Circular Systems Engineering

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Abstract

The perception of the value and propriety of modern engineered systems is changing. In addition to their functional and extra-functional properties, nowadays' systems are also evaluated by their sustainability properties. The next generation of systems will be characterized by an overall elevated sustainability—including their post-life, driven by efficient value retention mechanisms. Current systems engineering practices fall short to support these ambitions and need to be revised appropriately. In this paper, we introduce the concept of circular systems engineering, a novel paradigm for systems sustainability. After defining a conceptual reference framework to situate systems engineering practices within, we derive prerequisites for circular systems engineering. Finally, we outline the challenges and research opportunities associated with circular systems engineering.

Keywords: circular economy, digital thread, digital twins, digital fabric, sustainability, systems engineering

1. Introduction

The steadily accelerating innovation pathways of humankind have rendered prevailing systems engineering paradigms unsustainable. By Brundtland's classic definition of sustainability [1], systems engineering falls short of "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*". Our systems engineering practices fail to fulfill the four essential sustainability dimensions of technical systems [2]: technical (long-term usage); economic (financial viability); environmental (reduced impact); social (elevated utility). Some even argue that fulfilling these goals is not feasible due to the limitations of our current frame of thinking, as "*computing continues to incur societal debts it cannot pay back*" [3]. Despite, or perhaps because of our current inability to support sustainability ambitions, it is expected that in the decade ahead of us, users and organizations will reward and demand efforts toward sustainability. The importance of reuse and repurposing will increase and become a key driving force in systems engineering. Sustainability as a system characteristic will become a leading principle in systems' design, operation, maintenance, and post-life. These trends have been collectively identified in the Systems Engineering Vision 2035 report [4] of the International Council on Systems Engineering (INCOSE), the leading systems engineering society, as the top "*global megatrend*" that will instigate the development of radically new systems engineering frameworks, methods, and tools. The European Commission has also identified sustainability as a critical enabler of a more resilient European industry within the framework of Industry 5.0[1]. Expert voices call for immediate action in devising frameworks, methods, and tools for sustainable systems engineering practices [5] and fostering a circular economy [6].

Digital transformation trends chiefly associated with Industry 5.0 have created opportunities—such as highly evolved digital capabilities, access to large volumes of data, and a better view of the end-to-

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[1] https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en

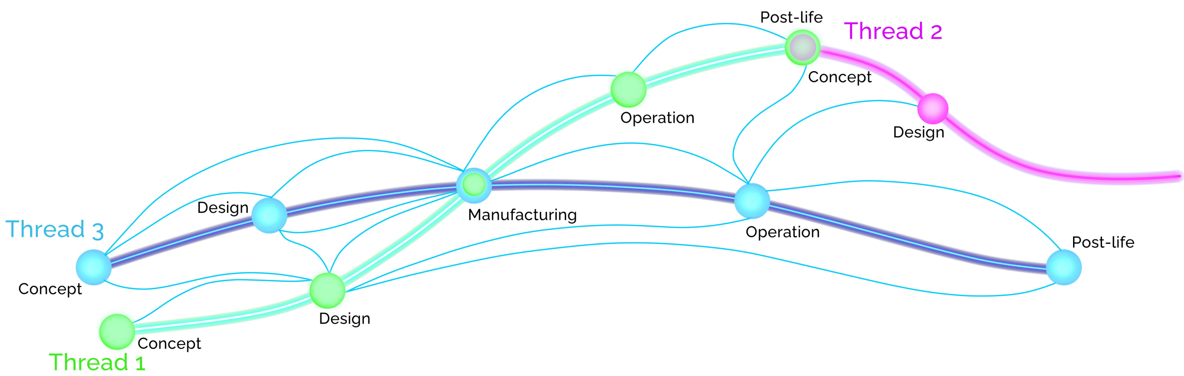

Figure 1: Digital Fabric composed of three Digital Threads, highlighting an example of circular value retention at the intersection of the *Post-life* of *Thread 1* and *Concept* design of *Thread 2*. An additional example of improved sustainability is shown at the intersection of the *Manufacturing* phases of *Thread 1* and *Thread 3*.

end engineering endeavor-to introduce sustainability into systems engineering [7]. To leverage these opportunities, we must contextualize sustainability ambitions within advanced digitalization—a set of technologies that themselves must become sustainable as "*an unsustainable digital society is prone to fail*" [8].

In this paper, we define one of such potential contextualizations: *circular systems engineering*, which we anticipate to be the paradigm of sustainable systems engineering practices ahead of us.

2. Circular Systems Engineering

Circular systems engineering is a digital technology-centered, actionable implementation of sustainability ambitions; a systems engineering paradigm of developing and operating systems in sustainable ways, including retaining a substantial portion of their value after service time, preferably over numerous circles (lifetimes).

