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Adaptive production control for agile disassembly systems in remanufacturing

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ABSTRACT

Uncertainties in disassembly lead to low efficiency and high disassembly costs, prohibiting remanufacturing for economic reasons. While agile hybrid disassembly systems (AHDS) could provide a capable platform, they require a sophisticated production planning and control (PPC). This work presents a dynamic production planning and control approach for disassembly (D-PPC) for AHDS, consisting of a reactive control with CON-WIP order release and an automated logically adapting Multi-Priority Rule order allocation. Results show that the approach can handle disruptions due to process failure and leads to improved throughput and lower costs, especially reducing delay costs.

1. Introduction

Sustainability is becoming an increasingly pressing challenge for our society. The circular economy can be a promising option to allow our society to both meet its material needs and the environment impact reduction targets [1]. Demanufacturing and remanufacturing are fundamental technical solutions to the circular economy [2]. Both, demanufacturing and remanufacturing, need disassembly processes. The low efficiency of current disassembly systems is responsible for the low performance of remanufacturing systems [3,4]. Complexities and uncertainties arise due to the used products being of high variability in variants and conditions, with small lot sizes and volatile quantities [5]. A high flexibility of the production system itself and the planning and control is necessary [4], as focused in the Collaborative Research Center on circular factories (CRC 1574) as acknowledged in the funding and support. To master the inherent uncertainties flexible disassembly systems are required [6,7,8,9,10]. Accordingly, an agile hybrid disassembly system (AHDS) is investigated in this paper. The AHDS consists of manual disassembly stations (MS), flexible robotic stations (FRS) and automated stations (AS), which are characterized by a limited range of application and deterministic process execution, but therefore have a high productivity. It is characterized by adaptability, flexibility, reconfigurability and responsiveness using a matrix structure with loosely linked modular stations and automated guided vehicles [9]. The AHDS needs a dynamic approach for production planning and control (PPC). This approach combines short-term capacity adaptations, e.g. reconfiguration in between shifts, and dynamic order release and order allocation to handle the dynamics and uncertainty in product quantity, variance and conditions as well as within the disassembly processes [11]. This dynamic production planning and control approach proposes short-term reconfigurations of the AHDS in order to adapt to fluctuating order loads and varying needed disassembly processes. Based on the current system configuration, the products to be disassembled etc. a dynamic order release and allocation mechanism is performed. The approach aims for a robust performance under uncertainty and the resulting disruptions which can occur due to process failures. It is based on the work from Wurster [11].

2. State of the art

There is a great and rising interest on disassembly planning and control in academia, with many relevant articles. However, none of the existing works fulfill the requirements for controlling AHDS. Multiple works were identified that address reactive disassembly planning and control. Works from Zussman, as in Zussman & Zhou [12], investigate adaptive planning of disassembly processes, such as process modelling and product modelling, using Petri nets to model the product structure and its associated disassembly processes. Tang et al. [13] model a flexible disassembly system and design a disassembly planning and control approach to optimize for system throughput. Guide et al. [14] investigate priority rules in scheduling a remanufacturing system. Control approaches for hybrid disassembly systems are presented in Kim et al. [15] and Kim et al. [16]. Duta et al. [17] present an approach for order allocation of disassembly operations. Hrdina and Zülch [4] present an adaptive and dynamic reactive disassembly control approach that can handle disruptions and highlight necessary flexibility aspects of matrix structured production systems. Paschko et al. [18] propose an order release control approach for remanufacturing while considering high uncertainties. On the topic of capacity planning and the reconfiguration of production systems in remanufacturing, Eguia et al. [19] present the vital term reconfigurable disassembly system and propose a methodology for designing, scheduling and sequencing in such a system. Andersen et al. [3] explore the challenges and enablers in designing and operating

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remanufacturing systems, presenting their reconfigurable system approach which builds on modularity and automatability. Flexibilities which constitute challenges include small lot sizes of one, deviations in product condition (represented as quality classes), high product variant variability, fluctuating product volume, individual routing, diverging product structure and risk of failure at the stations (stochastically modeled disturbances). None of the existing approaches sufficiently fulfills all of the necessary flexibility requirements of AHDS. This work highlights an adaptive production system control, which aims for a robust and performant AHDS.

