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A Control Architecture for Robust and Resilient Circular Factories under Uncertain Conditions

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Abstract

Resource depletion and environmental harm highlight the need for more sustainable manufacturing methods like circular manufacturing. Circular manufacturing methods such as remanufacturing introduce uncertainties that arise due to core variability, leading to the frequent occurrence of disruptions. Therefore, an automated control structure is needed that can maintain stable high performance in the face of such uncertainties and disruptions. We present a novel architecture that is designed to enhance the resilience and robustness of automated circular factories. To achieve this, we propose a two-level approach resembling a cascaded control system. The outer layer, the production system level, is designed to ensure resilience by maintaining overall factory operations during larger disruptions. In contrast, the inner layer, the station level, focuses on robustness, managing minor disturbances and failures at individual stations. We address the allocation of responsibilities between these two levels and the modeling of commands. Our approach considers a novel integration of production stations, inspection stations and an intelligent intralogistics system to allow for a flexible and adaptable automated production system. Our approach presents the first control architecture specifically designed to address the unique uncertainties and disruptions arising from core variability in circular manufacturing.

Keywords: Circular Manufacturing, Automated Control Systems, Production System Resilience, Factory Robustness

1. Introduction

In the face of escalating resource depletion and environmental harm, the need to move towards more sustainable manufacturing methods has become evident [1]. Remanufacturing is emerging as a critical approach in this context [2]. It serves as a strategic countermeasure to the inefficient consumption of raw materials and the increase in waste. It is an advanced recovery process that aims to restore end-of-life products to equivalent or superior functionality, thereby extending their life cycle and conserving embodied energy and materials [3].Circular Factories can be seen as flexible and autonomous production system in which linear and circular production is integrated [4]. However, implementing remanufacturing systems on an industrial scale with high levels of automation, which is crucial for widespread adoption, is challenging due to significant scientific and operational complexities. The inherent uncertainty in the quality and quantity of end of life or previously remanufactured components requires sophisticated decision making within the remanufacturing system [5]. The complex nature of processing end-of-life products introduces a distribution of possible product states due to variations in what has occurred over each product's lifetime. This variability makes processes nondeterministic in terms of process times and the likelihood of successful operations. The manifold of uncertainties increases exposure to systemic disturbances, where a single disturbance can cause widespread knock-on effects, complicating process control and reliability [6]. Disturbances can be linked to failing processes, breaking products or deviations in processing times. Automated systems are particularly affected by these disturbances, as they are primarily designed for deterministic en-

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vironments. For this reason most remanufacturing is currently driven by human workers. To prevent knock-on effects caused by these challenges, this paper presents a control architecture that aims to enhance the resilience and robustness of automated circular factories. We argue that effectively integrating remanufacturing within these systems requires a two-level architecture that, together, increases both system robustness and resilience. To understand the problems of current control architectures for remanufacturing systems, the related work in this area is first presented and the research gap is elaborated in section 2. Subsequently, the architecture developed in this work is presented in section 3 and is demonstrated on the basis of representative disturbances in section 4. Finally, the overall system is evaluated and the summary as well as the next steps are presented in section 5.

2. Related work and fundamentals

2.1. Robustness and Resilience

In the following we define the two terms resilience and robustness. According to the literature, the definition of robustness entails two qualities regarding the system's performance behavior. Robust systems stand out through a stable performance, having few and as minor deviations as possible from the original state, that is the target performance. Furthermore, they can tolerate different conditions while maintaining high system performance [7]. In our context, we employ the concept of a robust channel that defines the specific threshold and therefore the acceptable (stable) performance level. Achieving robustness is therefore the quality to stay within the robust channel, given disruptions to the system. Resilience on the other hand describes the quality to recover quickly from a disruption and to return to a stable state, but not necessarily its original state [7]. Thus, we define resilience as the quality to recover to the stable performance, that is a performance within the bounds of the robust channel, in case of large disruptions that affect the stability of the system.

