Towards a Digital Decision Support Tool for Sustainable Product Design and Production

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Abstract. The European manufacturing industry faces growing pressure to reduce CO_2 emissions while maintaining competitiveness. Digital transformation presents opportunities to improve ecological and economic sustainability via advanced tools for product design and production. However, existing digital solutions often neglect environmental aspects or depend on data and models with high uncertainty and low explainability, limiting user acceptance. This paper proposes a novel framework including an innovative Decision Support Tool to help product designers and production planners predict energy and material consumption, CO_2 emissions, and related costs across the product lifecycle. This paper discusses the key elements of the Decision Support Tool, which integrates hybrid models combining knowledge-driven and AI-driven methods to enhance prediction accuracy and interpretability along with advanced visualization to improve model transparency and user trust. This work highlights critical research gaps and outlines directions for developing a user-centered Decision Support Tool for sustainable product design and production.

Keywords: Decision Support Tool (DST), Hybrid Modeling, Visualization Techniques

1 Introduction

Europe's manufacturing sector is under significant pressure to reduce CO_2 emissions [1, 2]. One potential solution lies in digital transformation, which can improve both ecological and economic performance by leveraging digital tools for sustainable product design and production [3, 4]. Despite this potential, ecological considerations are still rarely integrated—primarily due to the lack of tools that can reliably predict a product's energy consumption across the entire product lifecycle. Consequently, ecological sustainability is often assessed only late in the design phase or even retrospectively [5]. To address this gap, this paper presents a framework for a digital Decision Support Tool and outlines essential research directions to enable future work in the field of digital supported, sustainability-oriented product design and manufacturing.

2 State of the Art

Currently available digital tools in the product creation process focus on technical but often neglect environmental sustainability [6]. Additionally, these tools are often based on data and models with high uncertainty and limited explainability [7]. Furthermore, despite 74% of manufacturers believing that such digital tools are valuable for employees, they often lack user friendliness and model explainability, leading to insufficient user acceptance [8].

This issue can be mitigated by using visualization techniques for data and models with high uncertainty and limited explainability [9] and post-hoc interpretation methods [10], such as data flow graphs [11][12] or node-link diagrams [13][14]. These methods enhance explainability and, when combined with a comprehensible decision framework and a user-centric design, can increase user acceptance [8][15][16]. Furthermore, visualizations are playing an increasingly important role in user acceptance of data and models through explaining high-dimensional data and artificial-intelligence-driven models (AIDMs) [17][18][19]. These AIDMs typically require a multitude of parameters and decisions regarding the training data, making it difficult for users to understand the results, especially with large and complex models and data [20][21]. Visualizations support tasks such as data exploration, hypothesis generation, visual communication of analysis results, and the selection of appropriate training data and parameters for AIDMs. They also help in gaining an overview of large data, interactively exploring details, and recognizing patterns [22]. Current research integrates data analysis and AIDMs with interactive data and model visualization to involve users and their expertise [17]. This approach is demonstrated in many promising examples for prediction, classification, and understanding relationships in complex data [21]. It has further been shown that visualizations revealing relevant information about AIDM decision-making increase user acceptance and trust [23]. However, interactive visualization techniques for hybrid models to predict energy and material/waste consumption based on product design and production data have not yet been applied [24][25][26][27].

Models for predicting energy and material/waste consumption, associated CO_2 emissions and costs can be built from first principles, from data, or a combination of both [28][29][30][31]. First principles based on knowledge-driven models (KDMs) are prevalent but often suffer from inaccurate or imprecise predictions [32][33]. AIDMs are an alternative to KDMs that have been tested in many instances [34]. However, AIDMs are not silver bullets and often fail due to insufficient labelled training data [35][36]. Furthermore, AIDMs are prone to suffer from the issues that energy and material consumption data exhibit, namely quality issues [37][38][39][40][41], inaccuracies [42][43] and outliers, biases/distortions or missing data. A promising way forward is the combination of KDMs and AIDMs to create hybrid models, i.e. models that have a knowledge- and an AI-driven part [44]. Hybrid modeling has demonstrated its ability to address data-related challenges [45] in areas such as power grids and building operations [46][47]. However, further research is needed to apply these techniques to production systems [44], ensuring that models remain interpretable by users [48][49].

3 Research Gap

To conclude from the state of the art above, current research reveals several critical gaps in the integration of digital tools within the product creation process. First, there is a lack of tools in the product creation process that effectively combine technical functionality with environmental sustainability, especially in the presence of uncertain and poorly explainable data and models. Second, although visualization techniques have shown promise in improving the explainability and user acceptance of AIDMs, their application in hybrid models—particularly those predicting energy and material consumption based on product and production data—remains largely unexplored. Third, while hybrid models that combine KDMs and AIDMs offer potential to overcome data quality issues, further research is needed to ensure these models remain interpretable and trustworthy for users in production environments.