3. Dynamic PPC approach

The dynamic PPC approach for disassembly (D-PPC) consists of two separated aspects: system reconfiguration and dynamic-reactive scheduling (order release and order allocation). The system configuration is based on a Mixed Integer Linear Programming (MILP) for capacity planning [11]. The system is reconfigured by adding, removing or substituting stations in order to adapt to fluctuating order loads in short-term periods (e.g. in between shifts) [20]. This paper will focus on the order release and order allocation part of the D-PPC but will also show its effect when combined with the system reconfiguration. The order release procedure aims to limit and optimize the work-in-progress inventory. The order allocation procedure is reactive in nature and employs priority rules for decision making, using a multi-priority rule procedure and an automated logical adaption of the rule weighting parameterization. The maximization of the system throughput is considered as the main optimization objective. Lead time is also examined in the experiments. The modeling and implementation of this approach build upon Wurster et al. [21]. Each disassembly order o is an instance of exactly one product variant v of quality class q. Main orders $o_{main} \in O_{main}$ generate corresponding sub orders o_{sub}, due to the disassembly operations and the resulting diverging material flow. The complete disassembly process after inspection is considered. It is assumed that product structures and their associated possible disassembly sequences are supposed to be known. Product structure and quality condition, which influence the required steps and the feasibility and likelihood of success in executing the individual disassembly tasks are considered. Potential fails in disassembly tasks are considered. Backup operations on manual stations, including the required rerouting are regarded. Feasibility and likelihood of success of disassembly tasks therefore depend on the station type $st \in \{MS, FRS, AS\}$, their resources R_s, product variant v and quality class q. Employing the capability-oriented reference model [22], stations have disassembly capabilities. Each station s is of a station type st, installs resources R_s with capability-space C^r_{OP} of resource r with the corresponding operation duration t_{op} and success-probabilities $p_{succes,\ op}$ of disassembly operation op. Operation durations vary depending on the station type, disassembly task and quality class, and are beta distributed. Each station has an input buffer ipb and output buffer opb with capacities $n^{max}_{ipb,\ s}$ and $n^{max}_{opb,\ s}$. The position of a station l in the production system layout is fixed for each period. The system-layout L defines these positions l including the positions of the source, stations (pos_x) and sinks by $L = \{src,\ pos_1, pos_2, \ldots, snk_1, snk_2, \ldots\}$. The transportation matrix is given by $D^{L \times L} \in \mathbb{R}^{|L|x|L|}_{\geq 0}$.

3.1. Order release

In the order release, orders of the order inventory O_{main} are moved to the work-in-progress order inventory O_{wip} with $|O_{wip}| = n_{wip}$. The focus is to restrict the work in progress backlog n_{wip} according to the CONWIP control principle. Orders are released until the maximal allowed work-in-progress inventory n^{max}_{wip} is reached: $n_{wip} < n^{max}_{wip}$. For non-static reconfigurable systems with varying order loads, fixing n^{max}_{wip} to a constant value is not advisable to prevent underload and overload, therefore in this work we aim for a dynamic capacity-oriented approach by coupling n^{max}_{wip} to the buffer capacities as the central parameter. We differentiate between two approaches. In the order-centric control approach OIP (orders in progress) the work-in-progress inventory is coupled to the number of main orders in the system $n_{wip} = n_{OIP}$ (number of main orders in progress). The alternative approach, based on the consideration of diverging material flow, that is the resulting sub orders o_{sub}, is a component-centric control approach CIP (components in progress) where $n_{wip} = n_{CIP}$ (number of components in progress).

The upper bound n^{max}_{xip} (xip standing for x in progress) of CONWIP is given according to the CONWIP coefficient c_{cw}, the scaling constant c_{scal} and the input buffer capacity $n^{max}_{ipb,s}$ of each station s within the existing stations S_k:

$$n^{max}_{xip} = c_{cw} * c_{scal} * \sum_{s \in S_k} n^{max}_{ipb,s} \tag{1}$$

Scaling constant c_{scal} serves for rough tuning of OIP and CIP, whereas conwip coefficient c_{cw} is used for fine-tuning. An additional criteria is that the amount of work in progress inventory (xip), must be lower than the upper bound $n_{xip} < n^{max}_{xip}$. When all release criteria are met, matching main orders are released into the system.