2.2. Control Architectures in Remanufacturing

Research on the control of remanufacturing systems is limited and predominantly focused on addressing specific types of disruptions through rescheduling strategies. Existing approaches often fail to account for the wide range of disturbances characteristic of remanufacturing, such as process failures, tool or station unavailability, and variability in product conditions. Furthermore, these approaches tend to emphasize either robustness or resilience without fully integrating both into a comprehensive control architecture. For instance, [8] propose a hybrid disassembly system with manual and automated stations, addressing disruptions such as unavailable tools by re-planning process selection and rerouting failed tasks to manual stations. However, the approach overlooks alternative automated solutions and fails to consider more complex disruptions, limiting both robustness and resilience. Similarly, [9] develop a dynamic process planning tool that adjusts disassembly plans based on tool and station availability but restricts its focus to these specific disturbances, relying solely on reactive rescheduling. [10] integrate dynamic disassembly sequence planning and workstation assignment, allowing the system to adapt to initial variability. However, their approach does not address typical disruptions such as failing processes, leaving a critical gap in system resilience. In another approach, [11] present an agent-based control architecture that combines scheduling for disassembly and transport processes but only focuses on creating a robust initial schedule. Their system does not account for disturbances that occur during production, such as resource failures or unexpected product conditions. A more flexible solution is presented by [12], who propose a hierarchical control architecture for modular disassembly systems. Their method addresses variability by distributing operations across production system levels, stations, and elementary units. However, decision-making is centralized at the production system level, which complicates real-time adjustments and limits the system's ability to respond effectively to disturbances such as station or process failures. Decentralizing decision-making to station levels could enhance the system's ability to manage these disruptions more effectively. In conclusion, while current research addresses specific types of disruptions—such as tool or station unavailability and initial variability—no existing control architecture comprehensively handles the full spectrum of disturbances in remanufacturing systems, including process failures, dynamic product variability, and resource allocation challenges. The gap lies in the lack of a robust and resilient architecture that integrates decentralized decision-making across multiple levels, enabling real-time adaptability to diverse and unpredictable disturbances.

2.3. A remanufacturing ontology

[13] introduces an ontology for the modeling of remanufacturing systems. In total the remanufacturing ontology consists of six sub-ontologies based on the differentiation between product, process and resource (PPR). Building upon these three sub-ontologies tasks and capabilities can be defined. Tasks represent specific processes which are performed on instances of products while capabilities are processes which resources are capable of executing. Tasks and capabilities can then be matched as an operation which includes the information of the process which is executed on a product by a resource. The ontology is illustrated in Figure 1 The PPR Model allows easy integration into a control architecture as typical control decisions can be seen as the matching of tasks and capabilities.

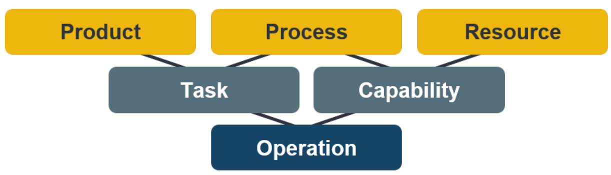

Fig. 1. Overview of the Remanufacturing Ontology based on [13]

Nevertheless the definition of resources and processes depends on the granularity of detail while looking at the remanufacturing system. This creates ambiguity as the PPR Model can be defined on different levels. For this reason we propose a control architecture based on a two level PPR ontology.

3. Control Architecture

3.1. Overview of the Circular Factory

The proposed control architecture is designed primarily for circular factories as described in [4] and [14]. It consists of modular and adaptable production hardware through which circular and linear production can be integrated within one production system. This is realized through a reconfigurable combination of different types of stations, including production and inspection stations. Depending on the demand of certain process steps, stations can be removed or added to the remanufacturing system. The individual stations are designed in a highly modular way, enabling frequent reconfiguration at the station level. The stations are interconnected by an adaptive intralogistic system consisting of a fleet of mobile manipulators which for the purposes of the control architecture is also treated as a station. The general idea is that the adaptability and flexibility allows the system to better cope with uncertainties. From a control architecture perspective this also means that there are a vast number of possible control actions the systems has to content with. For this reason a two level approach is employed.

