specifications with regard to quality transformation processes, remanufacturing process applications and the generation of feasible process plans.

3.2.1 Transformation definition

A transformation specifies a concrete product transformation from one quality class to another quality class. The developed approach thereby also considers potential product quality deterioration, resulting from process or machine failures. Each transformation is defined by the corresponding transition probability, the associated costs and the respective modification value for each quality parameter. Transformations need further specification with respect to their transformation types. Possible types of transformation are a simple replace operation, an additive or a multiplicative transformation. In the case of a replace operation, previous parameter values are substituted by the respective transformation values. For example, in remanufacturing a hydraulic motor, replacing a worn-out seal with a new one changes the quality parameter 'seal condition' from 'worn' to 'new'. In the additive case, the parameter-specific transformation values are added to the corresponding preceding values. For instance, if the 'surface roughness' parameter of a cylinder is improved by honing, the roughness value is decreased by a adding a negative number, representing an additive change to the surface quality. In the multiplicative case, the transformation values define the percentage change, according to which the previous parameter values are to be adjusted. An example is cleaning internal components to reduce contamination levels; the 'contaminant concentration' parameter value is multiplied by a factor less than 1 (e.g., 0.5), indicating a 50% reduction in contamination levels after cleaning.

Figure 2 illustrates a product transformation from quality class x to quality class y. The depicted transformation succeeds with probability p and creates costs in the amount of c. The particular modification of each quality parameter $QP_1 - QP_N$ thereby depends on the specified transformation type.

3.2.2 Task definition

In the following, production steps with one or multiple components as in- and outputs will be referred to as tasks (compare [39]). In this work, the definition of a task comprises every single transformation that may occur with a certain probability if this particular task is executed. This implies that the application of a task o to a core of quality class QC_{start} can yield various quality classes QC_{end} as process outcomes (see Fig. 3). The probabilities of all these potential outcomes need to sum up to 1 (see Formula 1).

$$\sum_{k=1}^{T} p_k = 1 \tag{1}$$

By considering all the potential transformations that can result from a specific task execution, the proposed approach achieves to account for the predominant process-related uncertainties in the remanufacturing context.

Fig. 2 Transformation

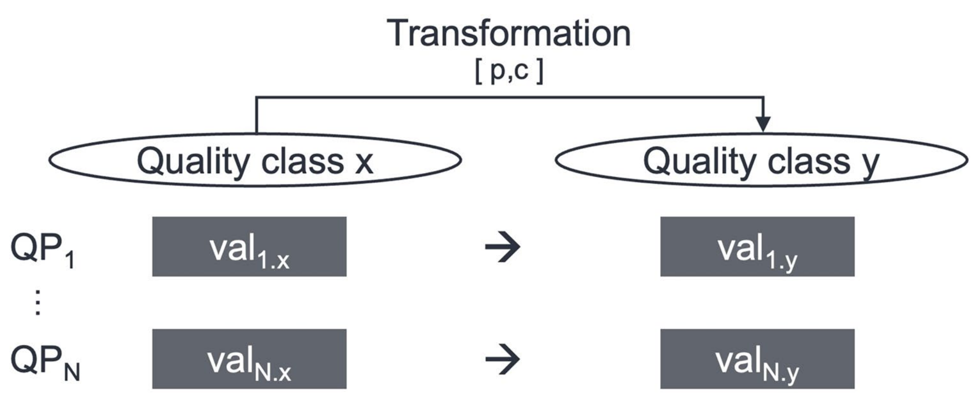
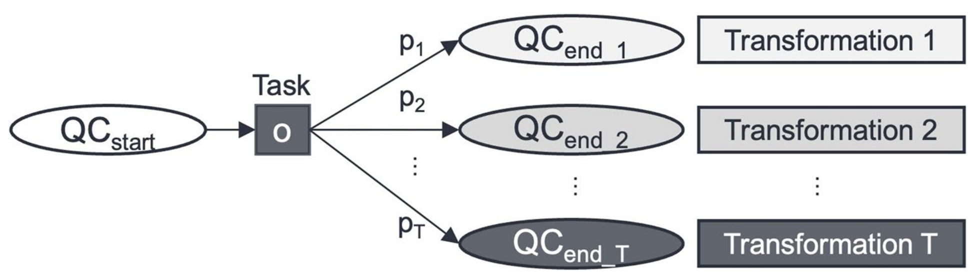


Fig. 3 Task



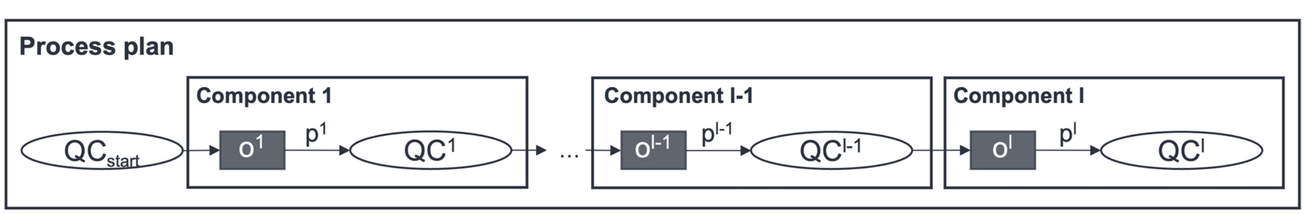


Fig. 4 Process plan

A task can thereby be applied to cores of varying quality classes, i.e., of distinct QC_{start}. Since in practice some tasks might not be applicable to every quality class, the developed approach allows to define parameter value requirements for task applications. More precisely, minimal and maximal parameter values can optionally be defined and need to be fulfilled in order to enable the execution of a particular task.

For a holistic analysis in terms of remanufacturing process planning, the developed tool considers a whole set of tasks O_A. This set comprises all remanufacturing tasks that a company is currently capable of, based on its available machines and equipment. The definition of the capabilities is done manually. By concatenating single tasks with matching output-input relations, so-called bill of processes, can be generated [39]. In the following, these will be referred to as process plans.

3.2.3 Process plan definition

In this work, a process plan describes a sequence of task applications.

For modeling purposes, process plans are logically split up into smaller components. The process plan depicted in Fig. 4, for example, consists of l components in total. Each process plan component is thereby characterized by a range of different parameters. Subsequently, we will illustrate these parameters for one particular component, i.e., for component l in Fig. 4. The first parameter specifies a particular task o^l out of the set of all feasible tasks. The second parameter describes a concrete quality class QC^l that can be obtained by applying this task. Hence, it refers to one particular transformation out of all the possible transformations that can be induced by performing task o^l. The corresponding probability p^l of this specific transformation forms the third parameter. Each component is additionally characterized by its accumulated probability p^l_{acc}. This accumulated probability also considers the transition probabilities of all previous components in the respective process plan. For component l, p^l_{acc} can be obtained by multiplying its transition probability p^l with the accumulated transition probability p^{l-1}_{acc} of the previous component $l-1$. Formally, this implies the following:

$$p^l_{acc} = p^{l-1}_{acc} \cdot p^l \tag{2}$$

Moreover, we define a parameter to specify the costs c^l that are associated with the execution of task o^l. To additionally quantify the accumulated costs for all tasks related to obtaining QC^l, we introduce the parameter c^l_{acc}. For its calculation, the costs c^l of performing task o^l are added to the accumulated costs c^{l-1}_{acc} of the previous component $l-1$ (see equation 3).

$$c^l_{acc} = c^{l-1}_{acc} + c^l \tag{3}$$

The last parameter new^l evaluates whether the attainable quality class QC^l in this component has already been reached in any of the preceding components of the respective process plan. In case we obtain a new quality class, new^l is set to true for the corresponding component l.

The proper definition of a process plan with all its components and the corresponding parameter values is essential in order to derive the set of the Pareto optimal process alternatives. The respective procedure is depicted in further detail in the Appendix 7.2.

3.3 Remanufacturing process planning model

In this section, the developed method of evaluating the feasible set of Pareto optimal process plans is presented. The first Sect. 3.3.1 provides a general overview of the respective procedure, whereas Sect. 3.3.2 and 3.3.3 further specify the underlying local and global optimization criteria.