Circular systems engineering is analogous to the concept of circular economy [9]. In a circular economy, value and material circulate across systems and products through various mechanisms of reuse, as long as possible, reducing waste and improving the economic outlooks of organizations. The idea of circularity has been around for decades and has been generally recognized as a desirable direction for humankind's overall sustainability and innovation endeavors [10]. Circular systems engineering implements sustainability ambitions through *i*) reasoning about trade-offs between functional, extra-functional, and sustainability properties; and *ii*) consideration within not only one engineering process but *across* multiple engineering processes. While the governing frame of thinking contextualizes sustainability within the lifecycle of one specific system, circular systems engineering emancipates sustainability from these confines. It unlocks a more holistic view of sustainability. By that, circular systems engineering subsumes and integrates state-of-the-art digital sustainability initiatives, such as manufacturing rationalization [11], process control for sustainability [12], software sustainability [13], sustainable digital twinning [14, 15], and green AI [16].

The prerequisites to circular systems engineering became available only recently, primarily due to the overall increase in organizations' digital capabilities, chiefly associated with Industry 4.0 and, recently, Industry 5.0 [17] endeavors. Some of the critical milestones along this digital maturation journey include the proliferation of Digital Thread based engineering methods [18] and the convergence to end-to-end enterprise process networks [19]. As the natural extension of Digital Threads to end-to-end process networks, we foresee the appearance of elaborate compositions of Digital Threads we call the Digital Fabric, in which threads can overlap and intercept each other, allowing for truly circular systems engineering.

Example. Figure 1 highlights the cardinal example of *Circularity*, along with a typical added sustainability benefit enabled by the Digital Fabric: *Manufacturing rationalization*.

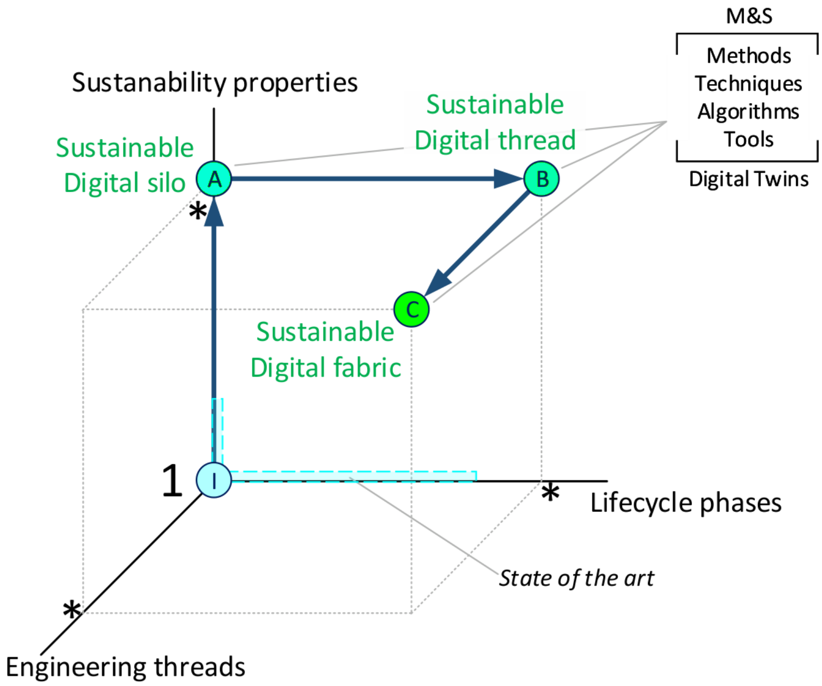

Figure 2: Conceptual reference framework of maturity levels required for circular systems engineering

1) Circularity. The *Post-life* phase of *Engineering Thread 1* and the *Conceptualization* phase of *Engineering Thread 2* overlap. This allows retaining value from *Thread 1* in *Thread 2*, e.g., by reusing material, refurbishing hardware elements, or reusing knowledge from *Thread 1*. Circular systems engineering allows for reasoning about such situations and factors reuse mechanisms [20] into the *Conceptualization* and *Design* phases of *Thread 2*. By that, circular systems engineering enables a higher level of sustainability.

2) Manufacturing rationalization. The *Manufacturing* phases of *Engineering Thread 1* and *Engineering Thread 3* overlap. Synchronizing the manufacturing phases of engineering threads and optimizing production scheduling is one of the major energy-saving factors [11] as about 80% of energy consumed by machine tools is reportedly attributed to idle state operation [21]. Thus, optimizing the manufacturing schedule would realize substantial energy savings. Circular systems engineering allows for reasoning about these situations, enabling a higher level of sustainability, specifically in environmental and economic aspects [2].