3.2. Overview of the Two Level Approach

To achieve robust and resilient control in a circular factory facing product-based uncertainty, we propose a two-level architecture resembling a cascaded control system. The outer layer, the production system level, ensures factory resilience, while the inner layer, the station level, manages robustness by handling minor disturbances and failures at each station. This concept is illustrated in Figure 2.

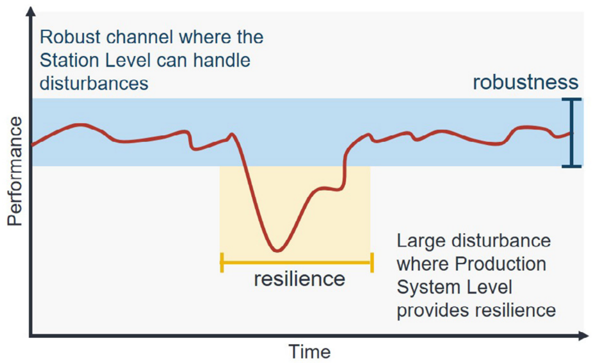

Fig. 2. Performance drops due to disturbances. The station level controller handles small issues, providing robustness. Larger issues are managed by the production system level controller, ensuring resilience.

The key question is how to allocate responsibilities between these two levels and how to model commands. Here we employ the PPR model [13], where an operation consists of a task (a change in product state) and a capability (system abilities), which in turn are made up of products, processes, and resources. A command is now formally defined as operation which specified what needs to be done on which product and with what resources.

The two levels differ mainly in their capability models. At the production system level, resources are stations offering high-level capabilities (e.g., lid removal). The resources providing these capabilities are the stations themselves. At the station level, resources are specific machines providing more granular capabilities (e.g., unscrewing a screw). This means that when a production system level operation (remove the lid of product A at station 1) is send to a station it first breaks this down into a set of station level tasks (unscrew the screw, grasp the lid, remove the lid) and then in turn matches these to the station's capabilities (unscrew the screw using robot 1, grasp the lid using robot 2, remove the lid using robot 2). If a disruption occurs the station level can formulate a new set of tasks to still achieve the production system level operation. We will call this capability to adapt plan healing.
In the case of a stuck screw, the station level could decide to mill the screw off, which would be a new set of station level tasks that can be matched to the station's capabilities. If plan healing fails (e.g., due to lack of milling capability), the problem escalates to the production system level, which might reroute the workpiece to another station. The full architecture is shown in Figure 3.

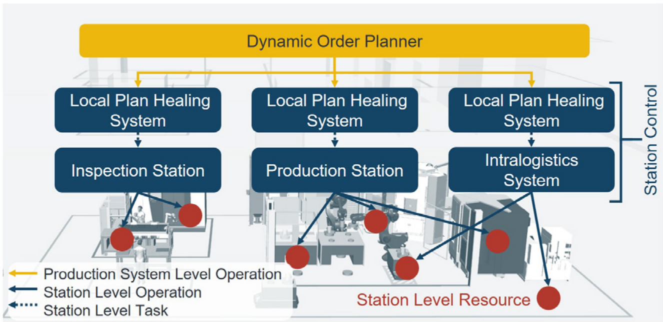

Fig. 3. The two-level architecture: the production level controls operations by translating them into station-level tasks, which are matched with capabilities under the PPR model to create station-level operations.

While the architecture outlines command flow, information flow is equally crucial. Unlike other control architectures, there is no direct information exchange between control systems. Instead, all systems write data (such as capability information) to a shared knowledge graph, which is accessed as needed. This decouples the sensing and knowledge system from the control systems, facilitating easy integration and adaptation. Figure 4 illustrates the knowledge and control flow. We will however not go into detail about the knowledge graph since it is already described here [15]. The following sections will now describe the two levels in more detail.

