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Condition-aware capacity planning for agile hybrid disassembly systems in remanufacturing

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ABSTRACT

Remanufacturing of used products is essential in the circular economy but faces challenges like high variant diversity and varying product states, requiring flexible production resources. Agile hybrid disassembly systems, combining manual and automated resources, offer a solution. These systems need a planning methodology to reconfigure capacity and structure effectively. This work proposes a foresighted condition-aware capacity planning method, using a mixed-integer linear optimization problem to adjust system capacity while minimizing costs. A capability-based framework models the hybrid system, considering product condition deviations. The system, tested on data grounded in a real industrial scenario, shows the benefits of frequent reconfiguration based on condition-aware planning.

1. Introduction

The origins of the linear economy, anchored in the consumption principle of *take-make-use-dispose*, can be traced back to the Industrial Revolution. It culminated in our present day economy with an exclusive focus on economic aspects [1]. However, due to various social, economic, and environmental factors, this model has proven unsustainable [2]. The United Nations' 2030 Agenda for Sustainable Development seeks to protect the planet from degradation, in part by promoting sustainable consumption and production, sustainable management of natural resources, and urgent climate action to fulfill the needs of present and future generations [3]. Addressing this requires decoupling of natural resource consumption from economic growth [4]. Circular economy principles, such as reuse, repair, and remanufacturing, aim to reintroduce products into the value chain post-use rather than disposing them of [5]. Notably, remanufacturing retains a significant portion of a product's value, with, for instance, remanufactured engines saving 50% of costs, 60% of energy, and 70% of material compared to new production [6]. Yet, efficiently implementing remanufacturing remains challenging for many firms. Demand for specific models is often low and unpredictable, compounded by varying product conditions, such as corrosion and deformation [7]. As such, the process remains labor-intensive [8].

The remanufacturing process chain consists of multiple characteristic steps: collection and sorting of EOL-products (End-of-Life products, also called cores in the remanufacturing industry), disassembly, cleaning, inspection, parts remediation and exchange, reassembly and final testing [9,10]. Disassembly is a key success factor within this process chain, yet very challenging for remanufacturing firms today [11]. Often times, disassembly costs exceed the value of recovered products limiting the economic feasibility of remanufacturing for many product types [12].

As conventional, rigidly automated systems cannot handle the variety of known and unknown EOL-product variants and conditions, today, manual operation is most common in disassembly systems [13–17].

However, new approaches leveraging machine learning and reconfigurable and scalable architectures allowing for flexible automation may empower factories to thrive in this volatile environment [15,18,19]. Furthermore, hybrid approaches, combining the dexterity of human operators and the persistence of automated systems show great potential towards cost reduction while preserving the ability to handle EOL-products with varying requirements [20].

As proposed and investigated in various research projects at the Karlsruhe Institute of Technology, **agile hybrid disassembly systems** are one such attempt [22,23]. Fig. 1 schematically depicts an agile disassembly system. It shows the system structure and a summary of the common challenges for disassembly systems in automotive remanufacturing such as **volatile quantities**, a **high product variance**,

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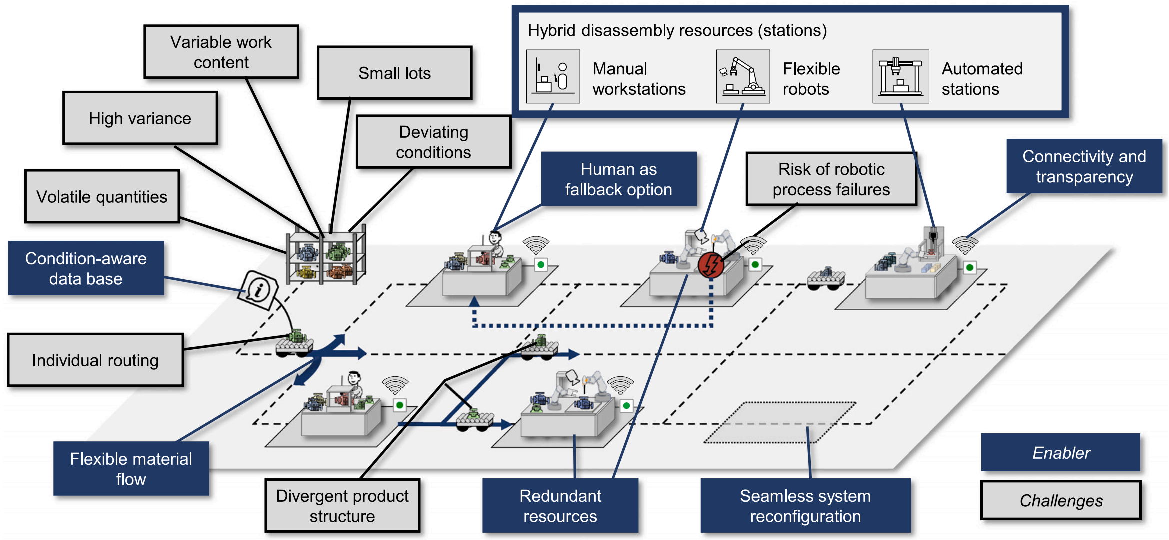

Fig. 1. Description of agile disassembly systems: challenges and enablers [21].

small lot sizes, **variable work content** due to **deviating product conditions** and a **divergent material flow**. Besides that, the key characteristics of agile hybrid disassembly systems are depicted, which are as follows [22,24,25]:

- **Matrix structure** [26]: Loosely linked disassembly stations allow a **flexible** takt-less **material flow**. Errors on individual stations do not disrupt the system operations. Bottlenecks can be prevented by deploying multiple **redundant stations**. EOL products can be **treated individually** based on their specific requirements. The qualitative and quantitative **capacity** of the systems can be **adjusted seamlessly** by adding, substituting or removing stations [27].
- **Hybrid automation**: Automatic resources are operated side-by-side with manual workstations. **Flexible disassembly robots** combine cognitive capabilities and decision-making competence, allowing them to derive suitable strategies in unpredicted situations. Flexible hardware, such as a flexible clamping device and a set of different tools allows for broad applicability. **Operations** are probabilistic and **can fail** due to a lack of skill. After re-routing to a manual workstation, a **human operator** steps in **as a fallback option**. Besides that **automated reconfigurable disassembly devices** are applied for reoccurring routine tasks. Manual and automated resources form a hybrid system.
- **Connectivity and transparency**: Resources in the system are connected, communicate with each other and, as such, form a cyber–physical production system. Besides information about each core as an instance, core quantity, information about **EOL-product conditions** becomes available and can be leveraged for planning and control purposes.

The fact that flexible robots can fail due to lack of skill has a major impact on the dynamics of the system. However, in this consideration, such operational failures must be distinguished from conventional assumptions of failure events. The latter are usually associated with unreliable machinery and categorized as operation-dependent, time-dependent or quality-dependent failures [28,29]. Furthermore, they are typically followed by downtimes and repair events or lead to parts scrapping. An operational failure, as considered in this paper and as introduced in [25], is attributed to the lack of capability of a robot to complete a disassembly task effectively and with success. This capability may depend on the state of the product, which is highly volatile for used products. An appropriate term for a conceptual distinction from conventional failure events would therefore be the term **capability-dependent failure**. A capability-dependent failure is not considered an exceptional event. A failed flexible robot does not require a repair event and can immediately resume its work with subsequent products queuing for disassembly. In this way, capability-dependent failures are critical to consider in probabilistic production environments that are prone to high levels of uncertainty but require properly structured processes such as hybrid disassembly systems.

Agile disassembly systems combine and leverage the dexterity of humans with the endurance of automated systems to remain flexible enough to deal with a wide variety of used products while increasing the systems' productivity. One key aspect of the approach is gradually transferring former manual tasks, suitable for automation, to automated resources like robots, by giving them cognitive abilities and problem-solving skills. The reconfigurable system architecture thereby allows for the adaption of the quantitative and functional capacity of the system.

Consequently, agile hybrid disassembly systems show great potential to increase competitiveness in remanufacturing. However, besides the hurdles on the process and technological level, incorporating automated resources like flexible robots into hybrid disassembly systems poses new and reinforces existing organizational challenges in remanufacturing. Production planning methods need to be reconsidered to cater for the newly-gained degrees of freedom and high dynamics of the system. High attention will have to be paid to new methods of capacity planning in order to make effective use of the new flexibility in capacity.

Severely affected by uncertain product conditions and quantities, production capacities in today's remanufacturing facilities are usually the result of imprecise planning activities leading to utilization losses or back order costs due to unsatisfied demand [30]. Adding additional resources with partially redundant capabilities further escalate this challenge. Hence suitable methods for disassembly capacity planning are required, accounting for the intricacies of an agile and hybrid system and the highly uncertain, volatile remanufacturing environment. Enabled by an increased transparency in the planning stage, extended capacity planning methods are tangible that leverage the available information on EOL-product conditions to better evaluate on disassembly efforts and subsequently optimize resource deployment. This work investigates such condition-aware methods, that perfectly align with the organization of agile hybrid disassembly systems but could also be applied to existing, less flexible systems within the remanufacturing industry.