3. Prerequisites of Circular Systems Engineering

In this section, we postulate the prerequisites for circular systems engineering. To this end, we define a conceptual reference framework of orthogonal concerns and contextualize the path to circular systems engineering in terms of these concerns.

Dimensions. As shown in Figure 2, the conceptual reference framework organizes circular systems engineering concerns along three dimensions of reasoning: *sustainability properties*, *lifecycle phases*, *engineering threads.* Systems engineering methods can implement reasoning capabilities in any combination and extent of these dimensions. Each axis spans from implementing one concern (1) to implementing many (*) concerns along the specific dimension.

Systems engineering maturity levels: from Digital Silos to the Digital Fabric. Figure 2 identifies four characteristic maturity levels of systems engineering practices along the path of implementing circular systems engineering: the state of the art, i.e., Initial maturity (Section 3.1, the Sustainable Digital Silo (Section 3.2), the Sustainable Digital

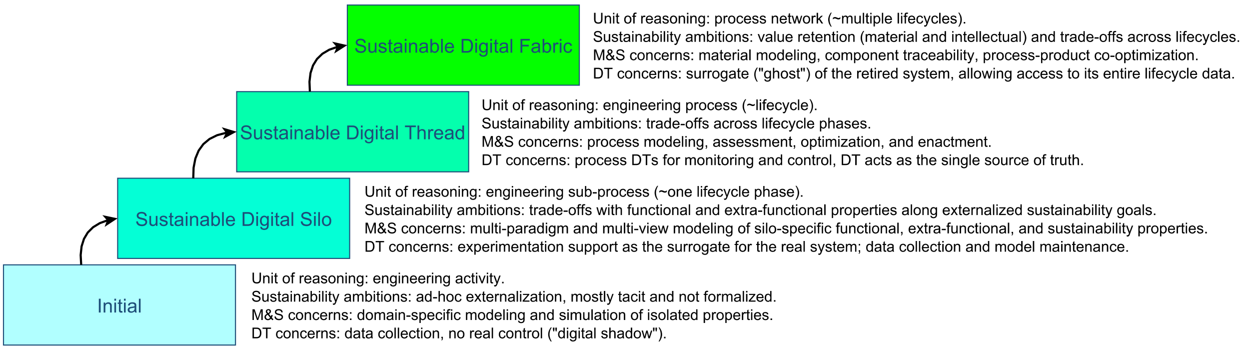

Figure 3: Sustainability maturity levels of systems engineering and their modeling and simulation (M&S) and digital twinning (DT) concerns

Thread (Section 3.3), and the Sustainable Digital Fabric (Section 3.4). These levels are attained by specialized enabler frameworks and technologies (Section 3.5).

Maturity levels are characterized by an increasing number of concerns they account for in the three dimensions of the framework, and by an increasing complexity of the underlying unit of reasoning they support.

Figure 3 summarizes these maturity levels and their modeling and simulation (M&S) and digital twinning (DT) concerns.

Below, we elaborate on these maturity levels in more detail and postulate prerequisites to reach them. To achieve circular systems engineering, an engineering methodology must meet all the prerequisites. In our discussion, we follow a typical maturity evolution pathway, denoted by the blue arrows in the framework. However, we note, that the conceptual reference framework does not impose any particular order in which strides along the dimensions must be made.

*3.1. Initial maturity (**I**) – State of the art*

The *state of the art* in systems engineering is the Initial level of maturity I. It is primarily concerned with two of the three orthogonal dimensions: *i*) end-to-end methods across the overall engineering lifecycle, and *ii*) improving the sustainability outlooks of systems at specific points of the engineering lifecycle. However, these efforts are independent of each other and fail to combine the two dimensions. As a result, the state of the art lacks lifecycle methods that would allow for reasoning about sustainability in an end-to-end fashion.

In terms of lifecycle methods, substantial work has been dedicated to engineering process modeling [22], assessment [23], optimization [24], and adaptation [25]. Sustainability efforts are mostly focused on energy consumption of software systems [26, 27] and advanced digital facilities [14], and reducing waste of engineering processes [28].

The combination of the two concerns is much desired, as demonstrated, e.g., by the impact of process scheduling on waste management [29]. A proper understanding of the underlying end-to-end engineering lifecycle allows for reduced makespan, minimized idle time, and improved task sequencing. Unfortunately, the stratified nature of sustainability [13], i.e., having different interpretations at different levels of abstraction, hinders the development of methods that would combine process-based longitudinal reasoning with reasoning about sustainability, despite the well-understood benefits [12, 30]. Recently, Digital Twins opened up opportunities for efficient data harvesting and rich decision support based on M&S [15]. Such ideas are the clear precursors of circular systems engineering.