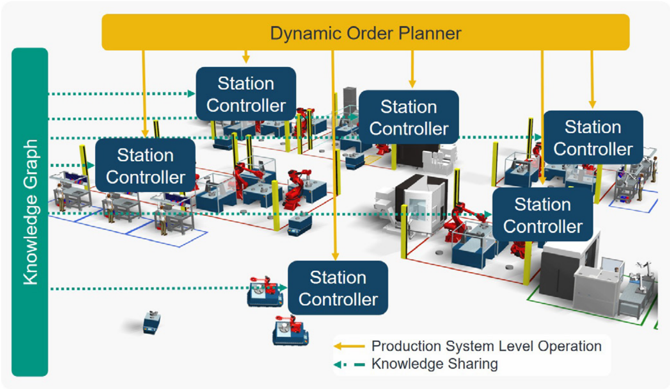

Fig. 4. Knowledge and control flow in the circular factory: all systems write to and read from the knowledge graph.

3.3. Production System level

On the production system level, the dynamic order planner schedules operations—deciding which actions to take, allocating them to stations, and ultimately controlling material flow. Due to high uncertainty in remanufacturing systems, a-priori scheduling is ineffective, as frequent rescheduling is required for failing processes and defective products. To address this, scheduling is handled dynamically in two steps: first, determining the task (e.g., remove rotor from product A), and then selecting a station to perform it. With multiple stations equipped with similar capabilities, the dynamic order planner decides which station will execute the task. This decision making is done using a reactive scheduling method, such as priority rules or reinforcement learning. The combination of product, process and station make the decision an operation on production system level. The output of the dynamic order planner are operations which consist of the following information:

- Process which is executed
- Product on which the process is executed
- Station resource which executes the process

Note that the capabilities of each system are necessarily probabilistic as the intrinsic uncertainty of the product means that cycle times or even binary capabilities follow probability distributions. These capabilities depend on the configuration of the system and are reported by each station through the knowledge graph. If new capabilities are required for a new product the production system level is also responsible for deciding which stations need to be reconfigured. Depending on the extent of required adjustments the reconfiguration takes place at different times. While smaller production modules can be relocated between stations during production dynamically, larger adjustments which require significant station downtime are executed between shifts. The continuous reconfiguration of capabilities aims towards increasing the resilience of the production system. As a reminder these capabilities are defined at the station level and are more general (i.e. remove the lid) than the station level capabilities (i.e. drilling, unscrewing, milling). Needless to say that tasks, capabilities, and operations which build on the definition of products, processes and resources also differentiate to the station level.

3.4. Station Level

In order to successfully implement the operation specified by the dynamic order planner, it is imperative to further refine and adapt the chosen operation to the unique circumstances of individual stations. This involves translating the broader objectives into specific actions tailored to the capabilities of a station.

3.4.1. Local Plan Healing System

Planning at production system level indicates, for a given station, the task to be carried out (removing the rotor from product A). To properly define an operation at station level, we need to change the granularity and be more precise. Therefore, resources are the various machines that make up a station, and processes are the actions that can be carried out (unscrewing screw 3). So an operation at station level is defined as follows:

- Precise process which is executed
- Product on which the process is executed
- Machine resource which executes the process

The next step is to propose a sequence of operations, which ultimately constitutes an operation at production system level (removing the rotor from product A in the station). However, disruptions can occur. In such cases, the aim is to be able to tell automatically whether the disruption can be corrected, and if so to rectify the schedule – this is the plan-healing (see Figure 5). Plan healing must be able to deal with stations in all their diversity, which is why strategies based on Reinforcement Learning, which would require learning for each possible station, are not used. Instead, a formal description of the station is employed to have an interactive feedback controller that proposes a deterministic policy. This policy relies on mathematical guarantees and allows, when possible, each process step to follow a sequence of operations that achieves the objectives set at the system process level. Station level is the right level to do plan-healing, because it is smaller and therefore easier to describe, is less sensitive to disturbances (which could accumulate along the production line), and gives more reliable results.