4 Requirements for a Future Decision Support Tool

Pioneering a change by creating a Decision Support Tool (DST) can help product designers and production planners predict the energy and material/waste consumption, CO_2 emissions and costs associated with their decisions. This tool must be embedded in the product design and production process to create a consistent, precise, digital, and user-centered solution and demonstrate increased sustainability.

The key requirements of a future DST comprise a user-centered decision-making framework, interactive visualization of data and models, and hybrid modeling approaches. These components are illustrated in **Fig. 1** and elaborated in the following sections.

The target group of the novel DST comprises stakeholders involved in the product creation process, primarily product designers and production planners. Their data—namely product design data and production data—serve as the foundational input and are subsequently used for hybrid modeling.

4.1 Hybrid Models

A future DST must combine the advantages of KDMs and AIDMs for material and energy consumption prediction with a new hybrid model based on the following pillars: First, the most promising KDMs (in terms of precision, accuracy and application range etc.) must be selected from the existing ones. Second, the most promising AIDMs (in terms of implementability, controllability and explainability, stability, robustness, and convergence, required quantity of data, etc.) should be trained on real world data that have been disaggregated using AI into product and production -specific parts. Third, visualization techniques should be used to derive additional parameters from the collected data to improve the KDMs, but also to increase the explainability of the AIDMs and hybrid models, thus fostering the acceptance by domain experts using these models. These hybrid models will excel in predicting quality, surpassing KDMs in terms of prediction quality, while at the same time outperforming AIDMs in training data requirements, complexity, and prediction quality.

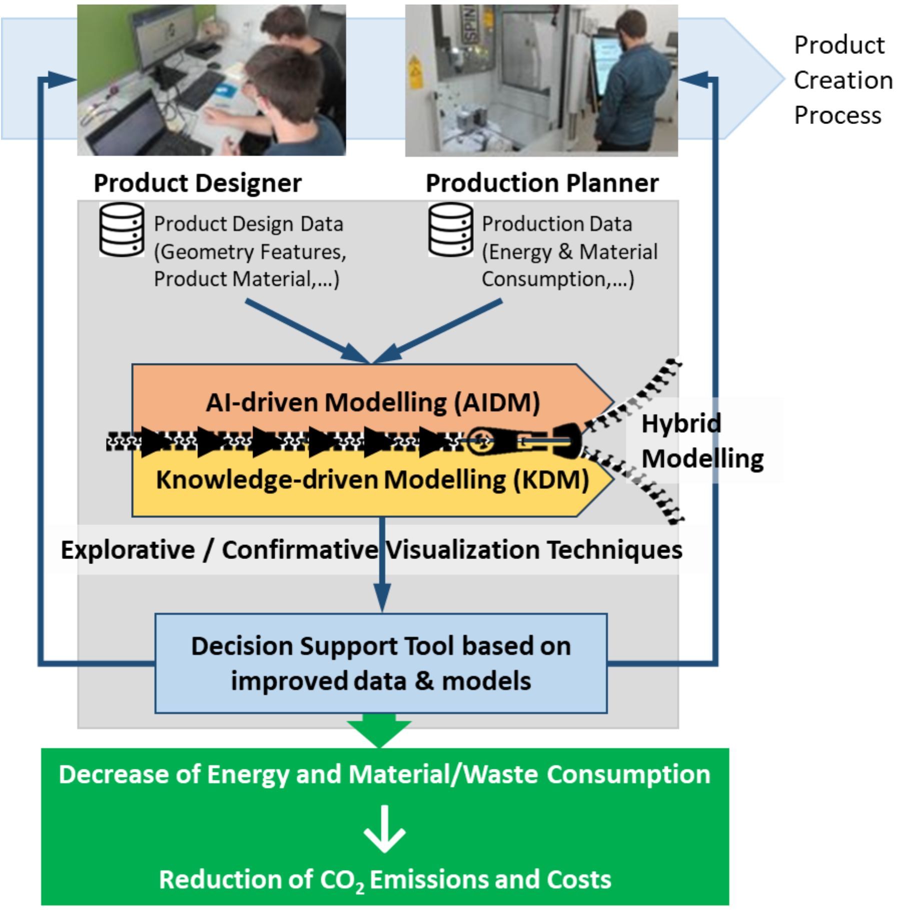

Fig. 1. User-centered decision-making framework, interactive visualization of data and models, and hybrid modeling approaches as key requirements for a Decision Support Tool.

