Review: Model-based Systems Engineering and Artificial Intelligence for Engineering of Sustainable Systems

What contribution can systems engineering and artificial intelligence provide for the engineering of sustainable systems as of today?

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1. Introduction

The early phase of product development has the highest influence (approx. 80 %) on the later properties of a product, such as costs, sustainability or environmental impact. (Eigner / Stelzer, 2013; Warnecke / Eyerer, 1997). Sustainability or sustainable development is one of the key challenges that society will have to face in the coming years (United Nations, 2015). The area of sustainability with its three sub-areas, ecological, economic and social sustainability, was described already in 1998 (Bundestag, 1998). Ecological sustainability aims at "... maintaining or restoring the diverse functions of nature for the benefit of people". Economic sustainability focuses on the "... preservation and sustainable safeguarding of competitive and market functions ...". Social sustainability focuses on the "... creation of a solidarity-based society that guarantees democracy, constitutionality, freedom, social justice, prosperity and ecological responsibility." (Bundestag, 1998). In the meantime, for example, the integration of waste prevention strategies in the product design phase is already part of the recommendations for a sustainable economy. (PBnE, 2020).

The United Nations (UN) describes in its Sustainable Development Goals (SDGs) the core aspects and targets that need to be addressed in the context of sustainable development in the coming years (United Nations, 2015). It defines 17 thematic fields and 169 derived sub-goals. The thematic fields and the goals described therein are viewed critically in the scientific community. Criticism of the defined SDGs includes the dynamics and complexity of the SDGs, which require a systemic and methodical approach that has not been developed yet. (Laurent et al., 2019; Yang / Cormican, 2021).

The International Council on Systems Engineering (INCOSE) picks up on the UN SDGs in its Systems Engineering Vision 2035 as one of the key challenges that can be addressed and supported by systems engineering. (INCOSE, 2021). INCOSE takes it a step further and postulates that the goals pursued by the UN explicitly require comprehensive, system-based solutions. Furthermore, INCOSE describes in its vision an increasing integration of and support by artificial intelligence in the

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development process of future systems. Yang and Cormican (Yang & Cormican, 2021) confirm that systems engineering has great potential for modelling, structuring and transparently demonstrating the interrelationships between the SDGs. In an analysis by Khamis et al., AI solutions are attributed major contributions to the achievement of the UN SDGs. However, the analysis does not focus directly on the development of products or systems (Khamis et al., 2019).

Engineering respectively product or system development, as a key element in the creation of tomorrow's systems, is currently facing a variety of challenges. Flexibility and speed of reaction to customer requirements need to be raised. So-called Advanced Systems (AS), which are characterized by autonomy, socio-technical interaction, dynamic networking, e.g. in the sense of Systems of Systems (SoS), and an increasing relevance of the business models accompanying the product in the form of product-service systems, increase the complexity of the product. (Riedel et al., 2021). SoS describe networks of individual systems that interact independently of time or place, that were developed independently of each other, that are networked for a specific purpose and that show emergent system behavior as a result of the networking, i.e. they provide more functionalities than would be expected based on the functionalities of the individual systems (Kopetz et al., 2016; Nielsen et al., 2015; Porter / Heppelmann, 2014). In Germany, in response to the increasing demands on engineering, the cyber-physical systems propagated within the framework of Industry 4.0 (acatech, 2013), and the new properties of future products and systems described, the paradigm of Advanced Systems Engineering was established (Riedel et al., 2021), which is part of the BMBF's "Zukunft der Wertschöpfung " program within the framework of the High-Tech Strategy 2025 (BMBF, 2021). The paradigm describes complex technical systems, the Advanced Systems (AS), the Systems Engineering (SE) for the efficient handling of complex systems and the Advanced Engineering (AE) for the technical, organizational and creative support of the product creation process. (Riedel et al., 2021).

The early phase of product development, which is the focus of this article, can be characterized by means of the V-model (Figure 1) (VDI/VDE, 2021). The V-model describes a development process for mechatronic systems. On the left-hand side of the V, a system is continuously detailed and developed based on requirements. On the right-hand side of the V, system properties are compared with the requirements and the designed system is validated and verified. System development on the basis of the V-model is an iterative process that may be repeated several times. (VDI/VDE, 2021). The early phase of development is characterized by requirements elicitation and description as well as the modelling of the architecture of the product to be developed. In this phase, desired characteristics of the product are defined and initial insights into the expected implications can be derived.