3.3.1 General procedure

First of all, companies need to identify the relevant quality parameters of the targeted product and provide information about all realistic values of these parameters with respect to product returns. Based on these parameter values, the algorithm automatically derives the set of potential core quality classes. For each of these quality classes, the algorithm then

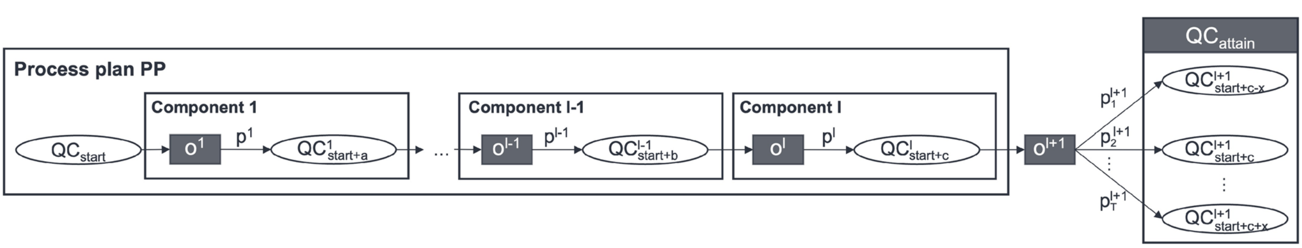


Fig. 5 Quality improvement

sequentially evaluates a set of Pareto optimal remanufacturing process plans S_{Pareto}. In this respect, it simultaneously considers attainable quality characteristics, associated costs and transition probabilities.

In every attainable quality state, all of the applicable remanufacturing tasks are therefore executed and possibly, the set of Pareto optimal process plans is updated. The associated update criteria will be outlined in the following subsection. The procedure terminates once no further quality improvement can be obtained. Thus, to be part of S_{Pareto}, the application of each task in the corresponding process plan needs to result in an actual quality improvement with respect to at least one quality parameter (see Sect. 3.3.2). In case we obtain a quality state that can also be reached by any other alternative in S_{Pareto}, we need to check for Pareto optimality of the respective process plan (see Sect. 3.3.3).

3.3.2 Local optimization criteria: quality improvement

Assume PP to be a particular process plan of S_{Pareto} with l components. The initial quality class before applying process plan PP is the quality class associated with the first element in PP, here defined as QC_{start} (see Fig. 5). After applying a set of tasks $\{o^1, ..., o^l\}$, we reach $QC^l_{start+c}$. As PP is part of S_{Pareto}, an actual quality improvement in at least one quality parameter must be obtained after each task execution. This implies that inequality 4 must hold, whereas $c > b > a$ and $a, b, c \in \mathbb{N} \backslash \{0\}$.

$$QC_{start+c} > QC_{start+b} > \ ... QC_{start+a} > QC_{start} \tag{4}$$

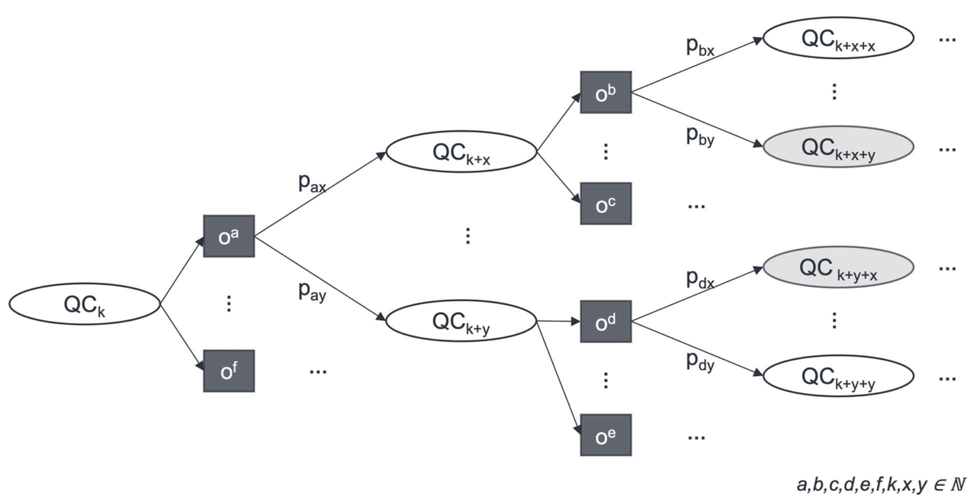
We now assume that task o^{l+1} is a feasible task and that $QC^l_{start+c}$ fulfills the parameter requirements for its application. The feasibility of a task o^{l+1} is determined based on two main criteria:

- **Parameter Requirements:** Each task has specific parameter value requirements, such as minimum or maximum allowable values for certain quality parameters. A task is considered feasible for the current quality class $QC^l_{start+c}$ if all these requirements are met. This ensures that the task is applicable and can be successfully executed on the product in its current state.
- **Quality Improvement:** Applying the task must result in a quality class that is strictly better than the current quality class. This means there must be an improvement in at least one quality parameter without any deterioration in others. Tasks that do not improve the quality or lead to quality stagnation or deterioration are not considered feasible, as they would not contribute to an optimal process plan.

By enforcing these criteria in our solution automatically, we ensure that only tasks that are both applicable and beneficial are considered in the process planning.

As a result of performing o^{l+1}, we get a set of attainable quality classes QC_{attain}. For each of these attainable quality classes we check whether it has already been attained in any previous component in the underlying process plan PP. Only those paths that result in a better (higher) quality class than $QC^l_{start+c}$ will be respected for further analysis (see Fig. 5). This is a reasonable conclusion since the application of tasks is associated with costs. If no quality improvement is achieved, the respective quality class can be obtained at a lower cost and hence, this path can never be optimal. Within a single path, a quality class can therefore never occur more than once. For the example illustrated in figure 5, this implies that only the bottom path is added

Fig. 6 Extensive tree structure



to S_{Pareto} as it fulfills the following inequalities under the assumption that $x \in \mathbb{N} \setminus \{0\}$:

$$QC^{l+1}_{start+c+x} > QC^{l}_{start+c} > \ ... QC^{1}_{start+a} > QC_{start} \tag{5}$$

The remaining two paths in Fig. 5 are both not added to S_{Pareto} as they result in a quality stagnation (middle path) or even in a quality deterioration (upper path). Hence, the quality improvement criterion cannot be fulfilled (compare inequality 6 for the middle path and inequality 7 for the upper path).

$$QC^{l+1}_{start+c} \ngtr QC^{l}_{start+c} \tag{6}$$

$$QC^{l+1}_{start+c-x} \ngtr QC^{l}_{start+c} \tag{7}$$

3.3.3 Global optimization criteria: Pareto optimality

So far, we only considered the application of one single task in a particular quality state. In the next step, we extend this analysis to the whole set of feasible tasks, such that we obtain an extensive tree structure, comprising all Pareto optimal process plans for a specific quality class of cores.

For illustration purposes, we assume a core to be of quality class QC_k and determine all the attainable quality classes QC_{attain} by performing each task in O_A that is applicable to a product of class QC_k (compare $o^a - o^f$ in Fig. 6). Of the attainable quality classes we consider only those classes that represent an actual path-specific quality improvement. With regard to Fig. 6, we therefore assume that $QC_{k+x} > QC_k$ and $QC_{k+y} > QC_k$ with $x, y \in \mathbb{N}\backslash\{0\}$. Otherwise, the respective paths would end at this point. The underlying process plans for obtaining QC_{k+x} and QC_{k+y} are added to S_{Pareto} and captured in the so-called look-up table (compare PP_1 and PP_i in Table 5).The look-up table in this context is a structured table that records all the Pareto optimal process plans evaluated for each attainable quality class starting from a specific core quality class. It systematically organizes the following information for each process plan:

- **Core Quality Class:** The initial quality class of the core product before any tasks are applied.
- **Attainable Quality Class:** The quality class achieved after applying the sequence of tasks in the process plan.
- **Process Plan (PP):** A unique identifier for the process plan.
- **Tasks:** The sequence of tasks applied to reach the attainable quality class.
- **Costs:** The accumulated costs associated with the process plan.
- **Reliability:** The accumulated transition probability (success probability) of achieving the attainable quality class through the process plan.

By compiling this information, the look-up table serves as a comprehensive reference that allows decision-makers to quickly identify and compare all Pareto optimal process plans. It facilitates the selection of the most suitable process plans based on specific criteria such as cost minimization or reliability maximization. The look-up table effectively bridges the gap between the extensive tree structure of possible process plans and practical decision-making needs by presenting the essential information in an accessible format.