3.2. Order allocation

After orders are released, the orders must be recurrently allocated/dispatched to a station according to their disassembly operations. Heuristics such as priority rules are a suitable approach that is reactive and commonly used in scheduling production systems, due to their high efficiency, robustness, decision-making quality and explainability [23]. However, the solitary application of individual priority rules for order allocation may lead to short-sighted and greedy behavior. Therefore, a Multi-Priority Rule Procedure (MPRP), including an automated logical adaption is presented which is based on Wurster et al. [20], that combines multiple rules, enabling a robust and efficient system performance. The number and type of rules can be flexibly tailored to the specific intricacies of the individual use case. In this work, we focus on the following, most widely used rules: Lowest Buffer Utilization (LBU) promotes an even distribution of operations across the stations of the system based on the buffer capacity, Shortest Processing Time (SPT) prioritizes operations with short execution durations, Highest Success Probability (HSP) prioritizes effective operations with a high probability of success, Lowest Transport Effort (LTE) focuses on avoiding transport operations and Lowest Station Cost (LSC) prioritizes operations at stations with low costs. The individual decision values $v_\pi(op)$ of each priority rule π for an operation op are combined through a convex sum through a weighted rule combination:

$$v(op) = \sum_{\pi \in \Pi} v_\pi(op) * w_\pi \tag{2}$$

with priority rules $\pi \in \Pi = [LBU,\ SPT,\ \ldots]$, $v_\pi(op)$ being the value of the priority rule and w_π being the weighting of the priority rule, with $\sum_{\pi \in \Pi} w_k = 1$ and Op_{pot} being the action-space. According to Formula 3 the best operation $\widehat{op}$ is:

$$\widehat{op} = \underset{op \in Op_{pot}}{\operatorname{argmax}}\, v(op) \tag{3}$$

Further we will elaborate on the logical adaption of the order allocation. The MPRP consists of two essential components: a set of priority rules $\pi \in \Pi$ and their corresponding weightings w_π of weighting vector $W = [w_{\pi_1}, w_{\pi_2}, \ldots w_{\pi_n}]$. The impact of a priority rule is inherently tied to its corresponding weighting factor. Adjusting the weights allows a dynamic adaption to changing conditions, such as changes in the production program, production system configuration and system loads. The logical adaptation allows for an automated adjustment of the weights. This ensures the generalization of the order allocation procedure by finding and adapting to the optimal rule weightings W. Finding the optimal rule weightings W is only possible through simulation-based techniques. Considering a multi-dimensional search space and its search/computation time, combining the simulation-based approach with metaheuristics is a suitable method for the approximation and subsequent adaption of the optimal weights. This approach uses Particle Swarm Optimization (PSO) as the metaheuristic method for the maximization problem.

4. Results

The use case is built on remanufacturing of small electric motors in an AHDS [9] and implemented in a discrete-event simulation

Table 1
Configuration for the experiments

Attribute	MS	FRS	AS
Number of stations	12	12	6
Backup-station type *st*	–	MS	–
Stochasticity of the operation duration	beta distributed	beta distributed	deterministic
Capacity of input buffer $n^{max}_{ipb,s}$ [*Amount*]	20	20	20
Resource costs $c_{r,operation}$ [*MU*/min]	1	0.15 (variable)	0.1
Resource integration costs $c_{r,+}$ [*MU/s*]	50 (300)	100 (1500)	200 (1500)
Resource removal costs $c_{r,-}$ [*MU/s*]	25 (100)	50 (500)	100 (500)
Success probability $p_{success}$ [%]	100	$\leq$ 100	100
operation duration t_{op} [min]	0.2–4	0.5–4	0.7–0.9

which serves as interaction environment for the D-PPC. Six product types were defined, which specifically vary in quality classes, product structure and disassembly sequence. All product types consist of four to six components, that are disassembled in five to eleven disassembly steps. Product types with a strict disassembly sequence and product types with a complex and diverging disassembly sequence are considered. For most of the regarded products many different disassembly sequences are possible. Table 1 presents resource configuration parameters. In the experiments a base case is considered where all six different products are disassembled. A medium-sized disassembly system is considered. It consists of 12 manual stations *MS*, 12 flexible robotic stations *FRS*, and 6 automated stations *AS*.