*3.2. Sustainable Digital Silo (**A**)*

Implementing reasoning capabilities along the dimension of *Sustainability properties* within one engineering silo pushes toward a Sustainable Digital Silo A.

Engineering silos are organizationally and logically isolated units, typically associated with a specific lifecycle phase. Engineering silos come in various sizes and complexity. For example, an engineering silo can be a team of hydraulics experts in the development process of a complex cyber-physical system, or a separate business unit or company integrated into the supply chain. Digitalization transforms silos into *digital* silos, characterized by advanced digital and computer-aided capabilities, such as modeling, simulation, virtual experimentation, and optimization. These activities focus on the functional, extra-functional, and sustainability properties of the silo, and the trade-offs between them. Typical examples include reasoning for sustainability at design time [31], reasoning for sustainability during manufacturing [32], reasoning for sustainability at operation time [33], etc.

The prerequisites an engineering method must meet to implement the Sustainable Digital Silo, are the following.

P1-A: Must allow reasoning about *each sustainability dimension* of technical systems.

P1-B: Must allow reasoning about *trade-offs* between sustainability dimensions in a single lifecycle phase.

Unfortunately, siloed systems do not longer scale with the pace of innovation and the expectations of quality and efficiency [34]. Despite the high degree of digitalization, silos still give rise to quality and performance issues in organizations due to duplicated efforts, multiple sources of truth, and data inaccessibility. Although the most attainable maturity level for organizations, Sustainable Digital Silos fall short of supporting the sustainability ambitions of modern systems engineering.

*3.3. Sustainable Digital Thread (**B**)*

The Digital Thread resolves the pain points of Digital Silos by fostering propagation streams of information across silos, effectively integrating them along the system lifecycle. Singh [35] defines the Digital Thread as "*a data-driven architecture that links together information generated from across the product lifecycle*". West and Pyster [36] relate the Digital Thread to traditional Model-based Systems Engineering (MBSE) and its artifacts by defining the Digital Thread as "*a framework for merging the conceptual models of the system (the traditional focus of MBSE) with the discipline-specific engineering models of various system elements*". The numerous definitions of the Digital Thread all agree on the integrative nature of the concept, and that the Digital Thread extends the capabilities of the Digital Silo to the overall lifecycle of the system.

Extending the advanced reasoning capabilities about sustainability properties of silos (Section 3.2) to the entirety of *Lifecycle phases* along the end-to-end engineering process gives rise to the Sustainable Digital Thread B. By that, the unit of reasoning is extended from *sustainable engineering activities within a silo* to *sustainable engineering processes within a thread*.

The prerequisites an engineering method must meet in addition to prerequisites P1-A and P1-B to implement the Sustainable Digital Thread are the following.

P2-A: Must allow reasoning about *each lifecycle phase* w.r.t. sustainability along the end-to-end systems engineering endeavor, starting from the conceptualization phase up until post-life.

P2-B: Must allow reasoning about *trade-offs* between sustainability dimensions across different lifecycle phases.

*3.4. Sustainable Digital Fabric (**C**)*

The Digital Fabric is the extension of Digital Threads we envision as the next level of evolution in advanced digitalization of engineering. The Digital Fabric is the mesh of overlapping Digital Threads that intercept each other at various lifecycle phases. The Digital Fabric enables assessing and optimizing for systems properties, including sustainability properties across engineering endeavors. The Digital Fabric also provides foundations for maintaining a holistic view on the sustainability efforts of every involved party, a key mechanism of future sustainable digital infrastructures [37]. This will be achieved by the sound composition of Digital Threads. End-to-end enterprise process networks [19] create sound foundations for implementing the Digital Fabric. Ultimately, the composition mechanisms behind the Digital Fabric are the technical enablers of circularity in systems engineering, which will be leveraged to implement value retention mechanisms for sustainable practices.

The Sustainable Digital Fabric C allows for aligning activities and lifecycle phases, and by that, retaining value across engineering endeavors. This final step to achieving circular systems engineering is to link *sustainable engineering processes* into a *sustainable engineering process network*, with the Sustainable Digital Fabric as its digital manifestation. In the most characteristic cases, the post-life phase of one Digital Thread will be channeled into the concept and design phase of another Digital Thread; or two Digital Threads might synchronize their manufacturing phases for rationalized resource utilization.

Thus, the prerequisites an engineering method must meet in addition to prerequisites P1 and P2 to implement the Sustainable Digital Fabric are the following.