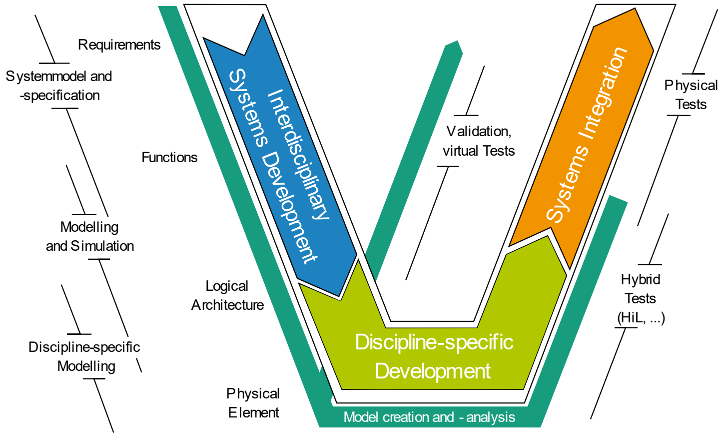

Figure 1: V-Modell according to (VDI/VDE, 2021)

2. State of the Art

The intersection of increasing requirements for the sustainable design of systems and the possibilities resulting from systems engineering and the use of artificial intelligence offers promising options for the efficient design of sustainable products and systems. In this paper, the current state of research in the intersection of the three topics is analyzed, presented and discussed on the basis of a systematic literature review (SLR). Options for action and research demands will be derived from the analysis. A brief overview of the three thematic fields is given in the following.

2.1. Systems Engineering and its Model-based Application

Systems engineering is a discipline that was mainly applied to complex, interdisciplinary projects such as the development of products for the aerospace industry (aircraft or satellites as well as military systems) in the past. With the ever-increasing complexity of systems as described above, the methods and approaches of SE are also gaining significant relevance in other sectors such as the automotive industry, mechanical and plant engineering or medical technology (Eigner et al., 2017; Riedel et al., 2021). In order to be able to develop products efficiently and exploit the possibilities of digitalization, SE today is mostly conducted in a model-based manner. Model-based systems engineering (MBSE) is defined by INCOSE as the formalized application of modelling to support system requirements, design, analysis, verification and validation. MBSE application extends from the conceptual design phase through the entire development and later life cycle phases (INCOSE, 2004). The application of MBSE is based on three pillars (1) a method, (2) a (graphical) modelling language, and (3) a software tool (Friedenthal et al., 2014).

The outcome of the MBSE application is a coherent model (understood as a model consisting of different sub-models) of the system that describes both its static structure and its expected behavior (Friedenthal et al., 2014).

Based on the design approach described in the V-model(VDI/VDE, 2021) Based on the design approach described in the V-model, the development process starts with defining the requirements and then progresses to the functional, logical and physical description of the system and its components. Once the system model is created, discipline-specific modelling begins, based on discipline-specific tools. Further verification and validation activities take place at different levels of granularity of the system until a working and verified product results.

The Systems Modelling Language (SysML) is a universal graphical modelling language that can be applied for the representation of systems (combination of hardware, software, human, ...) and supports the formal application of MBSE (Friedenthal et al., 2014).

In order to validate a system as early as possible or to be able to estimate its later properties, simulations are already carried out on the basis of the initial modelling. This usually involves a transition between the MBSE modelling tool and the simulation tool. Standards such as Open Services for Lifecycle Collaboration (OSLC) and Functional Mock-up Interfaces (FMI) can be used for the connection and transfer of information between the system model and the other simulation and modelling environments. (Bachelor et al., 2020).

Different methods for MBSE-based modelling of systems such as SPES, OPM, METUS, OOSEM are described and analyzed in detail in (Friedenthal et al., 2014; Halstenberg et al., 2019). None of the methods analyzed there so far addresses a direct integration of sustainability aspects into the development of systems.

2.2. Artificial Intelligence

Artificial intelligence (AI) has become an important topic in recent years, mainly due to the ever-increasing computing power, availability of data and storage capacities that enable real-time application of already existing algorithms. The AI approaches in focus today, inspired by neuroscience, focus on autonomous learning and self-optimization based on probability models and use cases (Goodfellow et al., 2016).

To date, there is no agreed upon definition of AI, although various definitions and tendencies are described in the literature. For this contribution, the following definition is adopted: "IT solutions and methods that autonomously perform tasks where the underlying rules of processing are not explicitly specified by humans. The execution of these tasks used to depend on human intelligence and dynamic capabilities. Now, AI takes over these tasks and learns based on the available data to better process orders, projects and workflows." (BMBF, 2018; SmartAIWork, 2020)

While there are numerous applications of AI in everyday products, the number of applications in the field of innovation management, research and development and engineering is generally still limited. In contrast to development, there are other areas within a company where AI solutions are already well established and partially implemented. Some examples of these other areas are services, marketing, production and logistics (Dukino et al., 2020). An analysis of 27 studies on the use of AI in companies shows that AI applications in engineering are only treated implicitly in most studies. Only very few studies provide elaborations or an analysis that goes beyond simple cross-references, these are (BMWi, 2019; Gil / Selman, 2019; Hatiboglu et al., 2019; Kaul et al., 2019). Therefore, this study aims to analyze which support possibilities artificial intelligence can currently offer for optimizing the sustainability of products in the early phase of product development.