4.1. Order release

In the experiment on order release, a comparison of the two CONWIP-order release approaches, CIP (components in progress) and OIP (orders in progress), was conducted in terms of average throughput and average lead time, with the CONWIP limit varied through the CONWIP coefficient c_{cw} (Fig. 1).

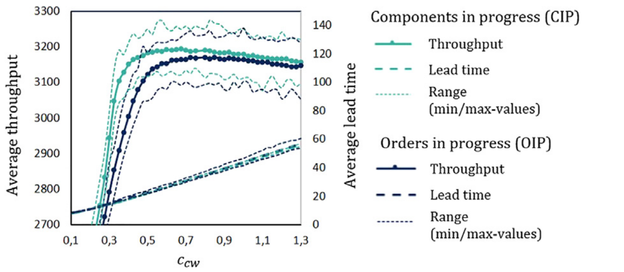

Fig. 1. Performance comparison of CONWIP order release approaches CIP and OIP and showing the impact of varying the CONWIP limit through CONWIP coefficient c_{cw} [11].

According to the dilemma of process planning, a typical characteristic curve for production systems can be observed for both metrics. For low c_{cw}, the potential system performance is not reachable due to the low work-in-progress inventory, resulting in underutilization. Continuously increasing c_{cw} leads to a continual increase in performance. At a certain point, the maximum system performance is reached, representing the optimal point between under and overload, which is around $c_{cw} \approx 0.5$. When comparing CIP and OIP, CIP consistently performs better than OIP due to better throughput and comparable lead time. This can be explained by the material flow divergence, with CIP allowing for a more stable operation.

4.2. Order allocation

In the order allocation experiments, multiple evaluations were conducted to validate the order allocation approach.

A preliminary experiment was performed to compare the performance of single-criterion priority rules for order allocation. A random (RAND) priority rule is additionally used for benchmarking, which allocates operations at random. The results indicate that LBU significantly outranks the other priority rules in terms of throughput and lead time. Consequently, for further experiments, we focus on LBU for the multi-

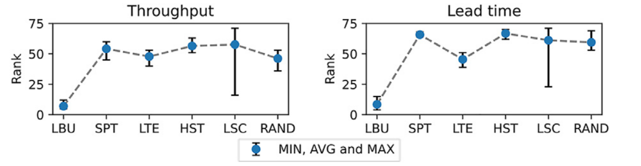

Fig. 2. Ranking of effectiveness of single-criterion priority rules in order allocation. Considered where various cases with varying product (mixes) and a variation in number of each station type, based on [11]. RAND providing a benchmark.

criteria priority rules in terms of usage and weighting, and it will also act as a benchmark. The detailed results can be seen in Fig. 2.

In the experiment for the proposed MPRP approach two combinations of 3-priority rules were considered: the LBU-HSP-SPT combination and the LBU-LSC-LTE combination. This experiment highlights differing performance in the same use case when using different priority rules. The impact of different weightings on the mean throughput is shown and visualized in the form of a ternary graph, as seen in Fig. 3. The results indicate significant potential in performance optimization through rule selection and changing the weights. For the LBU-HSP-SPT combination, the mean throughput ranged from a maximum of 2941.48 average finished main orders to a minimum of 1528.48. Similarly, for the LBU-LSC-LTE combination, the mean throughput ranged from a maximum of 2799.92 average finished main orders to a minimum of 1418.92. A high weighting of LBU consistently brought the best performances for both multi-rule combinations, demonstrating its effectiveness in optimizing throughput.