- P3-A: Must allow reasoning about *each design process* in their interception points.
- P3-B: Must allow reasoning about *trade-offs* between sustainability dimensions across different processes (resulting in the *Sustainable Digital Fabric*).
- P4: Must support effective value retention mechanisms across threads.

Apart from the usual reasoning and trade-off prerequisites, this level of maturity also requires closing the loop between Digital Threads and rendering the engineering method *circular.* Prerequisite P4 is best approached through the known value retention frameworks, such as 10R [20].

3.5. Enablers

Circular systems engineering runs on two important enablers at each level of maturity: *Modeling and Simulation (M&S)* as the methodological foundation, and *Digital Twins* as the technological foundation. Model-based techniques and in particular, model-driven engineering [38] help manage the different levels of abstraction at which sustainability can be interpreted [13]. In addition, process methods allow for controlling engineering processes for sustainability [12]. Finally, explicit models about product and process enable the rapid development of Digital Twins [39], the other important enabler.

Built on these enablers, each level of maturity is supported by the appropriate *methods, algorithms* and *tools* to make strides towards circular systems engineering. However, the development of capabilities that eventually result in the Sustainable Digital Fabric, needs to be carefully coordinated and approached in a systematic fashion. We need (*i*) a governing framework and (*ii*) identified enabler technologies.

The prerequisites of these two concerns are orthogonal to the previous ones (i.e., independent from them but can be applied with any of them) and can be formulated as follows.

- P5: The governing framework must be extensible to be able to accommodate newly encountered sustainability goals, different lifecycle models, and various value retention strategies.
- P6: The enabler technologies must support the rapid development of capabilities through advanced digital accelerators, such as Digital Twins.

4. Challenges and Research Opportunities

In this section, we outline some of the main challenges and research opportunities in implementing circular systems engineering.

4.1. Governing knowledge infrastructure

To understand the complex notion of sustainability and to effectively support sustainability ambitions, systems engineering needs to develop a governing knowledge infrastructure with actionable principles. In the absence of such a knowledge infrastructure, we will keep failing to understand the synergies between systems engineering and sustainability, resulting in ad-hoc attempts at sustainable practices that fail to generalize to larger classes of problems.

The challenges and opportunities in this regard pertain to the following.

4.1.1. Frameworks

To reason about the alignment of sustainability principles with systems engineering paradigms, coherent governing frameworks [40] are required that encompass (*i*) the lifecycle phases of systems, (*ii*) the various dimensions of sustainability, (*iii*) specific sustainability activities, and (*iv*) systems engineering techniques and tools. Such frameworks will foster a better understanding of sustainability, e.g., through model-based means and advanced visualization [41, 42]; and will help make actionable decisions about how and when to address specific sustainability properties of systems, and which tools to use for that purpose. Example questions include: which elements of the 10R framework are the most pressing in current and future engineered systems; and what extensions are required to MBSE techniques to successfully incorporate sustainability principles?

4.1.2. Taxonomies and ontologies

Comprehensive taxonomies, such as the one by Bischoff et al. [43], are the first step toward a sustainability framework. A taxonomy is a formalization of concepts, typically organized in a hierarchical way and can be used to elicit various meanings of sustainability related to systems engineering.

In addition to organizing concepts, ontologies also allow for formalizing relationships between concepts and domain axioms [44]. By that, ontologies are particularly apt structures for capturing domain *knowledge*. Ontologies have been successfully employed in interdisciplinary knowledge management, and specifically, in systems engineering [45]. Once domain knowledge is properly formalized, automated analysis of concepts and their relationships can aid systematic reasoning about sustainability principles and properties. This capability, in turn, helps to tackle the multi-systemic nature of sustainability.

The automated reasoning capabilities of ontologies also help in taming the complexity that comes with reasoning about multiple sustainability dimensions. State-of-the-art efforts often focus on one dimension of sustainability and omit or fail to combine other dimensions [30, 46]. In engineering-related domains, this dimension is typically related to energy consumption aspects [47, 27].

4.1.3. Standardization

Eventually, standardized notions of sustainability-related concepts, actions, and processes are required to replace the abundance of definitions that suggest different dimensions and focus points of sustainability in systems engineering. Since Brundtland's original three-dimensional framework of sustainability [1]—consisting of environmental, economic, and societal aspects—numerous attempts have been made to tailor the notion of sustainability to systems and software. For example, Penzenstadler [48] define sustainability as "preserving the function of a system over a defined time span". Lago et al. [2] emphasize system evolution as the key four dimensions software-intensive systems need to adhere to in order to achieve sustainability. The expert interviews by Groher and Weinreich [49] highlight that sustainability often is seen as a synonym or amalgamation of maintainability, extensibility, and changeability by experts.