2. Related work

This section reviews the existing literature on capacity planning in reconfigurable systems. As the number of approaches on reconfigurable systems, especially for the remanufacturing domain, is limited, the search was extended to related linear approaches. However, the linear domain exhibits less uncertainty compared to circular factories, which must be considered in both system design and capacity planning [31].

Evaluation criteria, relevant to this work, as outlined in Section 1, are defined and used to assess each piece of literature. The nine evaluation criteria are as follows: reconfigurability (1), (semi)automation (2), flexible resource allocation (3), disassembly or remanufacturing (4), product condition awareness (5), operational failures (6), configuration sequences (7), station level granularity (8), and capacity planning (9).

2.1. Capacity planning for reconfigurable manufacturing systems

Capacity planning for reconfigurable manufacturing systems (RMS) has attracted considerable academic attention in linear production. The initial motivation for adopting reconfigurable manufacturing systems (RMS) largely stems from the megatrend of mass customization, since RMS facilitates efficient production while maintaining a high responsiveness to customer preferences and market shifts [32]. The existing literature encompasses a broad spectrum, ranging from high-level strategic capacity planning to detailed operational configurations on station level, reflecting the multifaceted challenges and objectives associated with optimizing adaptive production environments.

Asl and Ulsoy [33] adopt a holistic perspective, avoiding detailed modeling of the production system. Their work addresses the time delay between decision-making and capacity adjustments by determining thresholds that trigger capacity expansion or reduction. Similarly, Marquez et al. [34] focus on high-level capacity planning using aggregated data, such as tool demand and availability, without delving into the specifics of individual stations. In contrast, Hees et al. [35] consider individual machines, integrating capacity planning with operational sequencing. However, their optimization framework is based on a low granularity level, modeling machines solely on their throughput capabilities.

More granular studies have explored production system modeling and available capacity in greater detail. Gyulai et al. [36] allocate products to reconfigurable or dedicated production lines, offering a deeper examination of the production system. However, their approach assumes that resources cannot be shared, with each product confined to its own line. Youssef and ElMaraghy [37] optimize the configuration of flow lines, enabling parallelization of identical tasks to extend system capacity. Nevertheless, their method does not accommodate flexible material flows. At the station level, capacity planning is addressed by Manzini et al. [38] and Colledani and Angius [39], who optimize the number of stations and the allocation of tasks or products. Their approaches comprise a high level of granularity. All approaches are rooted in linear manufacturing contexts and fail to address the specific challenges of the remanufacturing domain, such as uncertain core conditions and operational failures.

2.2. Capacity planning for disassembly and remanufacturing

While reconfigurable systems could enhance the remanufacturing industry [30], there are only a few approaches proposing efficient capacity planning in remanufacturing and disassembly. In general, the majority of the existing approaches examines capacity planning focusing on static remanufacturing systems with a low granularity level. Guide and Spencer [49] adapt conventional methods from Rough Cut Capacity planning for remanufacturing. In [31], they compare traditional capacity planning methods with adapted approaches in remanufacturing. Lee et al. [47] adopt a high-level abstraction, focusing on aggregated capacities and production quantities and neglecting reconfigurable systems. They propose a MILP approach to decide whether to increase, decrease, or temporarily augment capacity through subcontracting. Franke et al. [20], on the other hand, propose a combinatorial approach where an optimal configuration is first derived and then evaluated via simulation. However, their model adopts low granularity and aggregates remanufacturing and recycling capabilities to ultimately optimize the R-strategy applied to a product. Both studies take the condition of cores into account. Yanıkoğlu and Denizel [50] emphasize that core condition significantly affects system performance and must be considered during capacity planning. However, their work also aggregates capacity at the system level.

Aljuneidi and Bulgak [40] integrate the operational planning of a cellular hybrid manufacturing-remanufacturing system with tactical closed-loop supply chain planning, incorporating core quality to determine the optimal number of cores required. Yet, they do not leverage core quality in optimizing capacity. In a follow-up study, Aljuneidi and Bulgak [41] extend their approach by a broader MILP framework, incorporating disposal and recycling. While this extension includes core quality for determining the optimal core count, it assumes static product routings and does not account for flexible material flows.

Andersen et al. [30] use a simulation-based approach to determine whether reconfigurable modules should be added or removed, modeling core conditions to some extent. Nevertheless, they assume that all modules are capable of processing, leading to an aggregated capacity calculated based on average cycle times, which is unsuitable for planning matrix production systems. Colledani and Battaïa [43] fully incorporate core quality into capacity planning by creating individual quality clusters for each product and proposing line balancing for each instance. However, their approach is limited by static routing and does not address reconfigurable systems.

In general, there is a lack of approaches that examine reconfigurable systems for product disassembly with a sufficient degree of granularity. The only approach known to the authors is presented by Eguia et al. [44], which coin the term reconfigurable disassembly systems (RDS) as the counterpart to RMS in the circular economy. They define RDS as automated systems that can quickly adapt to fluctuations in unit numbers and changes in the variant mix through agility and a scalable, modular structure. However, they do not focus on capacity planning but scheduling, sequencing and RDS-design for recycling [44].

Another gap in capacity planning research is the consideration of potential operational failures. Although there is research in line balance and scheduling that explicitly addresses failing tasks, such as Altekin and Akkan [42] and Gungor and Gupta [46], this research presumes fixed production resources. Further works by Vlachos et al. [48] and Georgiadis and Athanasiou [45] focus on capacity planning considering product rejections based on the identified condition during the initial inspection. However, their approach examines supply chains in remanufacturing with an insufficient level of granularity.

2.3. Research gap

The presented literature is summarized and evaluated in Table 1 using the aforementioned criteria. In general, approaches on capacity planning for reconfigurable systems are limited and mainly focus on conventional manufacturing systems. In addition, existing studies on capacity planning in remanufacturing often do not consider reconfigurable systems [31,43,47]. Yet, the potential of reconfigurable systems in remanufacturing is well recognized due to its high flexibility [20, 30,40,41]. Planning based on product conditions helps to address the increased uncertainty in remanufacturing capacity planning [20,43]. These approaches provide valuable insights, but do not account for a reconfigurable and hybrid system architecture, nor do they consider operational failures. Only a few approaches account for failing operations. Altekin and Akkan [42], Gungor and Gupta [46], and Georgiadis

Table 1
Evaluation of relevant approaches to capacity planning in RMS and production planning in remanufacturing.

	Publication	(1) Reconfigurability	(2) (Semi-)Automation	(3) Flexible resource allocation	(4) Disassembly/remanufacturing	(5) Product condition-awareness	(6) Operational failure	(7) Configuration sequence	(8) Station level granularity	(9) Capacity planning
Capacity planning for Reconfigurable Manufacturing Systems	Asl and Ulsoy [33]	●	○	○	○	○	○	●	○	●
	Colledani and Angius [39]	●	●	●	○	○	○	○	●	●
	Gyulai et al. [36]	●	●	○	○	○	○	◑	◑	●
	Hees et al. [35]	●	●	○	○	○	○	◑	◑	●
	Manzini et al. [38]	●	●	◑	○	○	○	○	●	●
	Marquez et al. [34]	●	●	◑	○	○	○	○	○	●
	Youssef and ElMaraghy [37]	●	○	○	○	○	○	○	◑	●
(Capacity Planning for) Disassembly and Remanufacturing	Aljuneidi and Bulgak [40,41]	●	◑	●	●	○	○	○	◑	●
	Altekin and Akkan [42]	○	○	○	●	◑	●	○	◑	○
	Andersen et al. [30]	●	●	○	◑	◑	○	●	◑	◑
	Colledani and Battaïa [43]	○	○	◑	●	●	○	○	○	●
	Eguia et al. [44]	●	◑	◑	●	○	○	◑	●	○
	Franke et al. [20]	●	●	●	●	◑	○	○	○	●
	Georgiadis and Athanasiou [45]	○	○	○	◑	◑	◑	◑	○	◑
	Guide et al. [31]	◑	○	◑	●	○	○	○	○	●
	Gungor and Gupta [46]	○	●	◑	●	◑	●	○	◑	○
	Lee et al. [47]	○	○	○	●	○	○	○	○	●
	Vlachos et al. [48]	○	○	○	◑	◑	◑	◑	○	◑
	Wurster et al. [25]	●	●	●	●	●	●	○	●	○

and Athanasiou [45] focus on Assembly Line Balancing in remanufacturing, however, neglect reconfigurable systems as well as a flexible resource allocation. There is no literature known to the authors, that examines capability-based failures from a system level perspective.