4.2 Interactive Data and Model Visualization

Novel explorative and confirmative visualization techniques must support explainability, promote trust and support the derivation of influencing factors and additional relevant variables on energy and material/waste consumption data for product design and production from AIDMs and hybrid models. This enables effective decision support for both product/production experts and users (product designer and production planner), e.g. by what-if-analyses, and will improve resource-conscious decision making. A future DST must apply appropriate user-centered designs to create and evaluate the effectiveness of our visualization components. The key stone lies in the application of explorative and confirmative visualization techniques for data on energy and material/waste consumption, associated CO_2 emissions and costs, as well as KDMs and AIDMs, and their integration into the DST. This could be done through a monitoring dashboard that visualizes key metrics for the design of a product and its production, providing a range of tools to help users make more sustainable design and production decisions.

4.3 User-centered Decision Support Tool

A DST for product designers and production planners as users must show how the sustainability of products (energy and material/waste consumption, associated CO_2 emissions and costs) changes by varying various parameters such as material, machine strategies, etc., considering essential framework conditions, and making appropriate suggestions through what-if analyses of design and production alternatives. A key component of a DST is a basic decision framework, which contains appropriate decision and prioritization rules, considers company-specific framework conditions regarding material selection, processing steps, among others but also considers different types of users and their specific knowledge. The key stone is to create a comprehensive decision framework for sustainable product design and production and to integrate it together with accurate, precise and explainable data and hybrid models into a DST, thus improving user acceptance and supporting sustainability in the product creation process.

5 Solution Approach within the Project REDUCE

The aforementioned requirements serve as basis for the research project REDUCE (01.03.2025 – 28.02.2028) which will develop such a DST. Creating a DST for product designers and production planners will decrease energy and material/waste consumption and the associated CO_2 emissions and costs. The required approach is depicted in **Fig. 2.**

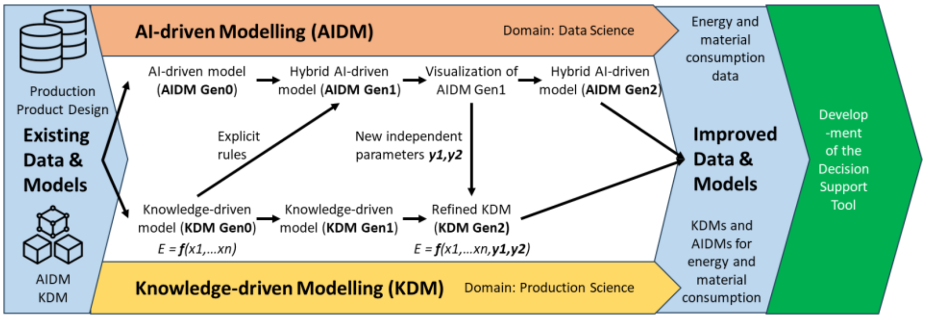

Fig. 2. Approach to create a Decision Support Tool within the project REDUCE.

First, accurate, precise and explainable data and models for energy and material/waste consumption must be created: Existing data and models must be evaluated in terms of quality, explainability and usability, and their respective potential for improvement. The most suitable data and models will then serve as a starting point for the development. The approach to creating hybrid models consists of interweaving KDMs and AIDMs: both are optimized through more accurate and precise disaggregated data. For AIDMs, also additional relevant parameters are used, and explicit rules are considered (Gen1 models), all of which are explored using visualization techniques. With the help of these visualization techniques, both data and Gen1 models are illustrated, and new independent parameters are derived, which are incorporated into the models, thus creating improved data and Gen2 models. Each iteration step / model generation is evaluated to clearly quantify the improvements. In addition, visualization components of data and models are developed, which serve as a major basis for the DST.

Second, accurate and precise data, models, and visualizations are incorporated into the user-centered digital Decision Support Tool. For this purpose, a comprehensive decision framework with rules for balancing relevant factors (e.g. energy reduction vs. cost efficiency) in product design and production, including interactive data and model visualization, will be developed. Besides this framework, the DST will include accurate and precise data, hybrid models and visualization components to help product designers and production planners understand the impact of their decisions. The DST will be developed and optimized in close coordination with users from two manufacturers from the plastics and metal industries. First results of the DST will be demonstrated already in the year 2026.

6 Conclusion and Outlook

This paper outlined the current state of the art in digital tools for sustainable product creationand highlighted gaps in research, particularly regarding the integration of visualization techniques and model explainability. On this basis, a user-centered decision-making framework was presented to derive the most important requirements for a future digital DST. Based on these requirements, a workflow was developed to serve as a guideline for development on hybrid models and interactive data and model visualizations. These are essential for improving transparencyand increasing trust and user acceptance. These activities have been carried out to date as part of the ongoing REDUCE research project and will be further refined in the future.

Future work within REDUCE will focus on the practical implementation and evaluation of the proposed concepts in industrial use cases. In particular, the effectiveness of hybrid modeling and interactive visualization techniques will be evaluated in real-world use-cases, with a special focus on their impact on decision quality and user acceptance. Additionally, further developments aim to extend the adaptability of the DST to various contexts within the product creation process, thereby enabling more sustainable and informed decisions.

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