Clearly, viewpoints need to converge and standardization is a proven way to achieve it. Manifestos (cf. the Agile manifesto [50]) and bodies of knowledge (cf. the Software Engineering Body of Knowledge [51]) are appropriate initial artifacts that may reshape engineering domains and may evolve into standards. These artifacts should be utilized by systems engineering professionals in the current state of fragmented and stratified sustainability efforts to make clear strides toward unification.

At later stages, links with already existing standards, such as ISO 14001[2] (Environmental sustainability) and ISO 26000[3] (Social responsibility) will have to be established.

4.2. Process methods

While the Digital Thread has been enjoying widespread success and rapid adoption, formal grounds for quantitative assessment are lacking. Many sustainability-related limitations of current systems engineering are related to this shortcoming. Contextualizing the Digital Thread as a formal process allows for the reuse of proper process methods to be integrated into Digital Thread-based frameworks.

The challenges and opportunities in this regard pertain to the following.

4.2.1. End-to-end process models as a formal underpinning of the Digital Thread

Proper assessment of sustainability requires reasoning about the properties of the engineered system in conjunction with the engineering process [7, 52] – or, in practical terms, along the Digital Thread. Unfortunately, systems engineering process models tend to lack formal rigor [30]. This staggering shortcoming renders the end-to-end assessment and optimization of engineering endeavors an insurmountable challenge and the identification of sustainability trade-offs unfeasible to solve. While isolated efforts have been made, e.g., in sustainable manufacturing [28] and business information systems [53], holistic end-to-end approaches for sustainable systems engineering are lacking.

Existing systems engineering process methods have the potential to be repurposed and tailored for the needs of circular systems engineering. For example, substantial research has been conducted in process methods for finding quality and cost trade-offs in multi-disciplinary design [54, 52]. These methods are likely capable to support technical and economic sustainability aspects of systems engineering. Extensions can be made in terms of supported lifecycle phases, e.g., by addressing the

[2] `https://www.iso.org/standard/60857.html`

[3] `https://www.iso.org/iso-26000-social-responsibility.html`

post-life of systems, and in terms of externalizing sustainability properties as first-class citizens of complex process models [55]. For the latter, environmental sustainability should be considered as an immediate target, building on isolated previous work, e.g., activity-based cost modeling and value stream mapping coupled with discrete event simulation [28].

4.2.2. Composition of process models into process networks

The key challenge in value retention mechanisms is that they are often situated at the intersection of two or more Digital Threads, and the hand-off of information requires elaborate techniques that are not yet supported in Digital Thread platforms. To better understand interactions between Digital Threads, a Digital Fabric needs to be developed. Implementing the Digital Fabric, in turn, requires the process models of single Digital Threads to be unified into a composite process network [56]. Current methods for the comprehensive modeling, analysis, and optimization of such process networks are limited. Notably, process monitoring and prediction frameworks that are able to leverage the entirety of enterprise data sources, are completely missing from the state of the art [19].

There are research opportunities in extending process-based monitoring, analysis, and reasoning capabilities to complete process networks, especially in the domain of complex digital systems. Supporting systematic value retention in the Digital Thread requires novel theories and tools.

4.2.3. Enactment and control

Once processes underpinning the Digital Fabric are optimized, they must be properly executed. However, as highlighted by Daoutidis et al. [12], sustainability practices create operational challenges, motivating the employment of well-established process enactment methods. Process enactment is commonly defined as the use of software to support the execution of operational processes [57, 58]. Enactment strategies allow for adhering to the process model along the Digital Thread. This allows for a better understanding of the prevalent state of the Digital Thread and the context in which the engineering process is executed, e.g., resources and stakeholders.

Digital Process Twins [59] further improve enactment and run-time process model adaptation capabilities. A Digital Process Twin is a virtual representation of the real process that captures the process's context and provides control capabilities. In contrast to traditional Digital Twins of systems or their components, the focus of a Digital Process Twin is the run-time management of the process with typical goals of controlling the quality of the produced product, reducing energy consumption, and ensuring compliance with the underlying process model [60, 61]. The rich sensor infrastructure and data generation points in engineering processes bode well with the deployment of any Digital Twin, including Digital Process Twins. By that, Digital Process Twins are primary candidates in circular systems engineering to govern and guide day-to-day activities.

4.3. Optimization methods and design space exploration

Finding global sustainability optima in realistic settings is rendered unfeasible by the multi-dimensional and multi-systemic nature of sustainability. Therefore, in the scope of circular systems engineering, the goal of optimization methods should be finding *acceptable* sustainability trade-offs across different sustainability dimensions and different system lifecycle phases.

The challenges and opportunities in this regard pertain to the following.