Prior work by the authors [25,51] considers hybrid disassembly systems, consisting of loosely coupled manual and robotic workstations. However, these approaches are limited to material flow control. The present paper builds on the framework introduced in [25] and extends the model to fit the purpose of capacity planning.

More specifically, to tackle the derived deficit, this work proposes a methodology for reconfiguring agile disassembly systems. As Fig. 2 depicts, the matrix system is periodically changed by adapting the number of disassembly resources to set the ideal capacity and degree of automation. The core component of the approach is a condition-aware, foresighted capacity planning tool. This tool aggregates the required capacity derived from a given production program and allocates cost-efficient resources, while assuming a transparency increase in the reverse logistic supply chain. The planning tool and the evaluation scenario of this paper are based on and extend the approach initially proposed in [21].

The remainder of this work is structured as follows. First, a capability-oriented framework to model hybrid disassembly systems, prerequisites for reverse logistics and the capacity planning approach is introduced in Section 3. In Section 4 the problem is formulated as a mixed-integer linear programming problem. Section 5 deals particularly with the modeling of uncertainty in disassembly operations. Afterwards, the approach is rigorously tested in Section 6, by applying it to a real industrial remanufacturing case including data of a whole product family and the underlying disassembly factory. The outcome of the simulation study is then critically discussed in Section 7 with respect to the simplifying model assumptions and the given research questions. Eventually, the findings are summarized in Section 8 including an outlook for future research.

3. System configuration and capacity planning model

3.1. Basic problem statement

Before implementing the formal system model, a capability-oriented framework according to Pfrommer et al. [52] is introduced, marking the structure and basic rules of the production system. The framework

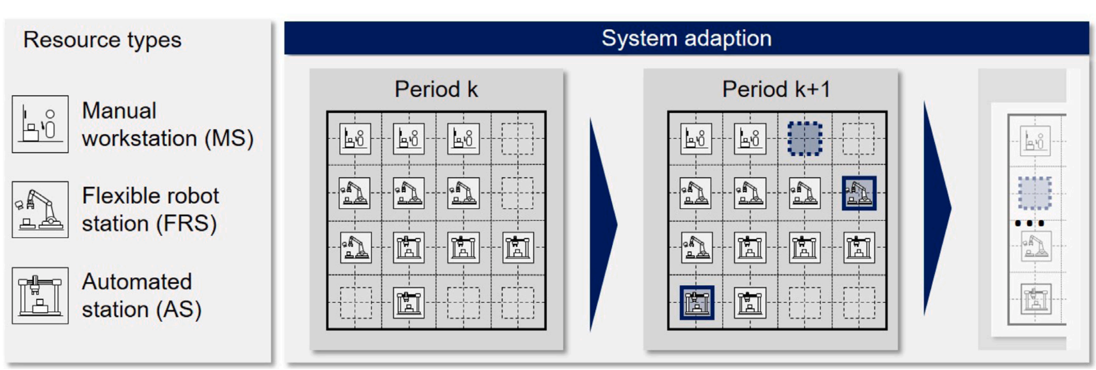

Fig. 2. Periodic system adaption.

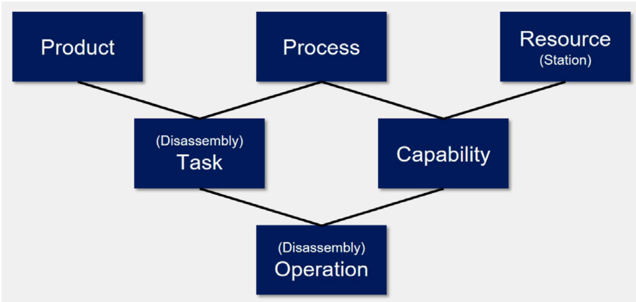

Fig. 3. Capability-oriented Product-Process-Resource-concept to link products, resources and disassembly operations as a framework to describe the agile production system [52].

as depicted in Fig. 3, building on the well-known Product-Process-Resource concept, which comprises a product-agnostic description of disassembly resources of different types and a resource-neutral description of disassembly tasks, with both perspectives ultimately merging in concrete disassembly operations.

In the following, agile hybrid disassembly systems as introduced before and previously described in [22,53] are modeled. With the clear goal of industrialization, the modeled system is embedded in an industrial remanufacturing environment. Furthermore, the model enables the formulation of the capacity planning problem. Partially extending [25], the model comprises the following components and assumptions:

Product variants (01):. During initialization, product variants $v \in V$ are defined. Unlike linear production, remanufacturing deals with high-variance product returns. Each variant comprises a set A_v of disassembly tasks for potential execution. Associated Disassembly Petri Nets determine feasible task sequences, cf. [25]. During production, a product instance is treated as a disassembly order. The condition of a disassembly order is described by its quality class $q \in Q_v$.

Quality classes (02):. Quality classes comprise representations of core states and have been well-studied in literature, e.g. in [43,50]. In our model, each product variant v is associated with a set of quality classes Q_v. These quality classes, representing generic product conditions, influence further operations. For proactive capacity planning, early classification is mandatory, e.g. through visual inspection [54,55].

Tasks and operations (03):. An individual disassembly step is termed task and is product-specific. These tasks are represented as $a \in A$, with a subset $A_v \subset A$ correlating them with product variants v. The product structure and the precedence relationships of tasks are determined by Disassembly Petri Nets as defined in [25]. Production control primarily drives the disassembly sequence and some tasks might be optional. The unique execution process of a specific task on a product on a disassembly resource is termed an operation. Accordingly, each operation can be noted as op_{raq} and is completely defined by a triplet: $op_{raq} = \{\kappa, t, p\}$.

Resource types and capabilities (04):. Different resource types $r \in R$ are available to conduct disassembly operations (cf. Fig. 2). In both, manual (MS) and flexible robotic stations (FRS), the station $s \in S$ corresponds to the executing resource. A distinct feature of automatic stations (AS) is their modular resource configuration. Every resource type has a fundamental capability κ_{raq}, an anticipated duration t_{raq} and success probability for each task, following circular manufacturing practice [27,53,56].

Operation times (05):. The time required to complete a task a is termed as process duration or time t_{raq}. Just like time in linear production depend on products [57], this duration varies based on the task, its quality class $q \in Q_v$ and resource type r [25]. Within the simulation model, process times for an operation are randomly drawn out of a distribution function linked to the respective average processing time of t_{raq}.

Operation failures (06):. In remanufacturing automated setups, an operation might not always be successful, with a non-uniform and time-invariant failure rate [53]. The likelihood of successful execution represented as p_{raq}, depends on the resource type r, the task j, and the quality class $q \in Q_j$. Tasks that fail are rerouted to an alternate fallback station conducting a backup task. In this work, it is assumed that only MS conduct backup tasks. Furthermore, only FRS are prone to capability-dependent failures. AS on the other hand are limited to well-defined routine tasks that are executed in deterministic operations based on rigid, sequential (PLC) programs. Ensured by production control, AS instances will not be confronted by products in unpredicted product conditions. As a consequence, they do not fail and do not require a backup resource. AS represent conventionally automated resources. These assumptions allow for a clear differentiation between FRS and AS, while accepting the risk of a limited applicability of AS in real disassembly scenarios. For a clear scope and focus, failure events associated with unreliable machinery as mentioned in Section 1, which may correlate with tool degradation, require repair events or lead to scrapped parts, are neglected in this work.

Production periods (07):. The model is segmented into periods $k \in K$. Each period k signifies a production run with a designated duration t_k and production program. Capacity adjustments are only permissible between two periods, following the standard distinction between production planning and control in linear and circular manufacturing [51].

Production program (08):. The production program indicates the demand d_{kvq} for disassembling specific products v in their quality class $q \in Q_v$ during period k. If orders are not processed in a given period, they are transferred to the subsequent one, signifying a backlog [58] with the constraint of no explicit storage modeling and the assumption of non deteriorating quality of the cores, as is industrial standard.

Cost structure (09):. In the context of capacity planning, various cost factors are pivotal when modeling the economic efficiency of resource allocations. The primary component, c_r^t, represents the costs incurred per time unit, for operating a resource of type r [51]. This is particularly significant when comparing automated resources against manual ones [25]. Addressing reconfiguration, two distinct costs are identified: c_r^+ and c_r^-. These signify the costs associated with the one-time setup and dismantling of a resource r, respectively [53]. Another vital consideration is c^{BO}, which quantifies back order costs per period, incurred due to the unmet demand from d_{kvq}. These components collectively underscore the intricate cost structure that underpins decision-making processes in capacity planning.