2.3. Sustainability

Sustainability is a key factor for the economy. The EU taxonomy launched in 2020 aims to financially assess the activities of companies in terms of their contribution to sustainable development. The aim is to provide incentives for investments in sustainable projects and thus make contributions to the goals agreed in the Green Deal (European Commission, 2020). A central role in the context of sustainability is played by topics such as the circular economy and the reduction of greenhouse gases. Both address all three dimensions of sustainability. The SDG's (United Nations, 2015) as mentioned before also play a crucial role as objectives or requirements to be considered in the early phases of engineering.

The circular economy describes an economy that is regenerative and restorative and aims to ensure that products, components and materials retain their highest utility and value at all times. A distinction is made here between technical and biological cycles (Ellen MacArthur Foundation). The circular economy is implemented in practice through frameworks for R-strategies (Refuse, ..., Reuse, ..., Recycle, ...), among others (Potting et al., 2017). Various methods and tools for integrating circular economy strategies into product development exist. Central aspects are the design of products for long life cycles, dismantlability, reparability, maintainability and recyclability, i.e. the consideration of R-strategies (van den Berg M.R. / Bakker C.A., 2015).

LCA analysis is a key tool in assessing the effects and impacts that a product generates on the environment over its life cycle. It is a variety of combined procedures for recording and evaluating the inputs and outputs of materials or energy and the resulting environmental impacts generated by a system or product during its life cycle (DIN EN ISO 14040). Since a large number of factors, process steps and parameters have to be taken into account and modelled for the balancing of a product, LCA analyses involve a great deal of effort and are subject to certain inaccuracies. Inaccuracies result, among other things, from the data sources and the selected accounting framework or system boundaries. (Karaman Öztaş, 2018).

In the field of mechatronic product and system development, LCA analyses are currently usually based on the bill of materials (BOM) and the resulting processes (e.g. the processes inside the combustion engine of a vehicle) of a finished product and are therefore not used for an early analysis of product concepts (Del Pero et al., 2018; Ling-Chin et al., 2016).

Sustainability is a thematic area that has been addressed for quite some time. Already in the late 1990s, driven by legislation, solutions were actively developed to optimize the sustainability of products in terms of reusability and the circular economy (Bullinger et al., 1999). Various methodological approaches such as checklists, examples, design catalogues, manuals, value analyses or so-called "Design for Recycling" (DfR) tools have been developed and described (Bullinger et al., 1999). At the time, however, only slightly more than 3% of German industry used DfR software tools (Hartel, 1997). A main reason for the low prevalence of such tools is the effort involved in using the systems. The modelling of the parameters and processes necessary for a DfR analysis, which has to be carried out in addition to the creation of the other product models, often results in a discrepancy between effort and benefit. (Bullinger et al., 1999). As of 2020, DfX approaches to address a circular economy are still a niche topic that needs to gain a broader attention (Sassanelli et al., 2020). Most current approaches are based in theory. The analysis of Sassanelli et al. conclude that still today, there exists a need for new DfX methods and according tools to support decision making and balancing the different DfX methods (Sassanelli et al., 2020).

2.4. Target System for the Early Phase of Product Development

The increasing complexity of products and systems, consisting of mechanics, electronics, software and services, as well as their interconnectedness into systems of systems (in the sense of advanced systems) pose a challenge. Furthermore, the systems should address where possible all levels of sustainability and thus have as little impact as possible on their environment. MBSE and the Systems Modelling Language are considered the de facto standard for the modelling of mechatronic systems. However, factors that affect sustainability have so far only been taken into account to a limited extent in the modelling of products and Systems. (Bougain / Gerhard, 2017). Artificial intelligence promises great potential but has so far only been used in limited specific cases in product development (Riedel et al., 2021). Bressanelli et al. recommend further work on the intersection between digital technologies and the circular economy, including the combination of different digital technologies to exploit their synergistic potential (Bressanelli et al., 2022). In the following, an SLR will be used to investigate which approaches for creating and evaluating sustainable product structures already exist in science and which role artificial intelligence can play in supporting the assessment of sustainability indicators in the early phase of product development.

3. Methodology

The implementation of the SLR is motivated by Blessing and Chakrabati's observation that research in the field of "engineering design", i.e. product development, often takes place in silos. The reason for this is that researchers frequently start out with an incomplete overview of the entire research landscape, relevant for the topic they are addressing (Blessing / Chakrabarti, 2009). The use of a SLR is intended to prevent this issue. The applied method is based on the guideline described by Lame (Lame, 2019) for conducting SLR in the context of scientific work in the field of research and development or design. In accordance with the recommendations of Lame (Lame, 2019), the "Preferred Reporting Items for Systematic reviews and Meta-Analyses" (PRISMA) (Page et al., 2021), which is considered standard in the field of medical research and describes 27 items that should be taken into account when preparing a review, is adapted as far as possible to the present objective and topic area. The procedure and the resulting findings are shown quantitatively in Figure 2 and are presented and discussed in Chapters 4 and 5. Table 1 shows the search terms used for the SLR.