4.3.1. Finding sustainability trade-offs

Due to a growing awareness of the need for more sustainability, the United Nations General Assembly formulated 17 Sustainable Development Goals (SDGs) [62], for which in total 169 targets have been set. These SDGs and targets aim to provide a general framework for sustainability and development. As mentioned at the outset, sustainability is a multi-faceted notion involving many different interrelated aspects. Consequently, optimizing towards one SDG target may have a negative impact on another one [63, 64], generally requiring a conscious and responsible *balancing* between the different goals. Or as it is put more explicitly in [64]: "*In terms of the SDGs, trade-offs are guaranteed to arise given the inherent contradictions across the 169 targets*" and in [65] "*Industry is confronted with the challenge of balancing economic and financial priorities against environmental and social responsibilities*".

In the context of circular systems engineering, a further challenge relates to the fact, that sustainability goals might differ from phase to phase throughout one, and across multiple overlapping Digital Threads. For example, environmental impact is less of a concern in the concept and design phases than in the realization phase of the system.

The ability to identify, analyze, and optimize the sustainability trade-offs within and across Digital Thread by different SDG targets, Key Performance Indicators (KPIs), and Key Environmental Indicators (KEIs) are key to fostering circular systems engineering. Capabilities for the analysis and optimization of single lifecycle phases for often contradictory functional and sustainability goals are required that also translate the rather global and socio-economical metrics like SDG targets and even KPIs toward sustainability-related metrics like KEIs[4]— analogous to the move from a conventional Balanced Score Card approach [66] toward a Sustainability Balanced Score Card [67, 68]. As a foundation for this trade-off analysis and optimization, methods are required that foster the translation of the generic metrics to fit the context of the current organization and domain.

Next to the multi-objective optimization and search-based techniques which we will elaborate on in the following, we believe more intuitive approaches like goal modeling can serve the identification and formalization of trade-offs and delineate extension and customization points for contextualization.

4.3.2. Multi-objective optimization

The research field of Search-Based Software Engineering (SBSE) [69] is actively applying search-based optimization techniques to software engineering problems like model transformation [70] and model modularization [71].

To cope with the complexity and interrelatedness of the many objectives to consider when aiming to optimize systems engineering toward sustainability—while not omitting other objectives—multi-objective optimization seems promising.

A formal specification of all objectives to consider by means of fitness functions, e.g., by incorporating the previously mentioned taxonomies and ontologies and the trade-offs, would ease the use of genetic algorithms in combination with meta-heuristic search techniques to explore the solution space and automatically produce a Pareto set of solutions. Such Pareto sets provide heterogeneous solutions where for each Pareto-optimal solution a further improvement regarding one objective cannot be achieved without worsening the results for at least one of the other objectives. Therefore, multi-objective search and optimization solutions are particularly relevant to balance the heterogeneous, often even conflicting objectives adhering to a holistic optimization of circular systems engineering.

4.3.3. Collaborative Design space exploration

Design space exploration (DSE) is the systematic method of searching through the space spanned by design alternatives with the intent of finding optimal design alternatives with respect to different objectives and complex structural and numerical constraints [72]. DSE is an apt method when human input to the search process is desirable to evaluate design alternatives, such as in interactive CAD design [73] and integrated circuit optimization [74]. Software engineering research and especially, model-driven software engineering [38] has also adopted DSE, mostly relying on rule-based [75] and human-guided [76] methods. However, DSE is limited in vastly multi-disciplinary scenarios that require optimization based on subject matter expertise from disparate domains. This limitation does not bode well with the multi-systemic nature of sustainability.

To combat this shortcoming, we envision the next generation of DSE techniques supporting collaborative joint exploration mechanisms in which experts of disparate domains can express their design choices and intuitions while computer automation ensures that the design choices are consistent with each other. Powerful multi-disciplinary DSE methods have been developed, e.g., for the design of complex cyber-physical systems [77, 78], but the collaborative aspect is yet to be researched.

As a specific case, one of the collaborating experts in the DSE process can be the machine itself, as demonstrated by Wong et al. [79]. In such cases, explainability and interpretability [80] of the computer agent's decisions is an open challenge [81]. However, the joint exploration experience already removes some hurdles in that aspect. To further improve explainability, powerful large language models [82], such as GPT can be tasked with generating human-understandable explanations of solutions beyond the humanly tractable horizons of the design space [83, 84].

[4] `https://www.eea.europa.eu/data-and-maps/indicators/land-take-3/oecd-key-environmental-indicators-kei`

4.4. Value retention mechanisms

Value retention refers to the act of retaining value from components (including digital ones, such as software), materials, energy, and knowledge after a system served its purpose. Value retention is the crucial enabler of circular systems engineering that, in fact, allows circularity: the model of developing, operating, and reusing systems over numerous cycles. As such, value retention mechanisms contribute to higher levels of sustainability. However, actionable directives are still lacking.