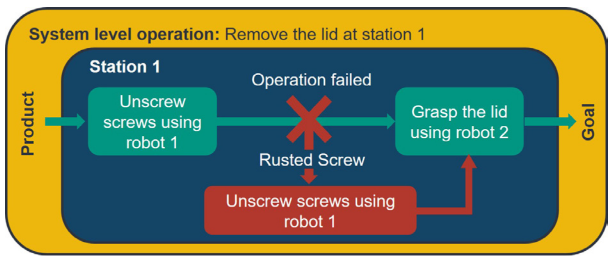

Fig. 5. Example of plan healing for a product disruption. Green marks the initial sequence of operations at the station level to achieve the goal given at the system level. Red marks the new plan.

3.4.2. Production and Inspection Stations

The production and inspection stations form the core of the circular factory, managing both remanufacturing and quality control. Each station builds a capability model that reflects not only the available modules but also their configuration, which plays a key role in determining the station's performance. These capability models are probabilistic, capturing success probabilities for production stations and measurement accuracies for inspection stations. They are used to match tasks from the local plan healing system with the station's resources and report possible operation times to help the production system optimize scheduling. The stations are highly modular and adaptable, allowing the production system level to reconfigure them by adding or removing modules. While the production system defines the required capabilities and provides the necessary modules, the station level is responsible for determining the optimal configuration of these modules, as the configuration significantly impacts performance [16]. Beyond reporting capabilities and optimizing configurations, the stations are responsible for in-process inspection and controlling their specific processes, such as robotic movements, sensor settings, or process parameters in additive manufacturing. They continuously monitor these processes and report any deviations to the production system level, aiming to resolve disruptions early to minimize the need for even just plan healing.

3.4.3. Intralogistic System

The intralogistics system in the circular factory is not only used to move products between stations, but also to pick material from storage and buffer modules and reconfiguring the automated stations. For this, the intralogistics consists of multiple mobile manipulators equipped with heterogeneous modules. The modules themselves are not capable of movement; however, they can be utilized by the mobile manipulators to fulfill the specialized processes of buffering, transporting and manipulating products. The intralogistics system operates at the station level, receiving production system level operations. Since the intralogistics system is a decentralized controlled system, consisting of self controlled units, the system level operations are broken up into individual station level tasks that are allocated to the different resources (mobile manipulators and modules), creating teams to fulfill unique station level operations. This can be modelled as a multi-robot task allocation problem, an overview of which can be found here [17]. The mobile manipulators are equipped with the necessary navigation capabilities to traverse the circular factory and dock with the modules. The buffer modules are mobile storage units with the capacity to accommodate a variety of products in different locations. Transport modules are employed for the conveyance of products from one location to another. The manipulator module comprises a robotic arm with the capability to recognize products with camera sensors and facilitate object-centric or affordance-constrained grasp execution, which is planned by the intelligent grasp planner with uncertainty quantification [18] and incremental learning mechanism. This enables adaptive manipulation and transfer of products across various stations and other intralogistics modules under the uncertainty-based constraint, as the first guarantee for operational success. In general, the manipulator acts as the reciever of operational commands generated by the module itself. In case of an unsuccessful operation, the intralogistics system will create operations to fulfill the production system operations utilizing the buffer in the schedule. These operations involve repeated grasp analysis and continual learning on negative data samples to refine grasp planning [19] for instance. If deviations from planned operations exceed acceptable thresholds, the system engages a feedback loop to communicate with the production level, prompting a revised schedule that better accommodates current operational demands and constraints. The reconfiguration of a transformer cell functions similarly, creating a sequence of operations to move the different units in the transformer cell.

4. Coping with Disruptions

Through the high degree of uncertainty in the circular factory disruptions occur in a frequent manner. Examples for such disruptions are linked to failing processes, breaking products and deviations in processing times. Depending on the kind of disruption this can have an affect on a production system level or on a station level. Depending on the kind of disruption the control architecture has to react on the according level.