We conduct a *breadth-first search* and follow the same procedure in each attainable quality state until no further quality improvement can be achieved by performing any of the applicable tasks in O_A. Information related to each individual Pareto optimal process scheme is captured in the look-up-table. As soon as the set S_{Pareto} of QC_k is not empty anymore, we must additionally assure Pareto optimality of each process plan that is added to this set. Thus, after ensuring the compliance of the respective attainable quality class with the local optimization criteria (see previous subsection), we evaluate whether this quality class can also be reached by applying any other process sequence in S_{Pareto} of QC_k. If this is not the case, we add the respective process plan for attaining this specific quality class to S_{Pareto} of QC_k. Otherwise, i.e., if this quality class can also be attained by at least one other process sequence in S_{Pareto} of QC_k, we compare the conditions under which it can be reached. We distinguish between three different cases, in which the respective quality class is either obtained under:

1. *strictly better*,
2. *strictly worse* or
3. *Pareto optimal* conditions.

If a process plan PP_{new} strictly dominates over all process schemes in S_{Pareto} of QC_k (case 1), we replace the current set of Pareto optimal process plans in S_{Pareto} with PP_{new}. Strict dominance thereby implies that the same quality class is either reached at lower cost (and equal or higher probability) or with a higher probability (and equal or lower costs). Thus, for *each* process plan $PP_h \in S_{Pareto}$ of QC_k either condition 8 or condition 9 holds.

$$\forall PP_h \in S_{Pareto}(QC_k) : \ \left(c^{PP_{new}} < c^{PP_h} \ \wedge \ p^{PP_{new}} \geq p^{PP_h}\right) \vee \tag{8}$$

$$\left(c^{PP_{new}} \leq c^{PP_h} \ \wedge \ p^{PP_{new}} > p^{PP_h}\right) \tag{9}$$

In the second case, *at least one* process plan PP_h in S_{Pareto} of QC_k strictly dominates over PP_{new}. Consequently, PP_{new} is not added to S_{Pareto}. Formally, this implies that there exists at least one process plan $PP_h \in S_{Pareto}$ of QC_k through which the same quality class is obtained at lower cost (and equal or higher probability) or with a higher probability (and equal or lower costs). Consequently, one of the subsequent conditions 10 or 11 is fulfilled.

$$\forall PP_h \in S_{Pareto}(QC_k) : (c^{PP_{new}} < c^{PP_h} \wedge p^{PP_{new}} \leq p^{PP_h}) \vee \tag{10}$$

$$(c^{PP_{new}} \geq c^{PP_h} \wedge p^{PP_{new}} > p^{PP_h}) \tag{11}$$

In the third case, PP_{new} is Pareto optimal. This means that the accumulated costs *and* the accumulated probability of PP_{new} are both either lower or higher, compared to *each* process plan in S_{Pareto} of QC_k. PP_{new} hence fulfills one of the following conditions in a direct comparison with *each* process plan $PP_h \in S_{Pareto}$ of QC_k:

$$\forall PP_h \in S_{Pareto}(QC_k) : (c^{PP_{new}} > c^{PP_h} \wedge p^{PP_{new}} > p^{PP_h}) \vee \tag{12}$$

$$(c^{PP_{new}} < c^{PP_h} \wedge p^{PP_{new}} < p^{PP_h}) \tag{13}$$

In the special case of equality regarding the associated costs and probabilities (see equation 14), PP_{new} is only added to S_{Pareto} of QC_k if the respective process plans PP_h and PP_{new} are not completely identical with regard to the sets of tasks that are applied. The order of tasks is thereby of no relevance.

$$c^{PP_{new}} = c^{PP_h} \wedge p^{PP_{new}} = p^{PP_h} \tag{14}$$

We denote that the same quality class may be repeatedly obtained under Pareto optimal conditions by performing distinct process plans, i.e. by following different paths in the tree structure. As a reminder, within a single path, i.e. within the single process plan, a quality class never occurs more than once.

This comprehensive analysis yields a lookup table displaying all attainable quality classes based on distinct core quality conditions. For the illustrated tree structure in Fig. 6 we record Table 2.

QC_{k+x}, QC_{k+y}, QC_{k+x+x}, QC_{k+x+y} and QC_{k+y+y} are added to S_{Pareto} of QC_k since these particular quality classes imply a quality improvement and are not obtained by any other process plan in S_{Pareto} of QC_k.

QC_{k+y+x} is equal to QC_{k+x+y} and therefore already part of S_{Pareto} for QC_k. Hence, a comparison of the corresponding process plans PP_n and PP_m is required in order to determine whether they are both added to S_{Pareto} of QC_k and thus, are to be recorded in the look-up table. Depending on the respective parameter values, the number of alternatives that are captured in the look-up table can vary (see Table 3).

For a comprehensive analysis, we conduct the same analysis for each possible core quality level to account for the varying quality conditions of cores. This results in an extensive tree structure, as it is depicted in Fig. 6, for each potential core quality class.

Table 2 Look-up table

Core quality class	Attainable quality class	Process Plan	Tasks	Costs	Reliability
QC_k	QC_{k+x}	PP_1	o^a	$c(o^a)$	p_x^a
	..	..	..	..	..
	QC_{k+y}	PP_i	o^a	$c(o^a)$	p_y^a
	..	..	..	..	..
	QC_{k+x+x}	PP_j	$o^a \rightarrow o^b$	$c(o^a) + c(o^b)$	$p_x^a \cdot p_x^b$
	..	..	..	..	..
	QC_{k+x+y}	PP_m	$o^a \rightarrow o^b$	$c(o^a) + c(o^b)$	$p_x^a \cdot p_y^b$
		PP_n	$o^a \rightarrow o^d$	$c(o^a) + c(o^d)$	$p_y^a \cdot p_x^d$
	..	..	..	..	..
	QC_{k+y+y}	PP_z	$o^a \rightarrow o^d$	$c(o^a) + c(o^d)$	$p_y^a \cdot p_y^d$
	..	..	..	..	..

3.4 Order management optimization

In the previous section, we pointed out how the developed approach enables companies to obtain a comprehensive overview of all feasible and simultaneously Pareto optimal process alternatives in the form of a look-up table. This overview is considered as the first main asset of the approach as it gives companies a general idea of their current scope of action, based on their expertise and available technologies.

In this section, we present two further functionalities of the approach that companies can embrace to enhance

Table 3 Requirements to be part of the look-up table (for a pairwise comparison of process plans)

Look-up table	Requirements costs and reliability	Further requirements
Add only PP_m	$c(PP_m) < c(PP_n) \wedge p(PP_m) \geq p(PP_n) \vee c(PP_m) \leq c(PP_n) \wedge p(PP_m) > p(PP_n)$	$x > 0$
Add only PP_n	$c(PP_n) < c(PP_m) \wedge p(PP_n) \geq p(PP_m) \vee c(PP_n) \leq c(PP_m) \wedge p(PP_n) > p(PP_m)$	$y > 0$
Add PP_m and PP_n	$c(PP_m) < c(PP_n) \wedge p(PP_m) < p(PP_n) \vee c(PP_m) > c(PP_n) \wedge p(PP_m) > p(PP_n)$	$x, y > 0; b \neq d$