Systems Engineering	Systems Engineering, Systems Thinking, Systems Theory, Systems Modelling, Systems Life Cycle, System of Systems, MBSE, SysML
Sustainability	Circularity, Circular Economy, Sustainability, Sustainable Development, Life Cycle Engineering, Sustainable
Artificial Intelligence	Artificial Intelligence, Machine Learning, Neural Networks, Data Science

Table 1: Overview of the search terms used in the areas of interest

The search terms were selected to capture the work of a broad range of different communities that might be using different wordings to describe similar topics. The databases were searched in such a way that the combination of a search term from the field of sustainability and a term from the field of SE or AI was always searched for. The aim of this was to identify as wide a range of relevant literature as possible. The analysis was carried out in May 2022. After searching the databases using the search terms, removing duplicate entries, and removing articles from 2011 or older, the resulting articles were analyzed in three phases. In phase one, based on abstract and title, it was examined whether a relevance of the document to at least two of the three described areas as well as the early phase of product development of mechatronic products or systems could be identified. The resulting articles were checked for their accessibility on the basis of the access and licenses available to the authors. The remaining articles were analyzed with regard to their relevance for the early phase of product development of mechatronic products or systems relevant in this analysis. The results of the search were supplemented with articles already known in advance and identified through external references. The articles identified as relevant were grouped into categories. The results of the analysis are described below.

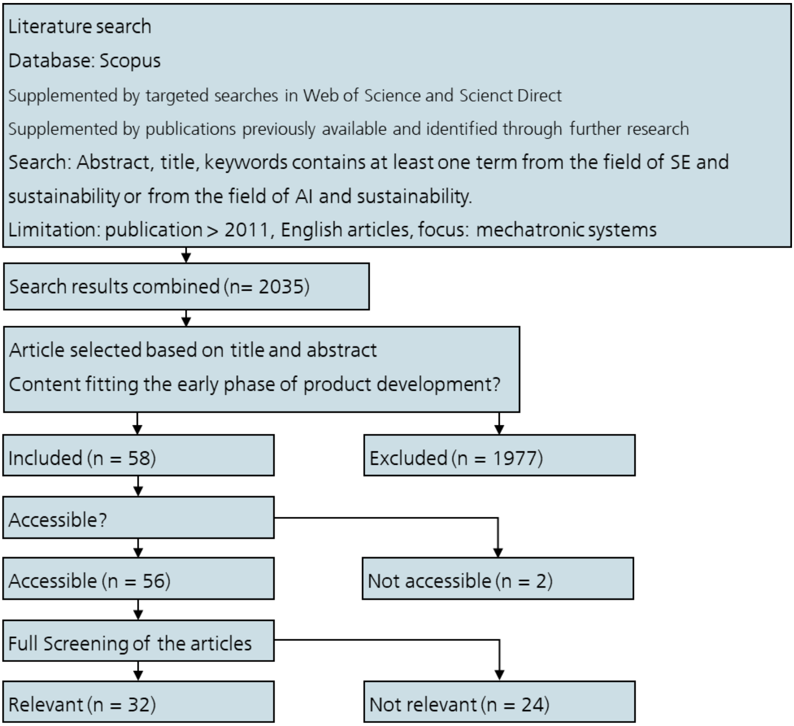

Figure 2: Procedure and quantitative results of the SLR

4. Results

After removing duplicates and applying the set criteria, 2035 articles remained for an analysis of title and abstract. Many of the identified articles were not related to the development of mechatronic systems but could be assigned among others to the fields of construction industry, urban systems, business models, learning and teaching and ecosystems. A small number (2) of the articles identified as relevant on the basis of title and abstract could not be analyzed further due to access restrictions. The publications identified and analyzed as relevant show an even trend between the years 2013 and 2021 and increase significantly for the analyzed first five months of 2022 (Figure 2). In 2022, a large number of publications could already be identified, which can be seen as an indication of the increasing attention being paid to the combination of sustainable development and the disciplines of MBSE and AI considered in this analysis, as well as the resulting increase in relevance of the topics and, in particular, the combination of the topic areas.

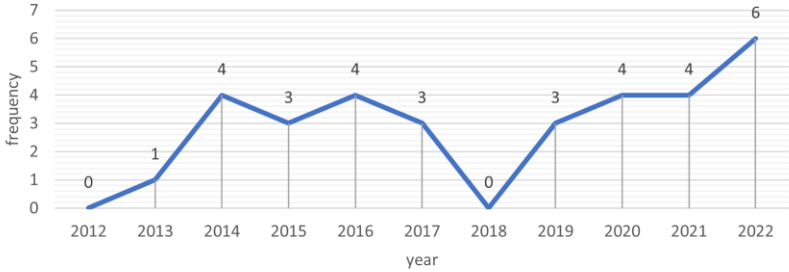

Figure 3: Frequency of the identified publications over the years

4.1. Artificial Intelligence and Sustainability

The early optimized design of products and systems can be supported by the use of artificial intelligence. Teksin et al., like many other authors, show an approach for the optimization of product properties using the example of a wind turbine. Here, experimentally determined data are used to train a model that predicts the behavior of the wind turbine based on various criteria. This model can be used to optimize similar turbines in the design phase (Teksin et al., 2022). Kadar and Kadar describe the support of regenerative design in the field of architecture based on AI (Kadar / Kadar, 2020). Doppa explains an approach for efficiently finding the optimal solution for complex system structures based on Bayesian optimization (Doppa, 2021).