4.1. Disruptions on station level

Station-level disruptions, based on the PPR model, are classified into product, process, and resource disruptions. Product disruptions occur when the product does not behave as expected, such as a rusted screw preventing unscrewing. These disruptions alter the product's state, which is recorded in the knowledge graph. Measurement of these altered states is performed by the station after the operation, and plan healing proposes new tasks —such as milling the screw— to achieve the desired state. Process disruptions affect the process itself, regardless of the product's condition. This could involve issues like a robot failing to pick up a part due to noisy sensor data or process parameterization problems like chatter. If detected immediately, these disruptions are handled similarly to product issues, but more subtle issues like chatter may only surface later, requiring escalation to the production system level. Resource disruptions involve failures in hardware or software, such as a broken tool or a robot controller crash. These disruptions change the system's capabilities temporarily causing a update in the knowledge graph. Plan healing adjusts to the new resource limitations, such as using a different milling strategy with the remaining tools.

4.2. Disruptions on production system level

Disruptions on production system level are of more serious matter and require an adjustment of the initial scheduling. The source of such disruptions is congruent as those handled on a station level also being based on product, process and resource disruptions. Note that we are using the station level product, process and resource definition here as station process or resource disruption are both types of production system resource disruption, but they need to be handled differently. Disruptions on production system level always go hand in hand with an adjustment of the schedule. A disruption gets escalated on production system level if the station signals that it can not react with the capabilities equipped at the station, ultimately meaning that the disruption exceeds the existing robustness corridor of the subsystem. The second reason for escalations on production system level is that necessary adjustments in the process selection have a large impact on subsequent processes and the overlying global schedule. If a station detects that a cap can not be removed in non-destructible manner as the originally determined process failed the station delegates the decision to the production system level, as the recovery of the components might be critical on a larger level. The latter example demonstrates that disruptions affect not only the disassembly process but also the reprocessing and reassembly processes within the circular factory.

5. Conclusion and Discussion

The control architecture introduced in this study addresses uncertainties and disruptions in circular manufacturing. Unlike existing approaches, which focus on isolated disruptions our framework enables real-time adaptability to a broad range of disturbances. By decentralizing decision-making to station levels, we enhance the system's resilience and responsiveness, allowing for more effective disruption management.

However its effectiveness is based on critical assumptions about the availability of information. It assumes that plan healing systems can accurately measure the state of products, processes, and resources. While process and resource supervision is well-established in manufacturing, product perception presents significant challenges due to the need to identify defects in highly variable and evolving products. This limitation underscores the reliance on advanced AI technologies, such as machine learning and computer vision, which are indispensable for detecting, classifying, and predicting product conditions. Without these technologies, the system cannot function as intended. Another challenge lies in ensuring that the system can handle the variability of product conditions inherent to circular manufacturing. Inaccuracies in defect detection or resource evaluation could compromise the system's ability to adapt effectively, even with proper plan healing and task scheduling. Interdisciplinary collaboration is essential to address the data, computational, and reliability demands of the AI technologies integrated into the system as outlined in [20]. By addressing these challenges, the proposed architecture can evolve to meet the demands of circular manufacturing, supporting more sustainable and resilient production systems.

