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R-Strategies and Artificial Intelligence for the Circularity of Tools in Forming Technologies

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Abstract: R-strategies can improve sustainability by circularity. At the same time, tool management in forming technologies is facing challenges in the transparency of tools conditions and in the efficiency of usage. Therefore, this work develops a framework which implements the R-strategies for forging tools and applies methods of artificial intelligence. Main research questions arising from the analysis are related to tool conditions, remaining lifetime, decision on the R-strategy, and scheduling.

Keywords: R-strategies, artificial intelligence, circularity, forming technologies, tool management

1 Introduction

Circularity refers to an economic and environmental model that aims to keep resources in use as long as possible, to minimize waste and to promote sustainability. R-strategies play a pivotal role in the integration of the circularity into manufacturing processes [1]. At the same time, effective tool management optimizes forming processes in manufacturing, enhancing efficiency, and prolonging their lifespan [2]. Artificial intelligence (AI) is not only capable of optimizing design for circularity, but also of improving sustainability and cost efficiency in manufacturing [3]. In this context, this brief study aims to develop a framework for the implementation of R-strategies in tool management of forming technologies, and to show AI methods applied to these R-strategies.

2 Theoretical Background

The **management of tools** in the field of **forming technologies for advanced materials** is confronted with a multitude of challenges that impede efficiency and effectiveness. These challenges originate from the growing complexity of manufacturing processes and the necessity for integrated systems that can manage tools with data and processes in an integrated and seamless manner. Wear, in particular, is identified as the main mechanism that reduces the lifetime of forging dies. [4] introduced an innovative approach to mitigate wear in closed-die forging by using sheet metal die covers. This protective cover, which is inexpensive and easy to replace, can reduce wear by up to 98 %. [5] reinforced these findings by demonstrating that the die cover concept did not only reduce wear but also decreased thermal and mechanical stresses on the die surface. In addition, [6] highlights another strategy for prolonging tool life by employing modular tool systems in forging. By utilizing segmented, modular tools, manufacturers can reduce the need for multiple dedicated preforming tools. The digital transformation necessitates the implementation of digital models for the monitoring of tool life cycles, which, however, present challenges in terms of failure prognosis, real-time monitoring, and data integration [7].

Crucial for the transition from linear to circular economy are the **nine R-strategies**, which encompass a range of strategies aimed to minimize waste and to maximize resource efficiency: **refuse, rethink, reduce, reuse, repair, refurbish, remanufacture, recycle** and **recover** [8]. Fundamental principles of AI can roughly be characterized into four groups [9, 10]: **Supervised learning** (SL) uses input and labeled data to update the AI model. If labeled data is not available, **unsupervised methods** (UL), which seek to find relevant patterns within the input data space or self-supervised methods, where surrogate objectives and labels are defined, are employed. **Semi-supervised learning** (SSL) combines unsupervised learning with easily accessible but unlabeled data and supervised learning with a much smaller, but labeled data set. **Reinforcement learning** (RL) refers a learning setting, where an agent learns to interact with an environment to fulfill predefined tasks.

3 Results and Discussion

3.1 Framework for 9R of tools in forming processes

Forming processes require significant energy and resources, making them important areas for the application of R-strategies. Refurbishing tools and machines can restore them, which further contributes to resource efficiency. Improved forming techniques with innovative tools can significantly **Reduce** material and energy excesses in preforms, leading to a more effective resource management. By refining the design and engineering of tools and components, manufacturers can achieve substantial reductions in material input while optimizing-performance and quality. Another important strategy is the **Reuse** of tools and tool segments. By minimally processing and reintroducing them into the production process, manufacturers can conserve resources and reduce waste. The application of sustainable alloys and coatings that can be used multiple times is crucial in this context. Tools and machines used in high strength metal forming are subject to considerable wear and tear. As a result, maintenance and **repair** become crucial to extend the lifespan of equipment. Regular maintenance not only ensures optimal performance but also reduces the need for new machinery. This practice has become standard in the industry, ensuring that equipment operates efficiently and reduces the risk of unexpected failures. **Refurbishing** tools by renewing tool coatings can significantly extend the life of these tools, ensuring they perform effectively for longer periods. This helps companies to maintain high-quality equipment while minimizing environmental impact. **Remanufacturing** focuses on the reprocessing of components within the metal forming sector to extend their lifespan. Many tools, in particular modular segmented ones, can be reintegrated into the production process after their use, allowing manufacturers to maximize the value of their resources. By **Recycling,** metallic tools can be reintegrated into the melting process at the end of their lifecycle, allowing them to be reprocessed for new tools. This recycling practice has become common in industry, ensuring that valuable materials are not discarded [11].

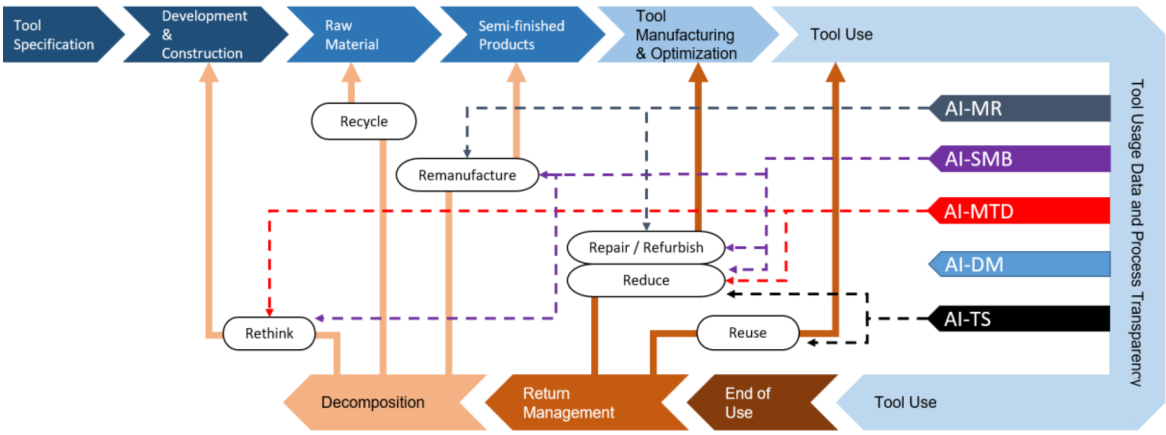

Figure 1: Framework for circularity of tools in forming technologies by R-strategies