Sakao et al. describe a vision of AI-based lifecycle engineering (AI-LCE). In their vision, AI approaches such as NLP (Natural Language Processing), CBR (Case-based Reasoning) and ML (Machine Learning) approaches are used to accelerate and optimize classic LCE activities. One component is the intelligent collection and use of data over the life cycle of products. The benefit lies in the reduction of time and the higher accuracy of decisions. Errors that occur in production could be caught by quick feedbacks for the same product generation through adjustments in development. (Sakao et al., 2021)

The approach of Tambouratzis et al. describes an AI-supported, sustainability-optimized material selection for plastics as early as 2014, in which general regression and artificial neural networks are applied. Furthermore, genetic algorithms enable the identification of an optimal material composition for the application at hand. The parameters considered in the optimization of sustainability are the CO2 footprint of primary production, water consumption, CO2 footprint of polymer molding and CO2 footprint of recycling. (Tambouratzis et al., 2014)

Diego-Mas et al. train an AI-based algorithm that can predict how environmentally friendly products are perceived by potential customers based only on their appearance. The algorithm is validated using tables as an example. Companies can use the results to optimize their own designs accordingly. (Diego-Mas et al., 2016)

Wisthoff et. al describe the use of a neural network or machine learning for estimating the general environmental impact of design decisions. The neural network links the LCA impact of 37 case studies on products with the respective product attributes. The interlinking enables developers to identify at an early stage which product attributes generate the highest environmental impact and to adapt their design accordingly. (Wisthoff et al., 2016)

In their review, Qin et al. identify several AI-based approaches for optimizing energy consumption in additive manufacturing. Several approaches describe indicators for optimizing the geometric design of 3D-printed components with regard to the expected power consumption during manufacturing. The authors identify a need for further research in this area (Qin et al., 2022). In their review, Ghoreishi and Happonen identify support for sustainable product development as one of three areas where AI can optimize the circular economy. AI supports the processing of large amounts of data, the development of new materials, the closure of material flows by reducing product defects and the number of prototypes needed, and the identification of alternatives to difficult-to-recycle materials (Ghoreishi / Happonen, 2020b).

In a further analysis, Ghoreishi and Happonen identify the fields of "optimization of modular designs", "fast, intelligent and precise creation of prototypes", "prediction of material toxicity", "cost reduction through testing" and "real-time data analysis" as promising application fields of AI in product development. (Ghoreishi / Happonen, 2020a)

Ertz et al. analyze the opportunities resulting from Industrie 4.0 technologies for the circular economy. Based on their analysis, they conclude that Big Data, Internet of Things (IoT) and AI technologies can contribute to extending the lifetime of products in various ways. IoT makes it possible to better adapt products to subsequent users and to optimize products in terms of maintenance and recovery. Big Data enables inferences to be made about product optimization based on user behavior and optimizing the sustainability of the product. AI can optimize product design through multi-criteria decision support systems and automated LCA analyses. (Ertz et al., 2022)

Kombaya et al. describe a procedure for the design and simulation of a Digital Twin Framework for reconfigurable production systems. The modelling is based on SysML. The framework uses the Digital Twin as well as ML for optimization in the design phase. (Kombaya Touckia et al., 2022)

In a literature review, Ghoroghi et al. investigated the current state of support for LCA analyses by machine learning approaches in the field of buildings, districts and cities, and " others". They identify four current limitations. LCA and ML are initially expensive and depend on large amounts of hand-crafted, structured training data. Computational costs and training time are other limiting factors for ML use. Many ML models (DNN, RF and SVMs) are designed as a "black box", which makes it difficult to understand the results produced. In early phases of development, the detailed information needed is often not yet available. Finally, not enough high-quality data sets collected under real conditions are available for training ML models. Currently, ML is most often used in the LCA context to generate missing data sets and optimize simulations. (Ghoroghi et al., 2022)

Choi et al. present an Engineering Machine Learning Automation Platform (EMAP) as the result of their study. This platform is cloud-based, aimed at suppliers of large and complex industrial plants and supports, among other things, the estimation of development costs and error checking for development. The focus is on risk management. The platform was validated using case studies and, according to the authors, can be applied to other use cases without the need for special machine learning experts. The tool is intended to support project managers in the area of risk management. (Choi et al., 2021)