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References

[1] N. Nasr, M. Thurston, Remanufacturing: A key enabler to sustainable product systems, Rochester Institute of Technology 23 (2006) 14–17.
[2] M. Kerin, D. T. Pham, A review of emerging industry 4.0 technologies in remanufacturing, Journal of Cleaner Production 237 (2019) 117805.
[3] D. A. Paterson, W. L. Ijomah, J. F. Windmill, End-of-life decision tool with emphasis on remanufacturing, Journal of Cleaner Production 148 (2017) 653–664.
[4] G. Lanza, B. Deml, S. Matthiesen, M. Martin, O. Brützel, R. Hörsting, The vision of the circular factory for the perpetual innovative product, at-Automatisierungstechnik 72 (9) (2024) 774–788.
[5] S. Sitcharangsie, W. Ijomah, T. Wong, Decision makings in key remanufacturing activities to optimise remanufacturing outcomes: A review, Journal of Cleaner Production 232 (2019) 1465–1481.
[6] J. Bokrantz, A. Skoogh, T. Ylipää, J. Stahre, Handling of production disturbances in the manufacturing industry, Journal of Manufacturing Technology Management 27 (8) (2016) 1054–1075.
[7] M. Benfer, B. Verhaelen, S. Peukert, G. Lanza, Resilience measures in global production networks: A literature review and conceptual framework, Die Unternehmung 75 (2021) 491–520.
[8] H.-J. Kim, M. Ciupek, A. Buchholz, G. Seliger, Adaptive disassembly sequence control by using product and system information, Robotics and Computer-Integrated Manufacturing 22 (3) (2006) 267–278.
[9] H.-J. Kim, S. Chiotellis, G. Seliger, Dynamic process planning control of hybrid disassembly systems, The International Journal of Advanced Manufacturing Technology 40 (2009) 1016–1023.
[10] Y. Tang, M. Zhou, R. Caudill, An integrated approach to disassembly planning and demanufacturing operation, IEEE Transactions on Robotics and Automation 17 (6) (2001) 773–784.
[11] S. Groß, W. Gerke, P. Plapper, Agent-based, hybrid control architecture for optimized and flexible production scheduling and control in remanufacturing, Journal of Remanufacturing (2020) 1–27.
[12] M. Wurster, J.-F. Klein, J.-P. Kaiser, S. Mangold, K. Furmans, M. Heizmann, J. Fleischer, G. Lanza, Integrierte steuerungsarchitektur für ein agiles demontagesystem mit autonomer produktbefundung, at - Automatisierungstechnik 70 (6) (2022) 542–556.
[13] J. Pfrommer, J.-F. Klein, M. Wurster, S. Rapp, P. Grauberger, G. Lanza, A. Albers, S. Matthiesen, J. Beyerer, An ontology for remanufacturing systems, at - Automatisierungstechnik 70 (6) (2022) 534–541.
[14] J. Fleischer, F. Zanger, V. Schulze, G. Neumann, N. Stricker, K. Furmans, J. Pfrommer, G. Lanza, M. Hansjosten, P. Fischmann, et al., Self-learning and autonomously adapting manufacturing equipment for the circular factory, at-Automatisierungstechnik 72 (9) (2024) 861–874.
[15] C. Hofmann, S. Staab, M. Selzer, G. Neumann, K. Furmans, M. Heizmann, J. Beyerer, G. Lanza, J. Pfrommer, T. Düser, et al., The role of an ontology-based knowledge backbone in a circular factory, at-Automatisierungstechnik 72 (9) (2024) 875–883.
[16] J. Baumgärtner, P. Gönnheimer, J. Fleischer, Optimal robot workpiece placement for maximized repeatability, in: M. Valle, D. Lehmhus, C. Gianoglio, E. Ragusa, L. Seminara, S. Bosse, A. Ibrahim, K.-D. Thoben (Eds.), Advances in System-Integrated Intelligence, Springer International Publishing, Cham, 2023, pp. 252–261.
[17] B. P. Gerkey, M. J. Matarić, A formal analysis and taxonomy of task allocation in multi-robot systems, The International journal of robotics research 23 (9) (2004) 939–954.
[18] Y. Shi, E. Welte, M. Gilles, R. Rayyes, vmf-contact: Uncertainty-aware evidential learning for probabilistic contact-grasp in noisy clutter, arXiv preprint arXiv:2411.03591 (2024).
[19] Y. Shi, P. Schillinger, M. Gabriel, A. Qualmann, Z. Feldman, H. Ziesche, N. A. Vien, Uncertainty-driven exploration strategies for online grasp learning, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2024, pp. 781–787.
[20] M. Heizmann, J. Beyerer, S. Dietrich, L. Hoffmann, J.-P. Kaiser, G. Lanza, A. Roitberg, R. Stiefelhagen, N. Stricker, H. Wexel, F. Zanger, Managing uncertainty in product and process design for the circular factory, at - Automatisierungstechnik 72 (9) (2024) 829–843.