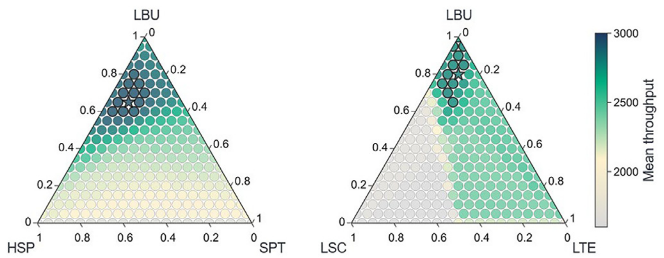

Fig. 3. Performance of order allocation using the Multi-Priority Rule Procedure showing the impact of varying weightings w_π. Both triangles show the combination of 3 priority-rules. LBU-HSP-SPT-rule combination (left) and LBU-LSC-LTE-rule combination (right).

In the following we want to highlight the sensitivity of throughput to changes in the number of stations, with a successive increase in the number of manual stations. The results indicate a significant shift in the optimal weighting of the rule combination due to these changes (Fig. 4). For example, for the LBU-HSP-LSC multi-criteria rule combination it can be observed that using only 2 manual stations (green star) has a lower HSP weighting (0.05) for the optimal performance than for 9 manual stations (0.45 at the green bordered diamond). This shift suggests that an adaptation of the weights is necessary to guarantee optimal performance. The results further support Wurster et al. [20] and show the importance of dynamically adjusting the weightings of priority rules in response to

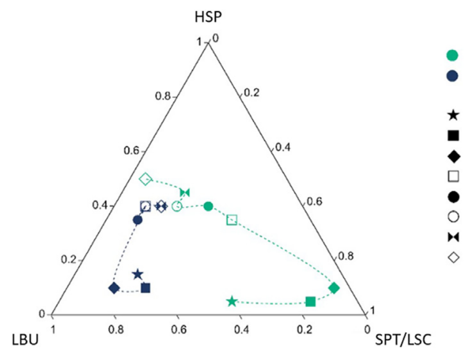

Fig. 4. The optimal MPRP performance of order allocation indicates a shifting of the optimal weightings w_π, when increasing the number of manual stations in two exemplary rule-combinations [11].

variations in the number of stations to maintain high throughput and overall system efficiency.

4.3. Analysis of the dynamic approach

In the final experiment of the dynamic D-PPC approach, the performance in terms of costs is compared between various settings in the D-PPC. This includes CONWIP and its parameterization c_{cw}, priority rules and their weighting W, as well as the automized logical adaption through Particle Swarm Optimization (see Table 2). Various use cases were considered in a multi-period experiment. In between the individual periods, system reconfigurations were employed according to the MILP-based capacity planning aspect of the dynamic D-PPC. This step is completely independent of the order release and order allocation procedure. However, changes in the system configuration might influence the effectiveness of the current order release and order allocation procedure. Only with logical adaption the control parameters will automatically be updated. A planning horizon in capacity planning of 10 periods was regarded. Initially, an experiment was conducted with immediate order release and random order allocation (*ior*) as a baseline. Subsequently, CONWIP order release was integrated with different allocation methods: random order allocation (*rnd)*, a single criterion priority rule approach based on LBU (*lbu)*, integrating the MPRP approach with a robust static parameterization (*rp)*, and the fully integrated approach with a logical adaptation of the weights using PSO (*pso)*.

Table 2
Specifications of the considered D-PPC configurations

D-PPC Abbreviation	D-PPC Field of action		
	Order release	Order allocation	Logical adaption
ior	Immediate order release	Random	–
rnd	CONWIP $c_{cw} = 0.5$	Random	–
lbu	CONWIP $c_{cw} = 0.5$	$w_{LBU} = 1$	–
rp	CONWIP $c_{cw} = 0.5$	$w_{LBU} = 0.55$ $w_{HSP} = 0.35$ $w_{SPT} = 0.1$	–
pso	CONWIP $c_{cw} = 0.5$	dynamic	PSO

Fig. 5 shows the results of the fully integrated D-PPC approach (*pso*) compared with other D-PPC configurations. The *ior* configuration exhibits the worst performance, while the *pso* configuration demonstrates the best performance. Successive integration of components and optimized parameterization leads to better performance. The biggest discrepancy among the configurations is observed in delay costs. The control approach lowers operation costs, when comparing random order allocation (*ior* and *rnd*) to single criterion PR (*lbu*) and MPRP (*rp* and *pso*). Between single-criterion PR (*lbu*) and MPRP (*rp* and *pso*), the differentiation in performance is only significant in terms of lowered delay costs. The results highlight that the lack of a structured order release and order allocation leads to a performance deficit and significantly higher delay costs. The dynamic logical adaptation of MPRP allows for optimization in a multi-period evaluation.