4.2. Model-based Systems Engineering and Sustainability

Eigner et al. present an approach for assessing the use phase, the phase in the life cycle of a product with the greatest environmental impact. The life cycle phases are modelled as an extension of the V-model in the early phase of product development. The approach exploits the continuity between requirements and physical elements of the product structure created by the MBSE-based approach to establish cause-effect relationships and identify the elements of a product structure to be optimized. The system behavior to be expected during the use phase is described using use case diagrams. In connection with other diagram types and modelling, it is possible, for example, to identify the CO2 emissions generated per activity during the use phase of a product. The calculation is based on the characteristic values of an engine (usage time, emissions, consumption) for different states. In this way, direct levers for optimization can be identified. (Eigner et al., 2014)

Bougain and Gerhard describe an approach to directly consider factors relevant for a sustainability assessment in the early phase of product development within SysML models. Here, the indicators "Green House Gas Potential (GHGP)" and "Cumulative Energy Demand (CED)" are considered for four life cycle phases (extraction, production, use and end of life). The approach differs from Eigner et al. (Eigner et al., 2014) in the sense that several life cycle phases are taken into account as early as possible and a dynamic eco-design strategy is added. The approach is presented using a 3D printer. The method focuses on incorporating sustainable design requirements at the very beginning of the development process. It describes the requirements for each phase of the life cycle in a separate and weighted requirements diagram. In order to be able to make early estimates of the expected GHGP and CED, the material and weight of individual components are captured in the SysML diagram and linked to a corresponding database. Later, a link to the PDM system can be established. Here, the expected maintenance activities are also taken into account and a "maintenance factor" is introduced. In order to balance the manufacturing phase, processes and machining times are modelled. Later, a link can be established with the ERP system. The utilization phase is described with SysML behavioral models. The evaluation shows in which phase the product consumes the most, which allows conclusions to be drawn about the corresponding design strategies. Furthermore, it is evaluated which requirement is responsible for a consumption. Limitations are the lack of modelling of assembly processes, the transport phases and the necessary connection of the tool to the various databases or IT systems in the company context. (Bougain & Gerhard, 2017)

Halstenberg et al. describe an approach for the development of sustainable product-service-systems (PSS), consisting of a method, (modelling) language and software tool. The focus is on the development of the PSS as well as the integration of circular economy (CE) design principles into the development. The approach is based on the principle of MBSE, but defines its own description language, which combines approaches of PSS development and MBSE. The consideration of circular economy approaches is anchored in each main process step of the methodology. Model transformations and analyses are carried out with the aim of deriving optimal CE strategies for the selected product components. This analysis can only be carried out once the final product structure and the trace links and dependencies have been modelled. Only at this point is a holistic view of the system and thus optimization with regard to the CE strategies possible. (Halstenberg et al., 2019)

Dickopf et al. describe an MBSE-based approach for the early simulation and validation of system concepts based on SysML. By using the integrated model, twin and system-in-the-loop approaches, all life cycle phases can be accompanied and analyzed in a model-based manner. Added value results, among other things, from an early optimization of product parameters. The optimization with regard to the sustainability of the product is not directly addressed, but a detailed analysis of the different life cycle phases is supported. Likewise, an IoT-based data feedback from the actual use phase of the system is described for further analyses and optimization. The method is based on the programming or provision of interfaces for commercially available simulation and modelling tools. (Dickopf et al., 2019)

Abdoli et al. analyze the environmental impacts of SoS on the basis of the SE and the V-model. They use measures of effectiveness (MoE) from the SE context to determine the environmental impact of a SoS. The authors apply object-oriented modelling and describe a representation of a product system in a multi-SoS perspective. Further, systems dynamics are used to model relationships between policy decisions and their impacts, thus enabling the analysis of rebound effects. The method can model the structure and behavior of complex SoS and thus assess the impact of optimizations on individual systems in the overall context of the Multi-SoS in which it operates. The authors further describe that the incorporation of fuzzy logic could be beneficial to support missing data and the generally complicated modelling of multi-SoS. (Abdoli et al., 2019)

Block et al. describe an approach to lifecycle engineering based on MBSE and SysML v2. The novelty lies in the modelling of variants and different states of a product over the life cycle on the basis of the new possibilities resulting from SysML v2. Specific properties of the product can be derived from the modelled states, e.g. properties that are relevant for assessing the sustainability of a product. The different states over the life cycle are derived from different underlying business models. (Block et al., 2022)

4.3. Further Articles in the Analyzed Areas

Beyond the articles that can be directly assigned to one of the two search fields AI or SE, further articles were identified that contribute to the understanding of existing approaches and methods for assessing sustainability in the early phase of product development. These are presented in the following.