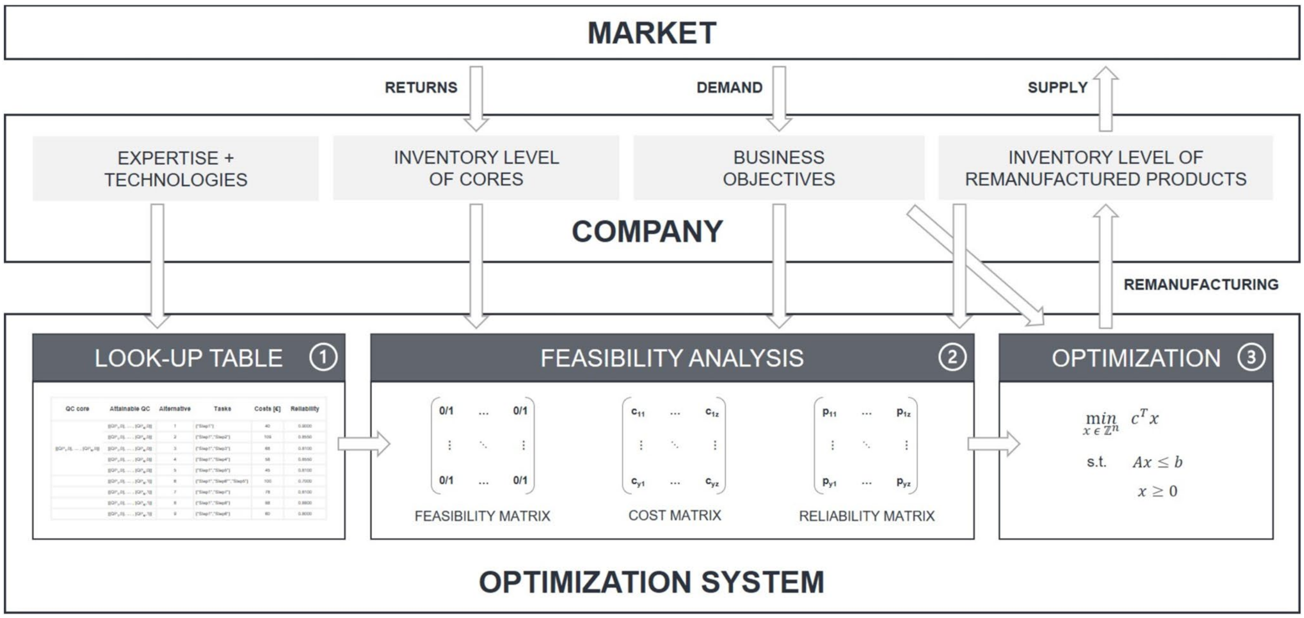


Fig. 7 Generic overview

their order management and RPP efficiency. One of them is the opportunity to conduct feasibility analyses for specific product quality classes by considering the current inventory levels of cores and remanufactured products. The second one is the ability to derive cost minimal process plans for optimal order completion.

Figure 7 provides a generic overview of these three main assets. The illustration highlights how the developed approach achieves to align companies' capabilities with alternating market dynamics.

3.4.1 Customized queries

Since the look-up table rapidly increases in size, it is essential to provide companies with the opportunity to request more targeted information. To achieve this, a practical understanding of how quality classes are formed and utilized is necessary.

In practice, quality classes are formed by first identifying the key quality parameters that define a product's condition and functionality. These parameters may include factors such as physical wear, functional performance, cosmetic appearance, and software version, among others. Each parameter is assigned specific values or ranges based on measurable criteria or inspection results. By combining these parameter values, distinct quality classes are created, representing unique combinations of product attributes (cf. Sect. 3.1).

By classifying products into these quality classes, companies can systematically assess and categorize their inventory. This categorization allows for efficient matching of inventory items to customer demands, optimizing the use of available cores and remanufactured products.

In our developed tool, companies can utilize the quality classes to address their current inventory levels in the following ways:

- **Inventory Assessment:** The company can evaluate the existing cores and remanufactured products by assigning them to the appropriate quality classes based on their inspected parameter values.
- **Demand Matching:** When a customer requests a product of a specific quality class, the system can quickly identify whether an exact match exists in the inventory.
- **Feasibility Analysis:** If an exact match is not available, the system can determine which cores can be remanufactured to achieve the desired quality class. This involves identifying the necessary remanufacturing tasks, associated costs, and probabilities of success.
- **Optimization of Remanufacturing Efforts:** By understanding the quality classes of inventory items, the company can prioritize remanufacturing efforts on cores that can be upgraded to meet demand with minimal cost and high reliability.
- **Inventory Optimization:** The company can make informed decisions about acquiring additional cores or disposing of surplus inventory based on the distribution of quality classes and anticipated demand.

Therefore, the developed tool allows companies to receive information regarding the feasibility of particular quality classes based on their current inventory levels of cores and remanufactured products. For each of the requested quality classes, the system evaluates whether a product of this specific quality class, or alternatively of a better quality class, is available in the company's current inventory. If this is the case, companies obtain the information that the product of the requested quality class can be supplied without performing any remanufacturing tasks.

Moreover, a list is provided, comprising all products in stock that are suitable for obtaining a product of the requested quality class through remanufacturing. The associated costs and transition probabilities are displayed in this list as well. This enables the company to make strategic decisions on which cores to remanufacture to fulfill orders cost-effectively and efficiently, ultimately enhancing inventory management and customer satisfaction.

The required information to create this list is derived from the previously determined look-up table. Based on customized inventory levels and a company's individual capabilities, a feasibility matrix for obtaining the requested quality classes is generated. The rows of this feasibility matrix represent the quality classes $d_1 - d_y$ which are to be attained, i.e. the market demand to be fulfilled. The columns define all cores and remanufactured products $i_1 - i_z$ that are currently available in the company's inventory. A matrix entry of 1 indicates that a core/remanufactured product is suitable for fulfilling the respective demand. In contrast, a matrix entry of 0 indicates that the demanded quality class is not feasible through remanufacturing the corresponding core/remanufactured product.

For all matrix entries of 1 in the feasibility matrix, the corresponding costs and transition probabilities are captured in two separate matrices, the cost and the reliability matrix.

With respect to single order management, this overview can provide sufficient support for decision-making in terms of RPP. However, when multiple orders need to be fulfilled, order management becomes more complex and hence, further solutions based on optimization algorithms are required.

3.4.2 Cost-efficient process planning

Sequential order handling can lead to inefficiencies when certain orders cannot be fulfilled due to the selected order of processing the incoming orders. For an efficient order management, companies need to encompass multiple orders simultaneously. In this work, an integer linear programming (ILP) problem is used to model the resulting optimization problem.

The optimization variables thereby represent all potential output-input-relations between the products currently available in stock and the demanded product quality classes. Their values indicate whether to select or not to select a specific output-input-relation in order to ensure the fulfillment of all incoming orders. The decision related to each output-input-relation is consequently a yes (selection) or no (rejection) decision. Thus, it is to be modeled as a binary variable with 1 indicating the selection of a particular output-input-relation and 0 indicating its rejection. For $d = d_1, \ldots, d_y$ and $i = i_1, \ldots, i_z$ we define:

$$x_{di} = \begin{cases} 1, & \text{if output-input-relation di is selected} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

If the quality classes of an incoming order and a product in stock are identical, then the costs of attaining the demanded product quality class are set to 0 and the transition probability is set to 1. The transition probability of infeasible relations, i.e., entries of 0 in the feasibility matrix, is set to 0. The respective costs are set to a very high value that exceeds the upper bound of permissible cost values, such that these output-input-relations can never be part of a feasible solution. Available cores/remanufactured products of higher quality classes that could potentially be used to fulfill a certain order are neglected in this work as they induce opportunity costs. In terms of further developments of the tool, these opportunity costs could be quantified and additionally included in the analysis.

The objective is to find the process plan/s that minimize/s the associated costs (see 16).

$$\min \sum_{d=d_1}^{d_y} \sum_{i=i_1}^{i_z} C_{di} \cdot x_{di} \tag{16}$$

$$s.t. \sum_{i=i_1}^{i_z} x_{di} = 1,\ d = d_1, \ldots, d_y \tag{17}$$

$$\sum_{d=d_1}^{d_y} x_{di} \leq 1,\ i = i_1, \ldots, i_z \tag{18}$$

$$x_{di} = 0\ or\ 1,\ d = d_1, \ldots, d_y,\ i = i_1, \ldots, i_z \tag{19}$$

$$x_{di} = 0,\ d = d_1, \ldots, d_y,\ i = i_1, \ldots, i_z \text{ if } x_{di} \text{ is infeasible} \tag{20}$$

Here,

- d refers to one specific demand of a customer.
- i refers to one specific core in the storage.

– x_{di} defines if demand d is to be fulfilled by remanufacturing of core i.
– C_{di} represents the cost coefficients corresponding to x_{di} derived by the available process plans.

Every feasible solution thereby has to fulfill four underlying constraints (17, 18, 19,20). The first constraint guarantees that each order is fulfilled exactly once. Each core/remanufactured product in stock can thereby be used at maximum once, which is ensured by the second constraint. The third constraint additionally restricts the solution space by only allowing value assignments of 0 or 1 to the optimization variables. The last constraint prevents infeasible solutions.

The javascript-lp-solver library is used in this work to implement and solve the above depicted ILP. As a result, the solver yields all feasible process plans that minimize the corresponding costs. These insights can help companies to enhance their order management and RPP efficiency.

4 Application in the automation industry

A variable speed drive that covers motor power ratings up to 15 kW serves as the study subject. In this section, we describe the exemplary application of the developed approach and present the corresponding results. The code was implemented with TypeScript and can be found together with all use case data in [40].