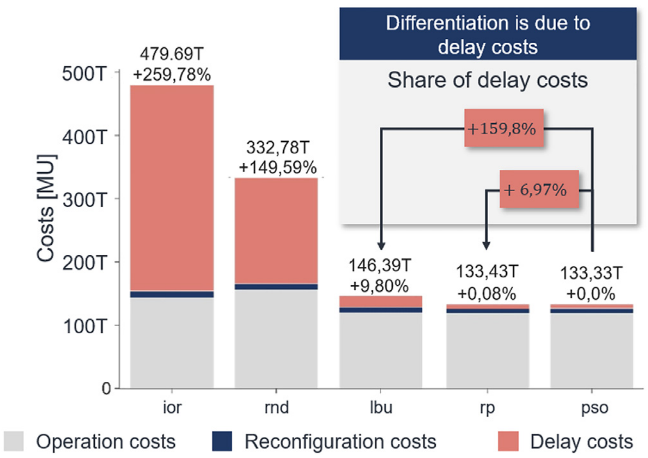

Fig. 5. Comparison of the resulting costs for the D-PPC configurations specified in Table 2, based on [11].

5. Conclusion

This work presents a dynamic D-PPC approach for hybrid disassembly systems in remanufacturing, highlighting its order release and order allocation. The reactive control consists of CONWIP order release combined with a Multi-Priority Rule order allocation, incorporating automated logical adaptation of weightings. Its advantages are: reactive nature, which is required in a remanufacturing environment with many uncertainties; explainability due to the easy-to-understand priority rules, real-time capable order allocation and automatic adjustment of the control parameters (weighing W). Experiments validate the effectiveness of the approach. It can be clearly stated that a CONWIP order release based on the number of components is more effective than based on the number of products in terms of average throughput and lead time. Within the order allocation, different priority rules lead to significant differences in throughput and lead time. LBU seems to perform good overall, however, a combination of priority rules is to be preferred. If the system configuration changes due to different order loads and other factors, the weighing of the priority rules is to be adapted. Consequently, the order allocation should not be a fixed ruleset. Especially in the very volatile field of remanufacturing a dynamic PPC is required. The economic results indicate that especially the delay costs can be reduced by the dynamic D-PPC. Operation and reconfiguration costs aren't affected significantly. Main improvements can be made with the component based CONWIP order release and the implementation of LBU as a single priority rule already. Consequently, this constitutes the minimal requirement of a PPC for an adaptive disassembly system. The implementation of the fully dynamic D-PPC including logical adaption would further improve the total costs by almost 10 % in the use case and is thus recommended. Especially in very volatile settings, the advantages of the logical adaption will gain importance as can be well observed for varying system configurations (Fig. 4). Overall, this promising approach showed that the ideal PPC depends on the system configuration and therefore should be adapted as the system configuration changes. Also, the ideal system configuration likely depends on the employed control. Therefore, the mutual influence must be taken into consideration both in configuration and control of the AHDS, especially when the system is reconfigured constantly. Further work in the CRC 1574 will focus on an even stronger consideration of the control in the configuration and vice versa, aiming for feedback and a strong integration of planning and configuration. An integrated procedure could further reduce output losses and costs.

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.

CRediT authorship contribution statement

Marco Wurster: Writing – review & editing, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fabian Erlenbusch:** Writing – original draft, Resources, Formal analysis. **Finn Bail:** Writing – review & editing, Validation, Software, Data curation. **Gisela Lanza:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Nicole Stricker:** Writing – review & editing.

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