Echeveste et al. analyze desirable properties of environmentally friendly products (Echeveste et al., 2013). Kim et al. describe several approaches for the identification and consideration or analysis of sustainability indicators during product development. Here, a causal chain is defined based on the system dynamics between indicators, customer requirements and product components. This is used to analyze the product with regard to the selected indicators. (S. Y. Kim et al., 2013; S. Kim et al., 2014)

Grüneisen et al. describe a system dynamics model that can be used to optimize the management of the PSS development process. The model considers 30 cycles and can be used to support decisions. The model contains a "Repair" and a "Recycle" cycle (Grüneisen et al., 2015). On this basis, further mutually influencing cycles could be created to approximate the optimal product design. Hoffenson and Söderberg also describe a system dynamics model that can be used to assess the impact of design decisions on product quality and sustainability. (Hoffenson / Söderberg, 2015)

Kulatunga et al. present a tool that can be used to support the development of sustainable products. The tool is structured in the form of an interactive checklist and can be applied to different products (Kulatunga et al., 2015). The tool is reminiscent of DfX tools (Bullinger et al., 1999), which suggest appropriate strategies for specific requirements.

Penciuc et al. describe a method based on Product Lifecycle Management (PLM) for the consideration and analysis of all life cycle phases and the resulting effects during the early phase of product development. The method is developed and validated using the example of lightweight aluminum construction. The method describes the integration of several plug-ins into the PLM, with the aim of being able to evaluate the consequences that development decisions cause in the different life cycle phases. The plug-ins use inputs from repositories, FEM simulations and CAD data. The design decisions can be evaluated on the basis of various, previously selected indicators. In order to select the optimal strategy, several scenarios are created within the framework of the method and the resulting results are compared with each other. In this way, a scenario could be identified that optimizes both the environmental impact over the life cycle and the recycling costs. The methodology relies on standardized data exchange formats and self-programmed plug-ins. The use of MBSE approaches or modelling languages, such as SysML, is not discussed. (Penciuc et al., 2016)

Reuter defines the "Metallurgical Internet of Things". He defines metallurgy as a key enabler for the circular economy. He defines a hardware-based connection and corresponding feedback loops of all entities involved in metal production and recycling on a global level. The aim is to optimize the cycles and thus to optimize the recovery of the materials produced and used. (Reuter, 2016)

Chandrakumar et al. describe an assessment framework based on the UN SDGs and the UNEP's Design for Sustainability (DfS) indicators (United Nations Environment Programme, 2006). Based on the indicators and the analysis methodology, different designs can be evaluated against each other in terms of their social, ecological and economic sustainability. The analysis is based, among other things, on weightings of the factors adapted to the respective application and the principle of pairwise comparison. (Chandrakumar et al., 2017)

Faludi / Agogino analyze on the basis of 27 expert interviews that Systems Thinking and "The Natural Step" method are used by several experts in the field of innovation and sustainability. (Faludi / Agogino, 2018)

Mennenga et al. present a process-oriented framework for Systems of Systems Engineering (SoSE). The framework is used for planning and supports the optimization of SoS. The framework is designed based on the requirements of the development of sustainable production systems. The authors do not describe an explicit modelling approach, but mention SysML as a language that is often used for modelling similar systems. (Mennenga et al., 2019)

Drachenfels et al. describe an approach for knowledge-based lifecycle engineering (KB-LCE) using battery technologies as an example. They follow the approach of ontology-based knowledge engineering. They integrate KB-LCE into existing lifecycle engineering (LCE) methodologies. Through the common ontology, the actual processes in the LCE can be directly supported by the knowledge stored in the knowledge database. (Drachenfels et al., 2020)

Gräßler and Pottebaum develop a Generic Product Lifecycle Model from an extensive literature review. The model integrates the perspectives of product development and the sustainability-oriented approach of the circular economy. Within the framework of the associated methodology, material and information flows of multidisciplinary product-service systems are first described as the basis of the CE. Then a differentiation is made between product classes and instances. Furthermore, the stakeholder perspective of producer and consumer/user is extended to other perspectives such as recycling/ reuse and society. (Gräßler / Pottebaum, 2021)

5. Discussion

The results of the analysis show that although AI and Sustainability as well as MBSE are topics that receive a lot of attention in academia and industry at the moment, only 32 publications could be identified that actually address the utilization of MBSE or AI as a support for developing sustainable systems. It can be concluded, that so far a limited focus has been put on the support of sustainable systems design in the early design or engineering phase supported by MBSE or AI. As shown in Chapter 1 and 2, sustainability of products and systems plays a crucial role for the future of society. Therefore additional efforts seem necessary to address the multifaceted challenges design of sustainable systems poses on engineering departments. A summary on the current status and possible future research perspectives is given in the following.