4.1 Introduction to the use case

The producing firm is a global specialist in energy management and automation that already conducts remanufacturing in a profitable manner for product variants of higher price segments. However, the prevailing lack of decision support impedes profitable remanufacturing for their lower price product variants. The high degree of manual tasks makes it challenging to withstand the prevailing cost pressure in those competitive market environments. In this use case, the processes primarily involve replacing and testing parts, without encompassing all typical remanufacturing steps such as cleaning that can lead to different quality classes. While the use case focuses on these specific replacement processes, the developed approach is designed to be general and applicable to the full spectrum of remanufacturing activities. By

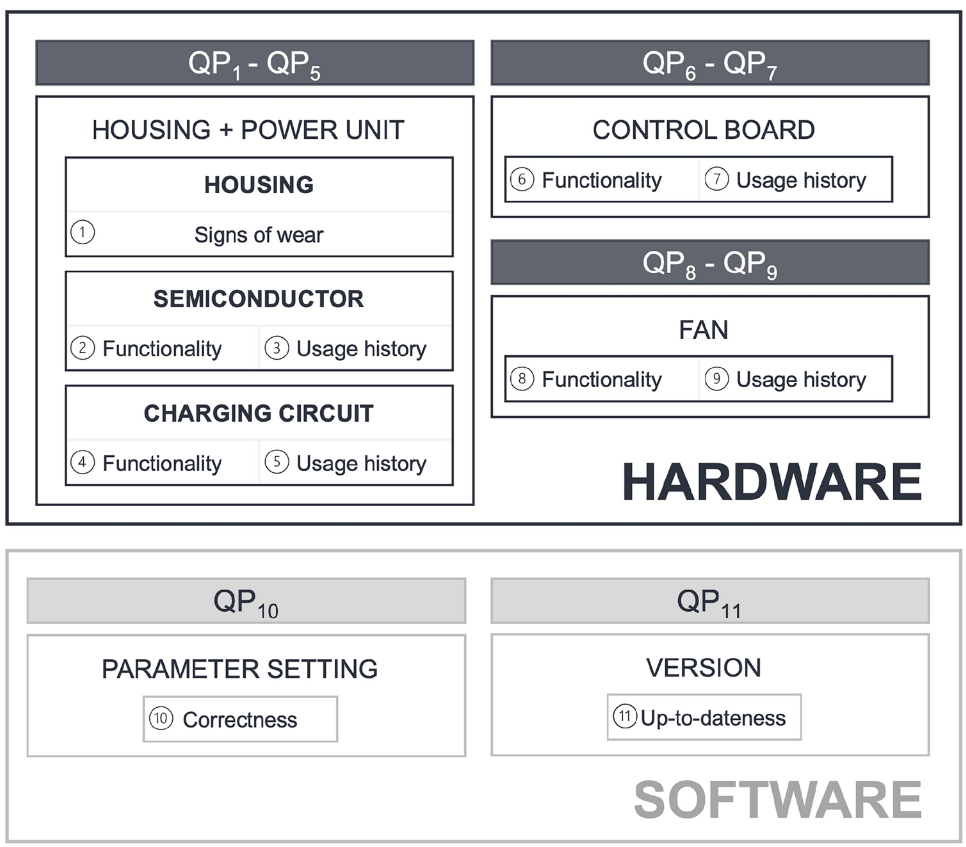


Fig. 8 Hardware- and software-related quality parameters

Table 4 Set of feasible tasks

Task	Definition	Costs [€]	Reliability	Parameter requirements
o_1	Replace housing and power unit with used spare part	40	0.90	None
o_2	Replace control board with new spare part	69	0.95	Yes
o_3	Replace control board with used spare part	28	0.90	Yes
o_4	Replace fan with new spare part	18	0.95	Yes
o_5	Replace fan with used spare part	5	0.90	Yes
o_6	Parameter reset	2	0.99	Yes
o_7	Software update	3	0.99	Yes

handling processes in an abstract way, the algorithm can accommodate additional remanufacturing steps, including disassembly, cleaning, repair, reassembly, and testing, which are common in remanufacturing practices.

First, we elaborated a process diagram that depicts the typical remanufacturing process of a variable speed drive, focusing on the remanufacturing steps practiced by the company. The obtained process diagram facilitated the identification of the corresponding quality parameters and the further specification of the associated remanufacturing tasks. In total, eleven quality parameters $QP_1 - QP_{11}$ were identified, nine of which are hardware-related ($QP_1 - QP_9$) and two are software-related ($QP_{10} - QP_{11}$). On the hardware side, each parameter can be mapped to one of the three main hardware components: the palower unit (housing included), the control board, and the fan. On the software side, quality parameters refer to the parameter setting or the installed software version. Figure 8 provides an overview of the characteristic quality parameters that we elaborated.

To achieve product quality improvements, seven tasks were identified that are available for application (see Table 4). The company acquires used products with the prospect of reusing their components. The control board and the fan can alternatively be replaced with brand new spare parts. The re-usage of used spare components is associated with a higher level of uncertainty compared to the usage of new spare components. This results in a lower process reliability, indicated by a lower success probability of the respective tasks.

Table 5 Extract from the obtained look-up table

Core quality class	Attainable quality class	Process plan	Tasks	Costs [€]	Reliability
[Housing,0], $\cdots$, [Software version,0]	[Housing,0.5], $\cdots$, [Software version,0]	1	o_1	40	0.9000
	[Housing,0.5], $\cdots$, [Software version,0]	2	$o_1 \rightarrow o_2$	109	0.8550
	[Housing,0.5], $\cdots$, [Software version,0]	3	$o_1 \rightarrow o_3$	68	0.8100
	[Housing,0.5], $\cdots$, [Software version,0]	4	$o_1 \rightarrow o_4$	58	0.8550
	[Housing,0.5], $\cdots$, [Software version,0]	5	$o_1 \rightarrow o_5$	45	0.8100
	[Housing,0.5], $\cdots$, [Software version,0]	6	$o_1 \rightarrow o_2 \rightarrow o_5$	114	0.7695
	[Housing,0.5], $\cdots$, [Software version,0]	7	$o_1 \rightarrow o_3 \rightarrow o_5$	73	0.7290
	[Housing,0.5], $\cdots$, [Software version,0]	8	$o_1 \rightarrow o_3 \rightarrow o_4$	86	0.7695
	[Housing,0.5], $\cdots$, [Software version,1]	9	$o_1 \rightarrow o_3 \rightarrow o_5 \rightarrow o_7$	76	0.7217
	[Housing,0.5], $\cdots$, [Software version,1]	10	$o_1 \rightarrow o_2 \rightarrow o_5 \rightarrow o_7$	117	0.7618
	[Housing,0.5], $\cdots$, [Software version,1]	11	$o_1 \rightarrow o_3 \rightarrow o_4 \rightarrow o_7$	89	0.7618
	[Housing,0.5], $\cdots$, [Software version,1]	12	$o_1 \rightarrow o_2 \rightarrow o_4 \rightarrow o_7$	130	0.8041
	[Housing,0.5], $\cdots$, [Software version,0]	13	$o_1 \rightarrow o_2 \rightarrow o_4$	127	0.8122
	[Housing,0.5], $\cdots$, [Software version,1]	14	$o_1 \rightarrow o_3 \rightarrow o_7$	71	0.8019
	[Housing,0.5], $\cdots$, [Software version,1]	15	$o_1 \rightarrow o_2 \rightarrow o_7$	112	0.8464
..	..	..	..	..	..
[Housing,0], $\cdots$, [Software version,1]	[Housing,0.5], $\cdots$, [Software version,1]	1900	o_2	69	0.9500
	[Housing,0.5], $\cdots$, [Software version,1]	1901	o_4	18	0.9500
	[Housing,0.5], $\cdots$, [Software version,1]	1902	$o_2 \rightarrow o_4$	87	0.9025

To derive the realistic quality classes of cores, all potential quality parameter values were considered, except for the parameter value 'no' for the 'usage history' parameters of QP_3, QP_5, QP_7, QP_9. The definition of a core justifies this conclusion. Consequently, 192 realistic quality classes of cores were obtained.

4.2 Results

The results were obtained by following the approach described in the previous sections. In the following, the details of the application are explained in two subsections. Section 4.2.1 outlines the evaluated set of Pareto optimal process plans. In Sect. 4.2.2, we consider an exemplary batch of incoming orders to exemplify the results of assessing the feasibility of order fulfillment and determining the corresponding cost-minimal process plan.