3.2. Reverse logistic prerequisites

Generally, the potential of an increased transparency on EOL-products and their condition in reverse supply chains is manifold [59]. To enhance foresight in operational capacity planning in this work, assessing and recording quality classes should occur before the storage of product returns. The proposed operational workflow for capturing these quality classes in an automotive aftermarket environment is depicted in Fig. 4. According to Kalverkamp and Raabe [60], core supply in the automotive aftermarket can be distinguished between potential customers (e.g. wholesalers, repair shops) and core dealers. While customers can trade in old cores while ordering remanufactured products, dealers are only represented on the supply side. The quality grading takes place before the remanufacturing process [61]. This process is typically performed onsite at the remanufacturing facility. Schlüter et al. [7] however aim to evaluate quality automated and decentralized. Since the early acquisition of quality data increases the reliable forecast horizon, this approach holds great potential for condition-aware capacity planning. After the grading, the cores are stored in the core warehouse, which keeps an optimized stock of returned products. When the customer triggers an order release, the core is disassembled to order directly from the warehouse, while core replenishment is decoupled. Thereby, lead time can be reduced and condition-aware capacity planning is enabled.

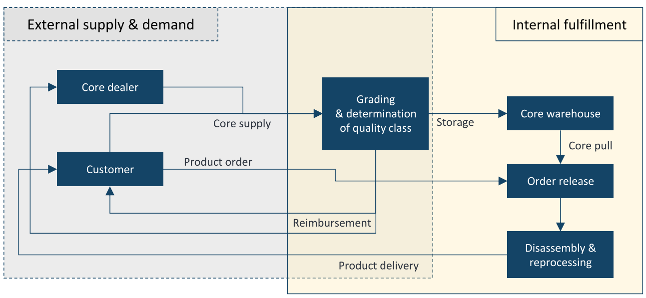

Fig. 4. Proposed framework for a quality-driven remanufacturing value chain.

3.3. Integrated capacity planning approach

When facing decision problems in the highly dynamic circular manufacturing environment, the ultra high degree of volatility in remanufacturing calls for flexible and adaptive planning approaches [25]. Fig. 5 shows three different optimization approaches regarding their degree of inclusion and flexibility towards future events.

The perfect foresight approach is inherently intuitive. It operates under the premise that future events and conditions can be predicted with absolute certainty [62]. Consequently, planning based on this method involves optimizing actions based on this deterministic view of the future. However, this approach tends to be inflexible, potentially leading to decisions that become quickly outdated as the environment evolves [63].

On the other end of the spectrum is the myopic approach. It emphasizes near-term outcomes with minimal consideration for long-term consequences. This short-sighted approach narrows the planning horizon to immediate events and conditions. While this can lead to swift decision-making in rapidly changing environments, there is a risk of overlooking potential long-term implications, which might result in suboptimal outcomes on the long run.

The rolling horizon represents a combination of the two aforementioned approaches. Here, the planning process is not a one-time, static event but a continuous and dynamic activity. The horizon or planning window, while being fixed in length, rolls forward as time progresses. At every decision gate, a plan is formulated for a predefined future time frame based on the most current information available. As new data becomes accessible or conditions change, the horizon advances and the plan is updated in an expected foresight-based approach [64]. This not only incorporates the benefits of perfect foresight by using all available information but also retains the agility of the myopic approach, adapting to changes as they occur. This fosters both foresight and flexibility, positioning it as a more robust method for planning in unpredictable, dynamic settings [65,66].

Consider a planning problem with imperfect foresight. In other words the actual realizations of relevant values only become apparent over time. One decision is in the structure of the response, i.e. a myopic approach that only reacts on the real time information or a rolling horizon approach that extrapolates into the reasonable future. Only then, the next decision, i.e. which optimization problem and solver to model and solve the problem should be applied [58].

When applying the classical rolling horizon approach, optimizations for a longer time period are followed by immediate reactions of the systems' short term period. While this might be realistic for certain use cases, in particular in low-level control, it is usually not realistic for

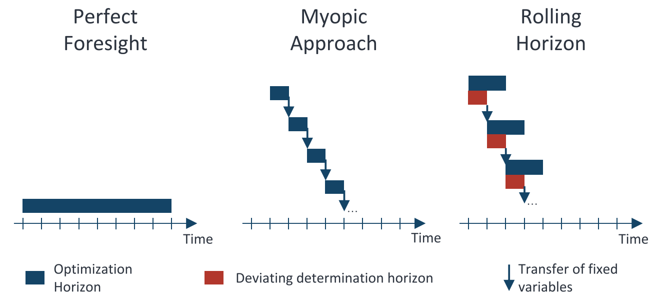

Fig. 5. Types of optimization models regarding their degree of inclusion of future events.

capacity planning of entire production systems. Even in highly flexible and changeable systems, capacity changes are exposed to inertia and a reaction time between planning and execution [67]. Instead of neglecting periods that cannot be influenced anymore, we introduce a reaction time ϵ, which comprises the periods $k \in \epsilon \subset K$, individually for each planning date (PD) [58]. This allows the consideration of dynamic changes in input factors for the next determination period, where the course of action is limited within ϵ, i.e. a restricted adaption. With the complete system configuration being defined at the same planning date, we define the approach as a static rolling horizon.

Conversely, an adaptive rolling horizon is introduced for an increased level of adaptability and foresight, which allows the definition of individual reaction times for the reconfiguration of each resource type accounting for individual capacity flexibility [53]. For instance, an additional manual station might be much faster to acquire, than customizing an automatic disassembly device or even ordering and training the customization. Thereby, decisions for complex resources can be made in the same capacity planning process without compromising the flexibility of short-term adaptions in the near planning horizon. Fig. 6 depicts schematically the difference between a static rolling horizon and an adaptive rolling horizon.

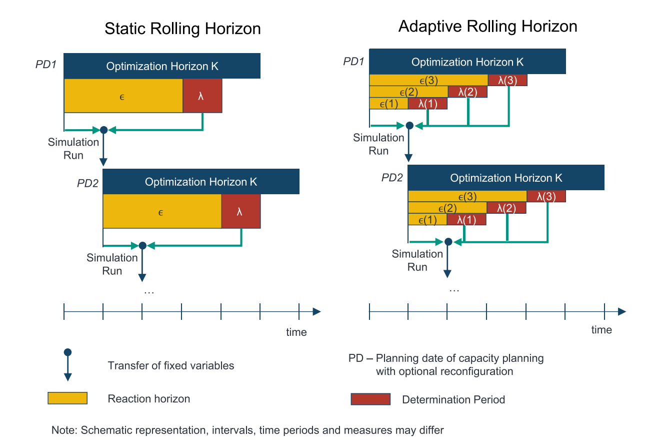

Fig. 6. Comparison of static and adaptive rolling horizon concept.

4. Problem formulation and objective function

Subsequently, based on the foundations and outlined constraints, a mixed-integer linear programming (MILP) model is introduced to solve the capacity planning problem. The model represents the decision problem at each planning date, i.e. from the perspective of the optimization at the beginning of each rolling horizon. The rolling of the horizon is inherently operationalized by production periods in this case. The planning and the determination date of a system configuration is detached from its actual implementation, due to the implementation and optimization delay. The derived MILP is linked to the well-known

Generalized Assignment Problem and its correctness could be verified with a Gurobi solver implementation and individual production period solution. The same solver and implementation is adapted, connected to the simulation of the described use case and later used for the case study. Its results are reported in Section 6.

The MILP model is defined as follows:

Parameters:

- R: Set of resource types, denoted as r, available for executing tasks j
- K: Set of periods, represented as k, within the optimization horizon
- ϵ_r: Set of periods, k, that lie within the response time of resource r
- λ_r: Specified period associated with resource type r
- V: Set of product variants, denoted as v
- Q_v: Set of quality classes pertaining to product v
- Q_a: Set of potential quality classes in which task a can be executed
- A: Comprehensive set of all tasks
- A_v: Set of tasks that may arise during the processing of product v
- $\eta_{a,q}$: Frequency at which task a occurs in a product of quality class q
- κ_{raq}: Binary variable, set to 1 if resource r is capable of executing task a in quality q, otherwise $\kappa_{raq} = 0$
- p_{raq}: Probability for which resource r successfully executes task a in quality class q, i.e., without failure
- t_{raq}: Expected time taken by resource r to execute task a in quality class q
- d_{kvq}: Demand in period k for product v in quality class q, as determined by the production program
- $m_{k_0 r}$: Initial configuration, reflecting the count of stations of resource type r in $k = 1$
- t_k: Duration of period k
- V_r: Set of resource types r, for which tasks are repeated in case of an operation failure at resource type r (fallback strategy)
- c_r^t: Cost per time unit t for operating a resource of type r
- c_r^+: Reconfiguration cost incurred when setting up a resource r
- c_r^-: Cost associated with the dismantling of a resource r
- c^{BO}: Back order cost per period for not processing a demand unit from d_{kva}
- $b_k^{free,max}$: Threshold for free backlog b_{kvq} in period k

Decision Variables:

- X_{kraq}: Number of tasks, represented as a, in quality class q, which are processed by resource type r in period k
- b_{kvq}: Backlog for product variant v in quality class q that remains unprocessed in period k
- b_k^{free}: Utilized threshold for free backlog in period k

Dependent Variables:

- F_{kraq}: Number of backup tasks a, in quality class q processed by resource type r in period k induced by failed operations.
- m_{kr}: The number of allocated resources for type r during the period k
- C_{kr}^t: Operational costs incurred for all resources of type r during the period k
- C_{kr}^+: Reconfiguration costs associated with adding resources of type r in period k
- C_{kr}^-: Reconfiguration costs related to the removal of resources of type r during the period k
- C_k^{BO}: The aggregated expected back order costs for all unprocessed orders across all products v and for all quality classes $q \in Q_v$ in the given period k

Objective function:

$$Minimize: \sum_{k=1}^{K}\sum_{r=1}^{R}(C_{kr}^t + C_{kr}^+ + C_{kr}^-) + \sum_{k=1}^{K} C_k^{BO} \tag{1}$$

Constraints:

$$s.t. \quad \sum_{r=1}^{R}(X_{kraq} - F_{kraq}) * \kappa_{raq} = (d_{kvq} - b_{kvq} + b_{(k-1)vq}) * \eta_{aq} \quad \forall k \in K,\ \forall v \in V,\ \forall a \in A_v,\ \forall q \in Q_a \tag{2}$$

$$F_{kraq} \geq \sum_{v_r=1}^{V_r}(1 - p_{v_r aq}) * X_{kv_r aq} \ \forall k \in K,\ \forall r \in R,\ \forall a \in A,\ \forall q \in Q_v \tag{3}$$

$$\sum_{a=1}^{A}\sum_{q=1}^{Q_v} X_{kraq} * t_{raq} \leq m_{kr} * t_k \ \forall k \in K,\ \forall r \in R \tag{4}$$

$$b_k^{free} \leq \sum_{v=1}^{V}\sum_{q=1}^{Q_v} b_{kvq} \ \forall k \in K \tag{5}$$

$$0 \leq b_k^{free} \leq b_k^{free,max} \ \forall k \in K \tag{6}$$

$$C_{kr}^t = c_r^t * m_{kr} * t_k \ \forall k \in K,\ \forall r \in R \tag{7}$$

$$C_{kr}^+ \geq c_r^+ * (m_{kr} - m_{(k-1)r}) \ \forall k \in K,\ \forall r \in R \tag{8}$$

$$C_{kr}^- \geq c_r^- * (m_{(k-1)r} - m_{kr}) \ \forall k \in K,\ \forall r \in R \tag{9}$$

$$C_k^{BO} = c^{BO} * (-b_k^{free} + \sum_{v=1}^{V}\sum_{q=1}^{Q_v} b_{kvq}) \ \forall k \in K \tag{10}$$

$$X_{kraq}, F_{kraq} \geq 0 \ \forall k \in K \ \forall v \in V \ \forall a \in A_v \ \forall q \in Q_j \tag{11}$$

$$b_{kvq} \geq 0 \ \forall k \in K,\ \forall v \in V,\ \forall q \in Q_v \tag{12}$$

$$m_{kr} \geq 0 \ \forall k \in K,\ \forall r \in R \tag{13}$$

$$C_{kr}^t, C_{kr}^+, C_{kr}^- \geq 0 \ \forall k \in K,\ \forall r \in R \tag{14}$$

$$C_{kv}^{BO} \geq 0 \ \forall k \in K,\ \forall v \in V \tag{15}$$

The objective function (1) consists of four different cost types, which it aims to minimize over all periods k. This includes the variable costs for the operation of disassembly resources, reconfiguration costs for adding and removing resources, and back order costs for unfinished orders.

Constraint (2) ensures the task assignment of disassembly operations of a resulting from demand d_{kvq}. X_{kraq} is the task assignment variable that defines the number of tasks a of products in quality q to be assigned to resource r in period k. F_{kraq} must be deducted from X_{kraq} as the non-productive representation of failed tasks. The right term represents the demand d_{kvq} in period k, which can be leveled by pushing backlog towards future periods. Because of the divergent characteristics of disassembly, mapped by the disassembly petri nets, not all tasks may occur for each disassembled product instance. Therefore η_{aq} represents the probability of a task a occurring in quality class q. Subsequently, F_{kraq} is defined by the complement term (3) of the related success probability.

Constraint (4) represents the capacity constraint. For all assigned tasks a there must be sufficient resources m_{kr} for each resource type, to cover the total expected processing time in each period k.

Constraints (5) and (6) allow the definition of a free backlog limit for demand units that are not punished by back order costs. Hence, limited shopfloor stock buffers can be implemented to avoid frequent production ramp-ups and ramp-downs and increase flexibility.

Constraints (7)–(10) comprise an aggregation of the four cost types. The variable production time cost is defined by the minute cost rate and the period duration. Reconfiguration costs occur if the amount of allocated resources for a type r changes between two consecutive periods k. Back order costs are charged for each reattained demand unit that exceeds the free backlog for every period k.

Constraints (11)–(15) ensure the formal correctness of the model by introducing non-negativity constraints for all relevant variables.

After optimization, the station variable m_{kr} contains the relevant capacity requirements for each resource type r for all periods $k \in K$. Hence, if $m_{kr} \neq m_{(k+1)r}$ $\exists r \in R$, a reconfiguration of the disassembly system is required between periods k and $k+1$.

5. Modeling disassembly uncertainty

This work proposes a capacity planning method to adapt disassembly systems in volatile environments that are prone to a high degree of uncertainty. Proper mapping of the uncertainty of disassembly operations is crucial to allow for rigorous testing and credible results. To achieve this, a discrete event simulation (DES) model is used to emulate the actual behavior of the agile disassembly system. Being directly coupled with the system configurator, the model allows multi-periodic test runs. Its main function is to roll out production periods with system configurations determined by capacity planning to generate terminal system states, which allow for a thorough evaluation of previous planning results and, combined with a given production program, lead to new consecutive system set-ups for subsequent planning cycles. Compared with queuing theory or other analytical approaches, discrete event simulation allows for an accurate mapping of the operational uncertainties.

5.1. General modeling and control approach

During system operation in a disassembly period k, the system configuration remains constant, however, a control logic is required to orchestrate the material flow. Its function is to continuously allocate vacant disassembly orders to available resources. Thereby, it is important to balance MS, FRS and AS allocations to maximize the system performance. In a previous work [51], a heuristic control system based on a multi-priority rule approach was proposed and will be used in the following. As the control system is not the focus of this work, a robust but constant parameterization will be used for the control logic. The simulation model inherits and builds on the control logic but the logic will not be investigated further in this work.

5.2. Uncertainty modeling for disassembly operations

The uncertainty in remanufacturing reflects itself in the properties of the disassembly operations specified in this work by their duration and success rate. Disassembly is known for greatly varying disassembly operation times, with a variance factor up to ten times and more higher compared to assembly [42]. One reason for this large variance lies within the varying product conditions [42]. While, in tendency, a degraded product often leads to a higher disassembly effort and unforeseen issues, a disassembly task conducted on a product in moderate condition is more likely to be finished faster within a smaller window of uncertainty. Nevertheless, there remains a lot of ambiguity in linking the product conditions with the actual duration of a disassembly operation, resulting in the need for advanced inspection [55].

However, to capture this interrelation and increase the level of detail, a new approach is proposed that links product conditions with the emulated execution times of disassembly operations. Quality classes, as proposed before, are therefore linked to modified beta distributions serving as random number generators for the respective values in the simulation model used for the evaluations. Beta distributions are common to model manual task times and are also applied to disassembly [31,68]. The density function $f_X(t)$ of a beta distributed random

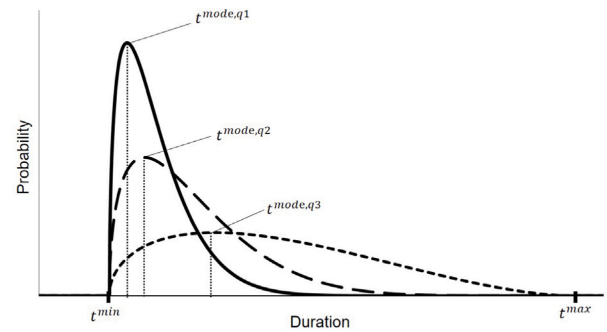

Fig. 7. Beta density function for three different quality classes.

number $X = BV(\alpha, \beta, t^{min}, t^{max})$ is defined with the Beta function $B(\alpha, \beta)$ as:

$$f_{BV(\alpha,\beta,t^{min},t^{max})}(t) := \begin{cases} \frac{(x-t^{min})^{\alpha-1} * (t^{max}-t)^{\beta-1}}{B(\alpha,\beta) * (t^{max}-t^{min})^{\alpha+\beta-1}}, & if\ t^{min} \leq x \leq t^{max} \\ 0, & else \end{cases} \tag{16}$$

α and β mark form parameters, while t^{min} and t^{max} notate the upper and lower time boundary. t^{min} is assumed to be a natural lower boundary that can only be reached if an operation is executed flawlessly. Therefore, t^{min} can only be approximated. t^{max}, the upper boundary, marks the time limit for which operations will be aborted. Finally, t^{mode} is another important parameter marking the most likely duration as a dependent variable determined as follows:

$$t^{mode} := t^{min} + (t^{max} - t^{min}) * \frac{\alpha - 1}{\alpha + \beta - 2} \tag{17}$$

While both, t^{min} and t^{max} do not depend on the product condition, t^{mode} is shifted in dependence of the quality class q. Fig. 7 depicts this relationship. While α is set to $\alpha = 1.5 = const.$ β is adapted according to the mode shift using Eq. (17). In Fig. 7 $q1$ can be seen as a quality class marking a moderate product condition, while $q3$ marks a quality class belonging to degraded product that is possibly slowing down task execution, e.g. corrosion. Therefore, there is a higher probability to realize these discrete values for the simulation. However, while the classification and the effect of $q3$ is uncertain, the likelihood of higher task times increases. This approach allows modeling products of the same variant distinguished by their condition while maintaining an overall high level of operational uncertainty. As a result, the quality class, types, a random factor modeled through the distribution, as well as task time and failure probabilities result in a scalar value for each case. That discrete data point can then be used in the simulation study.