Four approaches were identified which enable an estimation of the information available early in the development process and allow conclusions to be drawn about the later sustainability of the product to be developed on the basis of MBSE and SysML. Three of the four approaches allow the explicit consideration of several life cycle phases from the extraction of raw materials to the end of the life cycle. One approach is limited to modelling the use phase of the product coupled with the associated business models. Limitations of the approaches are the consistency of the models, the transition between different levels of modelling, the missing possibility to consider all life cycle phases such as transport and assembly processes as well as the necessity to include explicit data sets for the systems to be modelled in the system modelling tool. Furthermore, the recommendation systems based on DfX approaches are not directly integrated into the system modelling but must be triggered separately with data from the system model. Furthermore, only three of the approaches address the topic of modelling and balancing product variants. Individual component designs may initially appear to be disadvantageous for a variant under consideration, but similar to the SoS consideration below, when all product variants are considered, they could in turn be advantageous.

A positive note is that the authors describing MBSE-based approaches often follow the de facto language standard SysML. In the area of the description language, limitations are described for the modelling of the different life cycle phases and the continuous linking of the information and model elements. Nevertheless, the uniform language standard helps to easily comprehend the described procedures and at the same time conclusions can be drawn about optimization potentials of SysML. As was to be expected, only the most recent of the analyzed publications has so far relied on the successor to SysML, SysML v2, which is currently in the process of publication (GitHub, 2022; Object Management Group, 2019).

Systems-of-systems, which are particularly relevant for the future systemic consideration of sustainability, have received attention in the literature starting from 2019 onwards, when accounting for their combined impact on the environment. Since SoS are characterized by emergent system behavior, and thus provide more functionality in combination than would be expected based on the individual subsystems, further approaches must be developed in future to take this into account when assessing the environmental impact of SoS. Otherwise, there is a risk of optimizing subsystems locally without considering the overall context in which the systems operate.

Circular economy aspects are directly addressed by only few publications. Only Halstenberg et al. describe an approach to link corresponding indicators or evaluations directly with the modelling of the systems. The integration is based on a specially developed modelling language. The transferability and broad applicability of the approach must therefore be examined on a case-by-case basis. These findings are in sync with the findings of Sassanelli et al. which, while not focusing on systems engineering, describe the integration of CE related tools and methods in the engineering process as an underrepresented area in research and practice (Sassanelli et al., 2020).

The identified and described AI approaches promise potential for the optimization of product properties with regard to their sustainability and CE conformity. It must be noted that the identified approaches are to be regarded as proof-of-concept and only very rarely an actual integration into AI tools for direct application in the field is described. Only one article describes that the cloud-based solution developed, as usable in industrial context, without special prior knowledge in the field of ML. One challenge is to be able to apply the solutions created in the scientific field for very specific use cases to a broad range of different real world problems. For example, a solution developed for the selection of the optimal plastic will not necessarily produce equally reliable results in the selection of steel. When thinking about sustainability and circular economy, even more fundamental material or conceptual decisions must be made and supported, e.g. with regard to functional integration and hybrid materials. Suitable solutions could not be identified in the context of this analysis.

As expected in the field of research, the integration of the described approaches into the IT infrastructures implemented in companies is only addressed by a few articles. The articles that do address this pointed out the additional challenges that arise when implementing the solutions described, due to the need to realize additional interfaces to various data sources. A main challenge and future research direction is the actual transfer or direct coupling of results from research and the actual IT-infrastructures realized in industry. One approach could be to rely on standardized interfaces when developing solutions in academia.

On the basis of IoT and the concept of digital twins, it is expected that in the future it will be possible to calculate, for example, the consumption and emissions of products during the use phase on the basis of real or real-time data. Such data allows a detailed and exact evaluation of the emissions generated by the use of products and systems. One of the identified articles describes a vision for the active integration of real-time data using AI-based approaches. So far, corresponding approaches can be found in the area of Big Data analyses with regard to customer behavior, but without direct derivation of actual consumption or emissions.

6. Summary

Sustainability will be one of the main objectives for every product or system development in the future. Based on an SLR, this article presents the current status of the topics MBSE and AI with regard to the existing potentials for optimizing the sustainability of products in the early phase of development. In both areas, approaches were identified through the SLR-based approach. The limitations of these approaches were discussed in detail and future research needs are described. Beyond the identification in the two core areas, the review identified further approaches that contribute to a more comprehensive understanding of the current state of accounting for sustainability factors in the early phase of product development.

One main finding is that there is no integrated approach yet for combining the potentials of the two technologies MBSE and AI in the field of sustainability. A need for research can be identified here. Furthermore, most of the current AI-based approaches for the early phase of product development are still far from being able to be integrated into corporate processes with minimal effort, but they promise a certain potential. There is a particular need for research in this area, namely the direct and low-effort integration of AI approaches into existing processes in product development. None of the identified MBSE-based approaches covers all lifecycle phases and offers complete traceability. Furthermore, the aspect of circular economy and the choice of the right strategies have so far only been addressed in one of the identified MBSE-based approaches. A further need for research can therefore be identified in the efficient, model-based integration of circular economy factors or indicators in the early phase of product development.

Furthermore, the potentials resulting from SysML v2 for the modelling of sustainable systems must be used more extensively.

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