4.2.1 Process planning

For each possible quality class of cores, we followed the above-described procedure to determine the list of all Pareto optimal process plans. Based on the 192 potential conditions of cores, a total amount of 1902 Pareto optimal alternatives were evaluated (see look-up Table 5). For details regarding the individual tasks, refer to Table 4. Note that the parameter values of quality classes (compare first two columns in Table 5) were abbreviated for illustration purposes.

For example, a core with the worst possible parameter value combination can be processed through 15 distinct process alternatives (compare first 15 entries of the look-up table in Table 5). Thereof, alternative 2 is one instance of a feasible option that comprises two tasks, i.e., the replacement of the power unit with a used spare part as well as the replacement of the control board with a new spare part. Its execution is consequently associated with expenses of 109 euros (= 40 + 69) and a success probability of 85.5 percent (= 0.9×0.95).

The results clearly show that the look-up table rapidly increases in size as the number of potential core quality classes rises. Even by restricting the solution space through defining parameter value requirements for the application of particular tasks, the size of the solution space remains large.

4.2.2 Feasibility analysis and implications for order management

We generated an exemplary system query to assess the feasibility of fulfilling a set of incoming orders based on the company's capabilities as well as their current inventory level of cores and remanufactured products. Therefore, we consider a scenario where the company receives three orders of specific quality classes. To fulfill these orders, it can utilize four different products which are currently available in stock (see Fig. 9 for further specifications regarding the respective quality parameter values).

Based on the previously determined look-up table, we derive the corresponding feasibility matrix. Remember that the matrix rows represent the quality classes $d_1 - d_3$ which

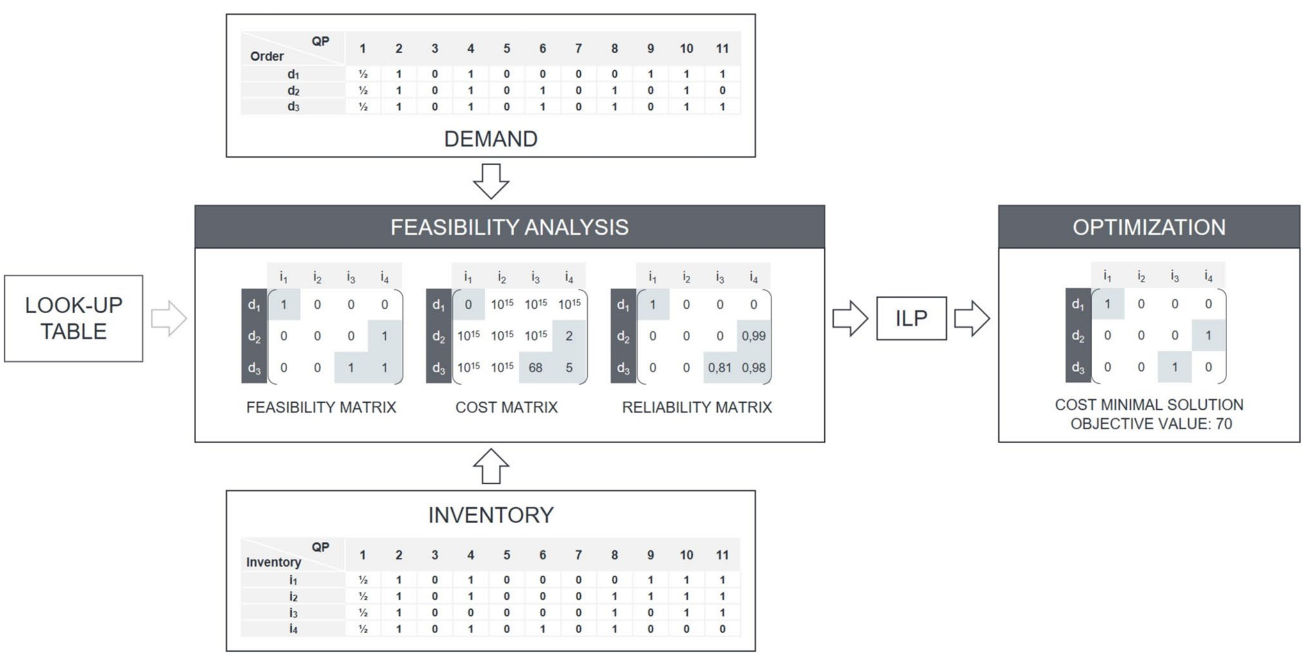


Fig. 9 Feasibility analysis and remanufacturing process planning

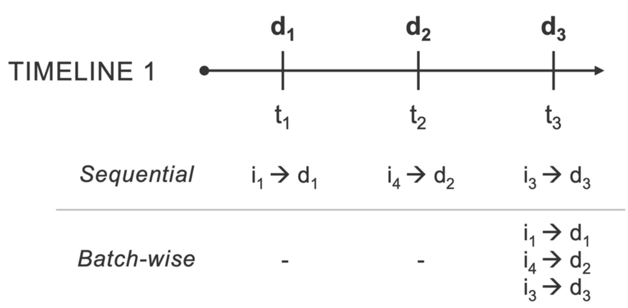


Fig. 10 Comparison of optimal sequential and batch-wise order processing with respect to timeline 1

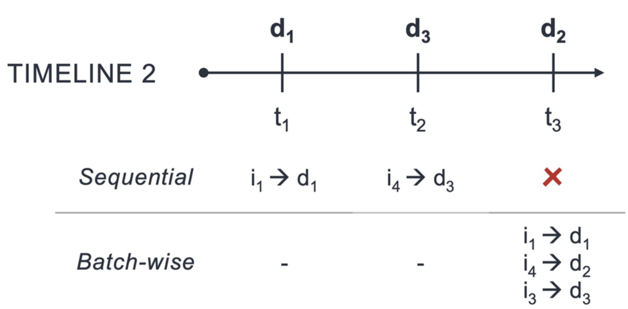


Fig. 11 Comparison of optimal sequential and batch-wise order processing with respect to timeline 2

are to be attained, and the columns define the products $i_1 - i_4$ that are currently available in the company's inventory of cores and remanufactured products. The obtained feasibility matrix indicates that from an isolated point of view, each of the incoming orders can *individually* be fulfilled as each row contains at least one entry of value 1. The demanded quality class d_3, for example, can either be attained by product i_3 or i_4 of the inventory. However, the individual feasibility of each incoming order does not automatically imply that the whole set of incoming orders can be completed *simultaneously*. For instance, if $d_1 - d_3$ were all only attainable through remanufacturing i_1, then solely one of these orders could be fulfilled, whereas the other two would remain unsatisfied.

Whenever a demanded quality class and an available quality class coincide in every quality parameter value, the corresponding costs for attaining this demand are set to 0 and the respective success probability is set to 1. This particular case applies for d_1 and i_1. Insights regarding the availability of cores/remanufactured products with a higher quality are provided in the form of a separate Excel sheet. With respect to d_1, we get the information that a product of a higher quality class, namely i_2, is available in stock. However, as we have no information about the associated opportunity costs, those products of higher quality classes in the inventory are not considered in terms of feasibility analyses. Refining the approach in this respect could be a future research direction.

By solving the ILP, we obtain the following cost-optimal solution with an objective value of 70 euros (see Fig. 9):

- d_1 is fulfilled by i_1 at costs of 0 euros (no remanufacturing required)
- d_2 is fulfilled through remanufacturing i_3 at costs of 2 euros
- d_3 is fulfilled through remanufacturing i_2 at costs of 68 euros

In the following, the advantage of batch-wise order management compared to sequential order handling will be highlighted by means of an example. Therefore, we consider two timelines which differ in their chronologies of incoming orders (compare Figs. 10 and 11). With respect to the timeline depicted in Fig. 10, order fulfillment can be achieved through sequential as well as through batch-wise order processing.

Based on the timeline illustrated in Fig. 11, order d_3 is received before d_2. Hence, in the case of sequential order processing, d_3 is obtained by means of remanufacturing i_4 since this implies the lowest expenses. As a consequence, the subsequent order d_2 cannot be fulfilled. In contrast, through batch-wise processing of $d_1 - d_3$, the order fulfillment rate can be improved since all incoming orders can be completed (see Fig. 11). To ensure economic viability, the time frame for batch-wise order processing must be adequately chosen.