6. Evaluation based on an industrial case study

In this section, both, agile hybrid disassembly systems and the approach for capacity planning are evaluated on a remanufacturing scenario based on real data of an industrial case company. Thereby, the following leading research items are addressed:

1. Benefit of a frequent reconfiguration of the disassembly system
2. Cost saving potential of flexible disassembly robots today and in future scenarios.
3. Impact of foresight
4. Impact of capability-dependent failures
5. Potential of condition-aware capacity planning

6.1. Data collection and preparation

To allow for a valid testing scenario, the simulation model is instantiated using product and process data gathered from an industrial case company. The company operates in the automotive remanufacturing sector in Europe. In this study we focus on the disassembly of car alternators which the case company recovers in a dedicated remanufacturing plant. While car alternators are established remanufacturing products, the disassembly process is still conducted manually or limited to process mechanization in a mixed job shop/flow shop environment. To emulate realistic scenarios for agile (hybrid) alternator disassembly, the instantiation of the simulation environment requires extensive effort. The data for the testing scenario as well as their origin and preparation is described in the following:

Production periods (07) and production program (08):. The production program comprising one year of operation and respective order numbers per product variant, inherits the time horizon of the simulation studies. One production period (07) corresponds to a working week. Assuming a two-shift system with 8-h shifts and neglecting breaks and off-days, one production period lasts 4800 min. The production program is furthermore anonymized and shutdown weeks are exempted. However, the actual variety of the product mix is maintained.

Product variants (01) and quality classes (02):. Based on the production program, 46 product variants (01) were identified and clustered by their product structure into five different clusters. For each product cluster, all main components, disassembly tasks and their precedence relations were determined to derive and construct suitable disassembly Petri nets. Based on surveys with operators of the actual disassembly system, corrosion and pollution were identified as the most critical degradation types towards disassembly execution. Both are treated as binary attributes and can overlap. Thus, four different quality classes (02) are distinguished. An overview of these quality classes and their mean occurrence rate is displayed in Table 2.

Table 2
Generic quality classes by attributes and their mean relative occurrence frequency.

Condition attribute	q1	q2	q3	q4
Corrosion		x		x
Pollution			x	x
Mean relative frequency [%]	50	20	20	10

Resource types, capabilities (04) and operations (03). The actual disassembly system is operated manually. However, this work investigates a hypothetical hybrid system that includes FRS and AS besides MS resources. A different approach is applied per resource type to completely specify all disassembly operations (κ, t^{min}, t^{max}, t^{mode}, $p_{v_r aq}$) for all tasks and quality classes. Manual tasks are assumed to never fail due to capability deficits. The success rate is 100% as scrap is generally neglected in this work. The instantiation of the disassembly task times is based on interviews with production planners and disassembly operators. MS operation times are based on an existing database comprising measured times from observations of disassembly operators. To cope with the great number of tasks, a time motion system, like Methods Time Measurement (MTM) or Maynard Operation Sequence Technique (MOST) [69], was selected for FRS and AS. Disassembly tasks, classified capable, are therefore analyzed and subdivided to derive reoccurring task primitives such as approaching, pulling, pressing, unscrewing, recognizing&planning and tool exchange. Each sub-task is determined as deterministic or probabilistic and assigned a specific task time or range. In the next step, each task is assembled by sequencing the task primitives. AS operations are limited to deterministic task primitives so that the cumulated time of all primitives equals the deterministic operation time. FRS tasks on the other hand also contain probabilistic task primitives with a volatile execution time and the risk of failure. FRS operations are therefore specified using Monte-Carlo simulation including an evaluation of 2000 random sequences per each task for a sufficiently high number of iterations. In general, task primitives and task sequences are discussed and adjusted with robotics and automation technology experts. Execution times are determined based on current findings in research and mark the results of a conservative appraisal. With the assumption of no failure and a deterministic and comparatively fast execution, AS operations are defined rather optimistically in this paper compared to FRS operations. To be more precise, the results of the expert-based instantiation comprise, that around 52% of the disassembly tasks can be covered by FRS, while only a quarter can be covered by AS. However, while 84% of AS operations are more cost-efficient than their MS counterparts, no FRS operation could outperform MS cost efficiency in this initial data set.

Table 3
Resource type specification.

Attribute	MS	FRS	AS/DVx
Resource types R	MS	FRS	DVx $x \in \{1, 2, \dots, 7\}$
Backup resource	n\A	MS	n\A
Stochasticity	Beta distr.	Beta distr.	Deterministic
c_r^t [€/min]	0,767	0,293	0,239
c_r^+ [€/station]	500	3000	3000
c_r^- [€/station]	200	1000	1000
p_{raq} [%]	100	≤100	100
ϵ_r [periods]	1	4	4

The specification of FRS operations underlies a high degree of uncertainty and therefore takes on a special role. As mentioned above, the initial FRS instantiation is based on verbatim estimations by robotic disassembly experts, approximating the technical maturity of flexible disassembly robots in research environments, yet neglecting industrial aspirations. Accordingly, this instantiation is also termed **conservative (FRS) instantiation**. Eventually, as the numbers show, FRS instances are obsolete in this case, as will be confirmed in the investigation in Section 6.3. In preliminary studies, the model instantiation was therefore altered by decreasing the likelihood of failing and the operation time for all FRS operations proportionally. In a sensitivity analysis, a reduction factor of 5 proved to be the first integer for which the assignment of FRS would led to a positive monetary outcome. Accordingly, the increased FRS maturity referred to within the **benchmark configuration** *f5-bench*, which will be introduced in the following section is based on this modification.

Table 3 lists the specification of all station types including cost parameters. While costs for reconfiguration and back orders are estimated, the operation costs for all station types are calculated based on a machine hour calculation approach assuming a short-term resource leasing model similar to [70], 8-h 2-shift scenario, German wage level and electricity cost rates, and six years of depreciation time.

6.2. Simulation studies and evaluation

In the following, the agile disassembly system and the planning approaches are analyzed based on different scenarios using discrete event simulation. The simulation model is implemented in Python using the SimPy simulation framework [25,51]. The extensive simulation environment allows long-term multi-period simulations studies including structural system reconfigurations without compromising relevant operation details.

The investigation is divided into three studies. First, the benefit of reconfiguration and automation and the basic behavior of the system is analyzed (research item 1 and 2). Second, different variations of the planning methodology are investigated (research item 3 and 4). Finally, the last study analyzes the impact of the degree of transparency during planning (research item 5).

Each simulation run is replicated ten times to prove the significance of the results. Mean total costs and costs by type for each configuration are listed in Table 7, boxplots show the variance in the total costs in Fig. 9.

The configuration *f5-bench* marks the general benchmark configuration and is specified as follows:

- **Reconfiguration**: System reconfigurations are enabled and guided by the capacity planning logic
- **Foresight**: Planning is conducted with five periods of foresight
- **Backlog**: Intended order backlog is neglected
- **Capability-dependent failures**: Failure-induced demand is considered
- **Transparency**: Planning is conducted based on perfect knowledge about operations, including distributions of operation times and actual failure probabilities
- **Automation**: Automation using FRS and AS is allowed. At the same time, an increase in the technical maturity of FRS compared to the initial conservative instantiation is assumed, s. Section 6.1.

Besides its benchmark function, *f5-bench* marks the default configuration. Changes to this default configuration are explicitly mentioned in the following within the specification of the modified scenarios.