3.2 AI for 9R in forming processes

Forming processes allow to collect huge amounts of data during the tool's lifecycle. Therefore, this study identifies several areas for informed decision making for 9R of forming tools which can benefit from data and AI.

3.2.1 AI-driven condition monitoring and remaining useful lifetime estimation

Forming tools are subject to mechanical, thermal, tribological, and chemical loads. This leads to abrasive wear, adhesive wear, cracks, and deformation which result in premature tool failure. Collecting annotated data from the production chain allows to estimate the tool condition as well as its remaining useful lifetime (RUL) using AI methods.

The data set composition governed from measurement devices inherently specifies the AI methods. Given target data, i.e. information about the tool's RUL or a label of the tool condition allows to use SL methods resulting in high performance AI models. However, as target data as well as balanced datasets with operating conditions equally represented are often unavailable, semi- and unsupervised methods can account for the unbalance and lack of labels.

AI-driven monitoring and RUL (AI-MR) constitutes as a base technology applied to different R-strategies of metal forming and as a supporting tool for informed decision making on which R-strategy shall be applied. Specifically, AI-MR predicts time and location of tool degradation and failure thereby **Reducing** redundant provision of tools. Similarly, such predictions can improve **Repair**, **Refurbish** or **Remanufacture**-strategies. Furthermore, estimating the severity of degradation can help choosing the correct R-strategy.

3.2.2 AI-driven simulation and model based approaches

A detailed and interpretable view on tool conditions can be obtained by integrating predefined degradation models into data based frameworks, extending AI-RM to AI-driven simulation and model based (AI-SMB), physics informed machine learning approaches.

Other AI-SMB approaches originates in the need for detailed, but real-time capable simulations. Finite element method (FEM) is a well-established but computationally complex tool for simulating forming processes. To reduce the computational burden of FEM, Graph Neural Networks demonstrate potential as a substitute for FEM models requiring considerably less computing times.

AI-SMB is applied in different R-strategies. Specifically, AI-SMB assists in tool design as a simulation model and hence, help to **Rethink** tool design. Further, AI-SMB enhances start-up processes by means of model based control loops to **Reduce** waste. Furthermore, similar to AI-MR, AI-SMB can increase the understanding of tool degradation assisting in strategies **Repair**, **Refurbish** and **Remanufacture**.

3.2.3 AI-driven material discovery and tool design

LLM and RL can be used to discover novel, optimized tool materials and designs. LLMs can map production conditions and product specifications to optimize tool material parameters and tool designs. RL methods allow to discover a broad space of optimal material parameters and designs. However, they require a detailed simulation or potentially expensive experiments which reflects the effects of varying material parameters and tool designs. Here, AI-SMB allow for faster simulations with sufficient accuracy.

Consequently, LLM and RL allow to **Rethink** tool material and design, enhancing production efficiency and allowing for environmental friendly material usage. Further, they lead to **Reduce** material consumption through optimized tools and more efficient forming processes as excess material and energy in preforms is reduced.

3.2.4 AI-driven decision making on R-Strategies and tool management

AI-driven decision making (AI-DM) allows an informed, data-based decision on the right R-strategy. Recommender systems assist users during decision making with tool state information by AI-SMB and AI-MR. Expert systems assist with rules defined by experienced users or inferred from data.

Apart from decision support, AI-driven tool scheduling (AI-TS) improves tool scheduling to **Reduce** redundant tools and optimizes the number of required tools while reducing tool wear due to optimal tool allocation. The latter can be enhanced by approaches from material discovery allowing for a more suitable application of tools. Furthermore, AI-TS improves insights into the availability of tools and allows to allocate used tools to R-strategies allowing to **Reuse** the tool in new production settings.

4 Conclusion and outlook

This work has shown how tools can achieve circularity in forging processes by implementing the 9 R-strategies into a framework which includes AI methods to help monitoring tool condition, estimating its remaining lifetime, improve formed components, rethinking tool material and design, scheduling tools, and deciding on most suitable R-strategy. Following research questions arise from the analysis:

- How can research develop more physically and mechanically transparent and locally observable forming processes?
- How do R-strategy aims and tool condition monitoring aims influence tool design and tool production process?
- How can innovative manufacturing and R-strategies influence tool management and R-strategies?
- How can adapted forming parameters optimize the material properties of formed components and reduce resources?
- How can sensors monitor the current forming tool condition?
- How can AI estimate the remaining lifetime of forging tools based on their current condition?
- Which R-strategy is feasible based on the current tool condition?
- Which among the feasible R-strategies provides most benefits in terms of ecologic and economic sustainability?
- How can tool condition data and chosen R-strategy optimize the combined scheduling of tools, jobs, and intralogistics?
- Which AI methods are most suitable to cover the four above mentioned areas to apply AI for 9R in forming?
- Which novel AI network architectures and algorithmic improvements allow for highly performant R-strategies?

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