The example clearly shows that in terms of sequential order management, the processing order determines whether a set of incoming orders can be completed or not.

5 Discussion

The use case shows that the developed approach effectively generates and identifies cost-minimal process plans for optimal order completion, considering the company's capabilities and inventory. By accounting for both quality and process uncertainties, it captures the unique characteristics of remanufacturing, helping companies understand their economic potential and identify opportunities for optimization and automation.

Although the use case focuses on replacement tasks such as replacing and testing parts, the approach is designed to be general and applicable to the full spectrum of remanufacturing processes. By modeling processes and quality parameters in an abstract way, it can accommodate typical remanufacturing steps like cleaning, repairing, and refinishing, which may lead to different quality classes. This flexibility allows companies to adapt the approach to various products and remanufacturing scenarios.

As highlighted in the literature review, many existing approaches either focus on predefined quality standards or lack comprehensive integration of quality data modeling, remanufacturing uncertainties, and optimization criteria. Our approach addresses these gaps by exploring all feasible product quality classes and integrating these key aspects into a unified framework. Unlike traditional methods that focus on predefined quality standards, this approach explores all feasible product quality classes, allowing companies to cater to a broader range of customer preferences. This can help assess the profitability of extending product portfolios and identify high-margin products, particularly in competitive lower-price segments.

However, several limitations should be considered when applying this approach. First, the effectiveness of the model depends on the availability and accuracy of quality data and cost estimates. Incomplete or inaccurate data can impact the validity of the generated process plans. Second, the model involves certain assumptions and simplifications, such as task independence, which may not fully capture the complexities of real-world remanufacturing operations. Third, while the approach was validated in the automation industry, its applicability to other industries may require adjustments to account for different remanufacturing characteristics and constraints.

Additionally, implementing the approach in practice may present challenges, including integration with existing systems, the need for staff training, and potential resistance to change. The approach also focuses primarily on economic optimization and may not fully consider environmental impacts or sustainability metrics, which are increasingly important in modern manufacturing. While the feasibility matrix offers a comprehensive list of potential solutions, the approach may be limited in handling highly complex planning problems. More advanced methods like reinforcement learning might be necessary for such cases. As noted in the literature, reinforcement learning approaches have shown promise in optimizing complex remanufacturing tasks [29, 31–33], but they often lack transparency and may not be suitable for companies with high manual labor. Our approach, while perhaps limited in handling highly complex planning problems due to computational time, offers a transparent and comprehensive method that can be understood and implemented by companies relying on manual processes.

However, we believe that providing a comprehensive overview of alternatives remains essential, especially during the current transitional phase of remanufacturing. Since remanufacturing processes are still predominantly manual, human decision-makers benefit from having access to all possible alternatives. This comprehensive overview supports transparency, allows for human expertise to be applied effectively, and aids in training and gradually introducing automation into the workflow. As remanufacturing scales up and more tasks are automated, methods like reinforcement learning may become more applicable. Nevertheless, our approach serves as a valuable tool to bridge the gap between manual labor and fully automated systems, supporting semi-automated processes and aiding in a smoother transition toward future advancements.

Overall, the approach provides valuable tools for optimizing remanufacturing processes, balancing comprehensiveness with the ability to identify optimal solutions. The economic benefits, including cost savings and enhanced efficiency, demonstrate its potential to improve profitability and competitiveness in the remanufacturing sector. However, a limitation is the computational time needed for the calculation.

6 Conclusion

The shift towards circular production is pushing companies to adapt their manufacturing approaches, particularly in managing the variability of product quality from returns. This study addressed quality modeling, process plan generation, and cost optimization based on customer demand and core inventory.

The main outcomes of this research include a comprehensive overview of Pareto optimal process plans across various quality levels and an algorithm that identifies cost-efficient plans tailored to a company's specific capabilities and inventory. These tools enable businesses to align their remanufacturing processes with market demands, enhancing profitability and supporting sustainable production.

Our approach was validated through a real-world application in the automation industry, demonstrating its practical relevance and potential. Moreover, the developed method is generalizable and can be applied to a wide range of remanufacturing processes beyond the case study, accommodating additional steps such as cleaning, repairing, and refinishing.

Looking forward, this algorithm lays the groundwork for further advancements in automated remanufacturing, including autonomous quality inspection and adaptive process control. By providing effective decision support, our approach facilitates a smoother transition from manual processes to higher levels of automation, ensuring that human expertise remains integral during this transformation.

Appendix

List of abbreviations

See Table 6.

Table 6 List of Abbreviations

Abbreviation	Full form	Description
c_{acc}	Accumulated Cost	The total cost accumulated while applying a sequence of tasks in a process plan
C_{di}	Cost Matrix	Cost matrix corresponding to x_{di}
$c(o)$	Cost of Task o	The monetary cost associated with executing a specific refurbishing task
$d_1 - d_y$	Specific Demands/Orders	Orders received by the company, each requiring fulfillment through remanufacturing to meet specific quality classes
ILP	Integer Linear Programming	A mathematical optimization technique used to find the best outcome in a model whose requirements are represented by linear relationships and integer variables
$i_1 - i_z$	Inventory Products	Products currently available in the company's inventory that can be used to fulfill incoming orders through remanufacturing
l	Number of Components	l represents the number of components and also describes the last component in a row
new	Parameter of a Process Plan Component	*new* indicates whether the associated quality class has already been reached within the tree structure
$o_1 - o_7$	Specific Refurbishing Tasks	Identified tasks involved in the remanufacturing process, such as replacing components or performing software updates
O_A	Set of Remanufacturing Tasks	All feasible refurbishing tasks available for application based on the company's resources and capabilities
p_k	Probability of Outcome k	The likelihood that a particular outcome will result from executing a specific task
p_{acc}	Accumulated Probability	The total probability of success accumulated while applying a sequence of tasks in a process plan
PP	Process Plan	A sequence of tasks or operations applied to remanufacture a product from its current quality class to an improved one
PP_h, PP_i, PP_j, PP_m, PP_n, PP_{new}	Specific Process Plan	A specific sequence of tasks used to remanufacture a product, identified uniquely in the look-up table. PP_{new} references a newly created sequence
QP	Quality Parameter	Specific parameters that define the quality attributes of a product, both hardware and software-related
QP_{mod}	Modified Quality Parameter	The quality parameter modified by the transformation in the remanufacturing task
QC	Quality Class(es)	Classification of a product based on its quality parameters, indicating its condition or performance level
QC_{attain}	Attainable Quality Classes	Attainable quality classes after performing one task
QC_{end}	Attainable Quality Class at the End	The quality class achieved after applying a sequence of remanufacturing tasks to a product
QC_{start}	Initial Quality Class	The starting quality class of a product before any remanufacturing tasks are applied
$QC_{start+c}$	Quality Class after c Tasks	The quality class of a product after applying c remanufacturing tasks starting from QC_{start}
RL	Reinforcement Learning	A method of the field of machine learning
RPP	Remanufacturing Process Planning	The process of planning and organizing remanufacturing operations to restore used products to like-new conditions
S_{Pareto}	Set of Pareto Optimal Process Plans	A collection of process plans that are non-dominated, meaning no other plans are better in all considered criteria simultaneously
T_{type}	Transformation Type	The type of transformation applied to the quality parameters, e.g., additive, multiplicative, or replace
x_{di}	Decision Variable x for demand d and inventory i	A binary variable indicating whether inventory product i is used to fulfill demand d (1 if used, 0 otherwise)

Algorithm

Algorithm 1 Remanufacturing process planning model

```
procedure LocalOptimization(QC_start)
    Initialize S_Pareto as empty set
    Initialize PP_list as empty list
    Initialize QC_current = QC_start
    for each task o in O_A applicable to QC_current do
        Initialize Process Plan PP with QC_current
        Initialize c_acc and p_acc to 0
        for each transformation t in task o do
            QC_end = DefineTransformation(QC_current, p, c, QP_mod, T_type)
            Update c_acc and p_acc
            Add transformation to PP
            if QC_end not previously attained then
                Add PP to PP_list
            end if
        end for
    end for
    for each Process Plan PP in PP_list do
        if PP meets quality improvement criteria then
            Add PP to S_Pareto
        end if
    end for
    return S_Pareto
end procedure
procedure LocalOptimization(QC_start)
    for each QC_current in all possible quality states do
        S_Pareto = EvaluateProcessPlan(QC_current)
        for each PP in S_Pareto do
            if PP results in quality improvement then
                Add PP to local Pareto set
            end if
        end for
    end for
end procedure
procedure GlobalOptimization(QC_start)
    Initialize tree structure for all quality classes
    for each core quality class QC_k do
        S_Pareto = EvaluateProcessPlan(QC_k)
        for each QC_attainable in S_Pareto do
            if QC_attainable is Pareto optimal then
                Add to global Pareto set
            else
                Compare conditions under which QC_attainable is reached
                if strictly better conditions then
                    Replace current process plan with new one
                else if strictly worse conditions then
                    Discard new process plan
                else
                    Add both process plans to Pareto set
                end if
            end if
        end for
    end for
end procedure
procedure RemanProcessPlanning(O_A, QC_start)
    Perform LocalOptimization(QC_start)
    Perform GlobalOptimization(QC_start)
    return Global Pareto set
end procedure
```

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Data availability The dataset and code that supports the findings of this study is openly available in the GitHub repository at https://doi.org/10.5281/ZENODO.11513761.