6.3. Impact of reconfiguration and automation (a)

The first study comprises a qualitative and a quantitative analysis of the system behavior and the impact of reconfiguration and automation. Therefore, four different configurations are compared as described in Table 4: a *static* scenario without system adaptions and an all manual scenario *f5-man*. Besides that, two scenarios where FRS and AS are allowed, *f5-org* including the conservative instantiation of FRS and finally the benchmark scenario *f5-bench*. Today's system practice can be classified somewhere between *static* and *f5-man* as there is no automation or systematic adaption of manual capacities.

Table 4
Specification of alternative configurations (a).

Alternative configurations (a)	
static	No reconfiguration, 5 MS
f5-man	Reconfiguration, all manual
f5-org	Reconfiguration, automation enabled
f5-bench	Reconfiguration, automation, FRS efficiency increase

Fig. 8 depicts the system behavior including the scaling path, the utilization and order backlog evaluation in the system for all scenarios. *static* remains in a 5 MS system configuration leading to an alternating capacity deficit and surplus. Compared to *f5-man*, the system builds up undesired backlog and there is greater volatility in the system utilization while through reconfiguration the system utilization in *f5-man* can be maintained at a high level at around 90% and all periods except for three >80%. For *f5-org* and *f5-bench* back orders are prevented effectively as well. In both scenarios, there is a heavy application of AS, however, only in *f5-* FRS seem economically reasonable. Concerning cost efficiency, the FRS with its initial conservative specification is generally outperformed by the MS.

The comparison of the total costs supports the qualitative analysis. For the *static* scenario, both, operational and back order costs are a lot higher compared to *f5-man*. Well-aligned with the qualitative analysis, the results depict the clear benefits of a systematic system adaption in the given use case. Despite the AS utilization deficit, a further significant cost reduction is possible with *f5-org*. The FRS efficiency increase in *f5-bench* allows a further reaching MS substitution leading to lower resource costs and total costs despite higher back order costs. Upcoming scenarios inherit the *f5-* instantiation including the FRS efficiency increase as the standard scenario.

6.4. Variation of the planning logic (b)

In a second iteration, the planning method is varied in four additional scenarios (cf. Table 5). To investigate the impact of the induced demand and the failure awareness of the approach, a scenario *f5-pd* is investigated where constraint (3) is neglected. In another scenario the foresight is increased to 10 periods (*f10*). Finally, two more scenarios are defined for which backlog is a legal measure during planning (*f5-bl* and *f10-bl*).

Table 5
Specification of alternative configurations (b).

Alternative configurations (b)	
f5-bench	Benchmark configuration
f5-nofail	Neglects constraint (3) assumings $F_{kraq} = 0$
f10	10 periods foresight $\|K\| = 10$
f5-bl	Backlog allowed
f10-bl	10 periods foresight $\|K\| = 10$, backlog allowed

As Fig. 9 shows, despite the small FRS share, neglecting failed operations (*f5-nofail*) in agile hybrid disassembly systems in the planning stage can lead to significantly higher costs. Therefore, considering the induced demand plays a crucial role. An increased planning horizon, on the other hand, can increase planning decisions. The results of *f10* show lower operation costs while back order costs are slightly higher, indicating an effective opportunistic planning behavior. Finally, *f5-bl* and *f10-bl* perform worse than *f5-bench*, although the solution space of e.g. *f5-bl* inherits the solution space *f5-bench* as a whole. In general, the existing back orders, e.g. in *f5-bench* or *f10* prove a gap between the ideal allocation of tasks and orders to the stations and their actual allocation in the operation phase. The increased costs for *f5-bl* and *f10-bl* point to the fact that allowing an order backlog during planning tends to exacerbate this gap. Unlike for *f10*, opportunistic planning strategies become rather ineffective due to this planning gap leading to even higher back orders for *f10-bl* compared to *f5-bl*.

6.5. Variation of planning transparency (c)

A core concept of this new methodology is condition-awareness and the classification of disassembly orders into quality classes. Thereby it is based on the assumption of increased transparency of the disassembly orders during planning. The following investigation is dedicated to this aspect and its impact on planning accuracy. To this end, four additional scenarios are compared, which differ in their respective degree of transparency, cf. Table 6.

Table 6
Specification of alternative configurations (c).

Alternative configurations (c)	
f5-bench	Benchmark configuration, perfect knowledge about time distributions and success rates, planning based on analytically determined expected values
f5-pcb	Planning based on operations tracking by product type and condition
f5-pb	Planning based on operations tracking by product type neglecting product conditions
f5-pd	Planning based on roughly estimated task times (mean values per task for all product types)

Firstly, the default configuration *f5-bench* which assumes perfect knowledge of the quality statuses and the effects on the disassembly operations. The parameters of the distribution functions are known so that capacity planning can be fed with the expected values of the execution time and the actual probability of success. These assumptions represent the ideal scenario, which cannot be achieved in reality as the actual distributions and values are usually unknown. Instead, the expected values could be approximated using historical measurements. The two scenarios *f5-pcb* and *f5-pb* simulate this case. The planned times for the execution duration and the success probability are determined by averaging the previously tracked times for all operations. The planning foundation thus improves over time. However, while *f5-pcb* distinguishes and tracks data by product type and condition, *f5-pb* neglects the quality class system. Finally, a last scenario *f5-pd*

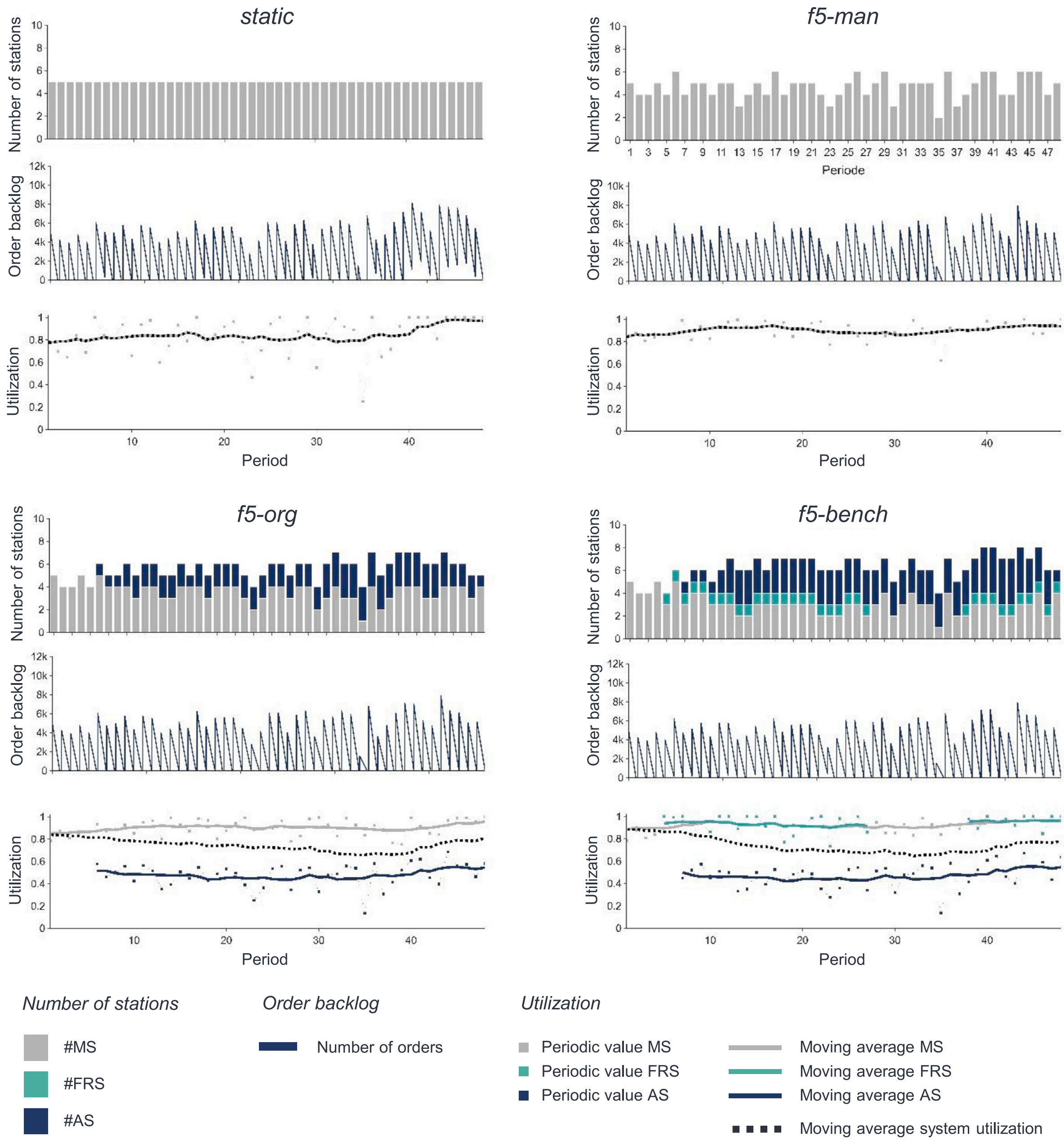

Fig. 8. Resulting system behavior comparing configurations of study a (*static*, *f5-man*, *f5-org*, *f5-bench*)- development of the system configuration (top), order backlog (middle) and resource utilization (bottom) over 48 production periods.

does not distinguish tasks by product type but builds on common data determined by the mean values of each actual task specification over all product types for planning. Today, disassembly planning in the case company is conducted based on estimates and rough time studies. Its transparency level is comparable to *f5-pb*, *f5-pd* or somewhere in between.