Declarations

Conflict of interest The authors declare that they have no conflict of interest

References

1. Tolio T, Bernard A, Colledani M, Kara S, Seliger G, Duflou J, Battaia O, Takata S (2017) Design, management and control of demanufacturing and remanufacturing systems. CIRP Ann 66(2):585–609
2. Golinska P, Kawa A (2011) Remanufacturing in automotive industry: challenges and limitations. J Ind Eng Manag 4(3)
3. Nikolakis N, Catti P, Chaloulos A, van de Kamp W, Coy MP, Alexopoulos K (2024) A methodology to assess circular economy strategies for sustainable manufacturing using process eco-efficiency. J Clean Prod 445:141289
4. Sitcharangsie S, Ijomah W, Wong TC (2019) Decision makings in key remanufacturing activities to optimise remanufacturing outcomes: a review. J Clean Prod 232:1465–1481
5. MacArthur E (2013) Towards the circular economy: economic and business rationale for an accelerated transition
6. Kurilova-Palisaitiene J, Sundin E, Poksinska B (2018) Remanufacturing challenges and possible lean improvements. J Clean Prod 172:3225–3236
7. Östlin J, Sundin E, Björkman M (2008) Business drivers for remanufacturing. In: Proceedings of CIRP Life Cycle Engineering Seminar , 15th edition, Sidney, Australia, 581–586
8. Ijomah WL, McMahon CA, Hammond GP, Newman ST (2007) Development of design for remanufacturing guidelines to support sustainable manufacturing. Robot Comput-Integr Manuf 23(6):712–719
9. Stavropoulos P, Papacharalampopoulos A, Athanasopoulou L, Kampouris K, Lagios P (2022) Designing a digitalized cell for remanufacturing of automotive frames. Procedia CIRP 109:513–519
10. Fernández I, Puente J, García N, Gómez A (2008) A decision-making support system on a products recovery management framework. a fuzzy approach. Concurr Eng 16(2):129–138
11. Wadhwa S, Madaan J, Chan FTS (2009) Flexible decision modeling of reverse logistics system: a value adding mcdm approach for alternative selection. Robot Comput-Integr Manuf 25(2):460–469
12. Jin X, Hu SJ, Ni J, Xiao G (2013) Assembly strategies for remanufacturing systems with variable quality returns. IEEE Trans Autom Sci Eng 10(1):76–85
13. Takahashi K, Doi Y, Hirotani D, Morikawa K (2014) An adaptive pull strategy for remanufacturing systems. J Intell Manuf 25(4):629–645
14. Dehghanbaghi M, Hosseininasab H, Sadeghieh A (2016) A hybrid approach to support recovery strategies (a case study). J Clean Prod 113:717–729
15. Yang SS, Nasr N, Ong SK, Nee AYC (2016) A holistic decision support tool for remanufacturing: end-of-life (eol) strategy planning. Adv Manuf 4(3):189–201
16. Cui L, Kuo-Jui W, Tseng M-L (2017) Selecting a remanufacturing quality strategy based on consumer preferences. J Clean Prod 161:1308–1316
17. Wang H, Jiang Z, Zhang X, Wang Y, Wang Y (2017) A fault feature characterization based method for remanufacturing process planning optimization. J Clean Prod 161:708–719
18. Aydin R, Kwong CK, Geda MW, Okudan Kremer GE (2018) Determining the optimal quantity and quality levels of used product returns for remanufacturing under multi-period and uncertain quality of returns. Int J Adv Manuf Technol 94(9–12):4401–4414
19. Ji W, AbouRizk SM (2018) Data-driven simulation model for quality-induced rework cost estimation and control using absorbing markov chains. J Constr Eng Manag 144(8):04018078
20. Ji W, AbouRizk SM (2018) Simulation-based analytics for quality control decision support: pipe welding case study. J Comput Civil Eng 32(3):05018002
21. Stavropoulos P, Spetsieris A, Papacharalampopoulos A (2019) A circular economy based decision support system for the assembly/disassembly of multi-material components. Procedia CIRP 85:49–54
22. Jiang Z, Jiang Y, Wang Y, Zhang H, Cao H, Tian G (2019) A hybrid approach of rough set and case-based reasoning to remanufacturing process planning. J Intell Manuf 30(1):19–32
23. Meng K, Qian X, Lou P, Zhang J (2020) Smart recovery decision-making of used industrial equipment for sustainable manufacturing: belt lifter case study. J Intell Manuf 31(1):183–197
24. Li S, Zhang H, Yan W, Jiang Z (2021) A hybrid method of blockchain and case-based reasoning for remanufacturing process planning. J Intell Manuf 32(5):1389–1399
25. Yanıkoğlu İ, Denizel M (2021) The value of quality grading in remanufacturing under quality level uncertainty. Int J Prod Res 59(3):839–859
26. Chen Y, Jiang Z, Zhang H, Yan W (2021) Integrated design of process-tolerance for remanufacturing based on failure feature. Appl Sci 11(14):6377
27. Stavropoulos P, Papacharalampopoulos A, Michail C, Vassilopoulos V, Alexopoulos K, Perlo P (2021) A two-stage decision support system for manufacturing processes integration in microfactories for electric vehicles. Procedia Manuf 54:106–111
28. Liu C, Chen J, Cai W (2022) Data-driven remanufacturability evaluation method of waste parts. IEEE Trans Ind Inf 18(7):4587–4595
29. Allagui A, Belhadj I, Plateaux R, Hammadi M, Penas O, Aifaoui N (2023) Reinforcement learning for disassembly sequence planning optimization. Comput Ind 151:103992

30. Liu C, Chen J, Wang X (2023) Quantitative evaluation model of the quality of remanufactured product. IEEE Trans Eng Manag, 1–12
31. Paraschos PD, Koulinas GK, Koulouriotis DE (2023) A reinforcement learning/ad-hoc planning and scheduling mechanism for flexible and sustainable manufacturing systems. Flex Serv Manuf J
32. Paraschos PD, Georgios KK, Dimitrios EK (2024) Reinforcement learning-based optimization for sustainable and lean production within the context of industry 4.0. Algorithms 17(3):98
33. Wang J, Zheng H, Zhao S, Zhang Q (2024) Energy-aware remanufacturing process planning and scheduling problem using reinforcement learning-based particle swarm optimization algorithm. J Clean Prod 476:143771
34. Garvin DA (1984) Product quality: an important strategic weapon. Bus Horiz 27(3):40–43
35. Denizel M, Ferguson M, Souza G (2010) Multiperiod remanufacturing planning with uncertain quality of inputs. IEEE Trans Eng Manag 57(3):394–404
36. Teunter RH, Simme DPF (2011) Optimal core acquisition and remanufacturing policies under uncertain core quality fractions. Eur J Oper Res 210(2):241–248
37. Weckenmann A, Hartmann W (2013) Function-oriented method for the definition and verification of microstructured surfaces. Precis Eng 37(3):684–693
38. Raphael Simon Wagner (2020) Strategien zur funktionsorientierten Qualitätsregelung in der Serienproduktion. Shaker Verlag GmbH, Karlsruhe
39. Julius P, Jan-Felix K, Marco W, Simon R, Patric G, Gisela L, Albert A, Sven M, Jürgen B (2022) An ontology for remanufacturing systems. at - Automatisierungstechnik 70(6):534–541
40. Stamer F, Sauer J (2024) Intelligent remanufacturing based on optimization of quality classes under uncertainty https://doi.org/10.5281/ZENODO.11513761