As expected, *f5-bench* generates the best results, followed by *f5-pcb* and *f5-pb*. *f5-pd* is lagging far behind with 14%–20% higher total costs compared to the other planning scenarios. It appears that *f5-pd* systematically overestimates the required capacity demand as it generates no back orders and the highest operational costs besides *static* of the former study. In general, the third investigation proves the potential of online tracking for disassembly operations to set up and establish a thorough database that decreases uncertainty, even in adverse and very volatile environments. Besides that, distinguishing product variants by condition within the condition-aware approach tends to increase the planning accuracy even further.

7. Discussion

Being tested on a real industrial case product in relevant industrial quantities and qualities, simulation studies unveiled multiple insights concerning the performance of agile disassembly systems and the potential to boost the accuracy of capacity planning activities and the efficiency in the remanufacturing industry in general.

Overall, the simulation results indicate:

1. **Efficiency gains**: System reconfiguration results in significant efficiency gains by avoiding capacity utilization losses and order delays.
2. **Automation potential**: Given the instantiation, which is prone to uncertainty, partial automation of repetitive, standardizable disassembly tasks enables significant cost savings. On the other hand, based on the instantiation according to expert knowledge and the current state of research, the simulation results

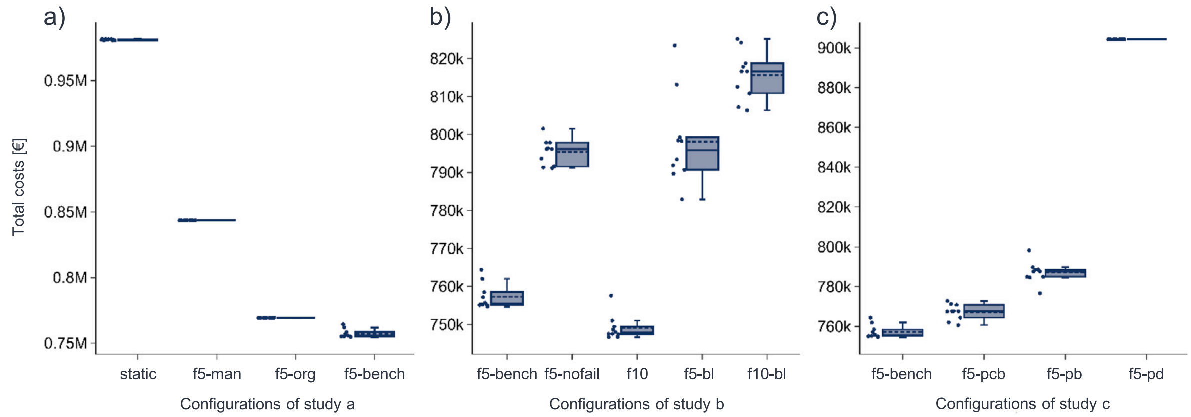

Fig. 9. Boxplot comparison of the resulting costs per system configuration sorted by study (a), (b) and (c).

Table 7
Mean total costs and mean costs by type for each configuration (in €).

Configuration	$\overline{C^{total}}$	$\overline{C^{operate}}$	$\overline{C^{reconf}}$	$\overline{C^{backorder}}$
f5-bench	757.28k	710.04k	36.49k	10.75k
Static	981.19k	883.58k	–	97.61k
f5-man	843.58k	824.68k	18.9k	–
f5-org	769.32k	742.22k	27.1k	–
f5-nofail	795.36k	705.64k	39.18k	50.54k
f10	749.05k	694.82k	38.62k	15.62k
f5-bl	798.11k	682.62k	28.25k	87.24k
f10-bl	815.63k	674.13k	30.61k	110.89k
f5-pcb	767.26k	728.99k	34.05k	4.22k
f5-pb	787.16k	732.36k	40.64k	14.16k
f5-pd	904.31k	853.21k	51.1k	–

prove that flexible disassembly robots are not yet cost-efficient. However, as technological maturity increases and labor costs continue to rise, flexible robots should be considered for a further increase in efficiency.

3. **Impact of foresight**: Increasing the planning horizon allows for opportunistic decisions and can decrease overall costs if actual system operation is closely linked to the ideal planning outcome. This additionally reinforces the value of information and quality of foresight and expectations as crucial for such planning and control tasks.
4. **Impact of capability-dependent failures:** Operational failures due to a lack of capability unfold a non-negligible demand for backup resources. Capacity planning methods should therefore account for failure-induced demand.
5. **Condition-awareness**: The great impact of uncertainty in disassembly processing times influences capacity planning. Reducing the uncertainty by tracking processing times and assigning them to disassembly operations can improve stability as *f5-pb* shows. Uncertainty can be even further decreased by considering product conditions during tracking as *f5-pcb* shows.

The investigation yields some auspicious insights and the condition-aware capacity planning approach appears to be a promising extension to disassembly planning in remanufacturing. However, the results need to be categorized with respect to the assumptions and simplifications of the model. Hence, some **limitations** should be borne in mind:

While being reasonably described, the selection of the beta density function could influence the behavior and the outcome of the simulation studies. Furthermore, the width of the distributions influences the performance, which has been reasonably set according to the industrial case but itself has not been researched in this work. Another limitation is the idealistic modeling approach, which is specifically focused on agile hybrid disassembly systems. By restricting the solution space to manual, flexible robotic and automated stations, a real-world manufacturing system's complexity with varying degrees of freedom and worker centricity cannot fully be modeled and hence might influence the real-world applicability or would require additional detailing. Besides that, a short-term leasing model might not be available for automated resources in certain industries. In this case, costing needs to be reconsidered and the optimization model requires adjustments, e.g. to fit long-term planning structures with investment costs and resell revenues for technical resources. With the advent of scalable automation in production more changeable and flexible manufacturing equipment could significantly reduce the impact of such costs due to lower change and adaptation costs. Ultimately, the results and findings regarding the cost efficiency of flexible robotic and automated resources are based on the instantiation by experts and not on real data. The actual cost efficiency can only be determined once, e.g. the flexible robot system has been realized and the duration of the operation has been measured. Furthermore, the cost efficiency applies primarily to alternators. This may vary considerably for other product families and should be specifically regarded in future studies.

8. Conclusion

This paper introduces a method for capacity planning in agile hybrid disassembly systems in remanufacturing. The problem statement for agile disassembly systems distinguishes from conventional approaches by incorporating varying manual and automated resource types and flexible disassembly pathways where certain operations may be redundant. Furthermore, the capacity planning devised herein hinges on product states characterized by quality classes. These quality classes account for quality-related deviations in the processing time of specific product types and the risk of failing processes related to resource attributes.

The proposed, MILP-based, capacity planning methodology enables nuanced decisions regarding the deployment of automated and manual resources with the implemented solver. Processes prone to failure are explicitly modeled, capturing both, the additional capacity requirement and the associated additional costs. Multi-period optimization via a rolling horizon assesses state transitions between periods, hence evaluating the sequences of configurations.

Considering EOL-product conditions in capacity planning reduces uncertainty, enables more effective planning strategies and allows for a more cost-efficient system operation. Eventually, the alternator disassembly simulation studies prove the ability of the capacity planning approach to decrease uncertainty and waste in disassembly systems towards operational excellence, automation and increased competitiveness of remanufacturing and the circular economy.

As the control system substantially influences the system performance, further research should focus on an integrated investigation of both, the planning and the control system. One major candidate for such an analysis is the implementation of advanced meta-heuristic algorithms to solve the proposed MILP-based capacity planning problem. Alternatively, as the current simulation is used for the validation and verification, a more simulation-based approach, for instance with foresighted digital twins is conceivable. Besides that, future investigations should further emphasize the transfer of the methodology to real remanufacturing systems. To increase the industrial relevance of the approach, the compatibility of the condition-aware methodology with existing disassembly systems should be strengthened. In particular, hybrid systems with conventional automation (MS and AS) or fully manual systems should be considered more closely. In particular, essential issues in product disassembly like yield uncertainty, varying worker capabilities or manual operations in general should be incorporated and modeled in more detail.

CRediT authorship contribution statement

Marco Wurster: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Timon Feuerstein:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Finn Bail:** Validation, Visualization, Writing – review & editing, Methodology. **Marvin Carl May:** Writing – review & editing, Validation, Formal analysis. **Lihui Wang:** Writing – review & editing, Validation, Methodology. **Gisela Lanza:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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