The challenges and opportunities in this regard pertain to the following.

4.4.1. R-imperatives

R-imperatives define activities for value retention, mostly motivated from the angle of circular economy [85]. Perhaps the most known of such imperatives is 3R advocating for reduce, reuse, and recycle—the three *R-tivities* in this particular framework, with fairly straightforward directives. Different domains adopt their own finer or coarser-grained R-imperatives with varying rigor and details. A thorough cross-domain analysis has been provided by Reike et al. [20].

Van der Aalst et al. [5] find that the 10R framework of Reike et al. [20] is particularly well-suited to support sustainable systems engineering. While indeed a good match due to the additional, refined R-tivities of remanufacturing and recovering energy, the activities of R-frameworks, in general, are still too high-level to be actionable, and they lack mechanisms for the formal assessment of sustainability under these strategies.

To combat this shortcoming, theoretical foundations and methods, preferably linked to standards are required to be developed. This will allow us to understand how engineering processes intercept each other and hand over system components, material, energy, knowledge, etc.—value, in short. Substantial amount of research has been done on reuse in the realm of digitized engineering domains, such as software [86]. Nowadays, it is hard to encounter top software conferences without dedicated tracks or focus topics on reuse, repurposing, or other kinds of value retention. As a consequence, the benefits [87] and threats [88] of reuse are fairly understood in the software engineering community. The rich literature on the topic merits a deeper look from a systems engineering point of view to identify methods and techniques that can be *reused* to foster circular systems engineering.

4.4.2. Lifetime component traceability and material sciences

Some extended R-frameworks refine the reuse-recycle mechanisms into more tangible ones. For example, half of the R-tivities of the 10R framework [20] focus on retaining value by disassembly and reassembly—either with the same components, configuration and purpose, or with completely new ones. Such advanced value retention mechanisms need to be properly supported by the traceability of system components (when parts of the system are replaced to extend its lifetime) and a thorough understanding of how materials can be reused or repurposed (when a system is permanently retired).

Component traceability has been a topic of interest in Internet of Production (IoP) initiatives [89, 90]. In electrical and electronic equipment waste refurbishing services, for example, traceability through transportation is an important enabler of the offering [91] as identifying transported products provides assurance of location, condition, and integrity. Despite the early results, traceability of components along *multiple* system lifetimes is still an open challenge.

Eventually, system components themselves are retired and disassembled, and in most cases, scrap raw material and energy are the only value that can be salvaged. Especially in circular systems engineering, the trade-offs of using better-choice materials [92] must be well-understood. To assist such an understanding, machine learning and AI methods have been proposed, e.g., to accelerate material development by physics-constrained AI [93] and design space exploration by active transfer learning and data augmentation [94]. Such advanced mechanisms improve the effectiveness of value retention mechanisms in circular systems engineering and therefore, their development offers research avenues with elevated utility.

4.4.3. Knowledge retention

Knowledge represents a particular class of values to be retained across system lifetimes and is a crucial element in fulfilling the vision of circular systems engineering. Efficient reuse of knowledge contributes to each aspect of sustainability as it allows for better design both in technical and economic terms, while also allowing for better-optimized manufacturing and operation practices. As such, reusing design knowledge and transposing previously learned lessons has been a topic of particular interest.

Traditional techniques for knowledge retention through the use of ontologies (Section 4.1.2) provide rich expressiveness but do not scale to the level of truly complex systems and their engineering processes [95]. This is partly due to the lack of methods for identifying truly valuable knowledge to be retained. Assessing the value of knowledge is particularly challenging due to its non-monetary and highly abstract and tacit nature. The discipline of infonomics [96] takes a middle ground and provides actionable metrics for information, instead of knowledge. Deriving similar valuation mechanisms for knowledge is an open challenge. More automated techniques of retaining codified knowledge have been a subject of active research in machine learning. Transfer learning [97] is the technique of applying previously learned knowledge in congruent tasks. Such techniques have been successfully applied in an array of complex problems, such as atmospheric dust aerosol particle classification [98] and poverty mapping [99], and very much technical problems, such as image recognition [100]. However, efficient codification of knowledge in statistical networks and the assessment of the similarity of problems and domains remains an open challenge, rendering transfer learning vulnerable to the reduction of accuracy after retraining [97].

4.5. Digital enablers

While Industry 4.0 could have been an enabler of sustainable development, the relative underdevelopment of digital intelligence has been limiting the ability of organizations to achieve true sustainability [101]. Industry 5.0 is expected to be more value-driven as opposed to the technology-driven Industry 4.0. That is, Industry 5.0 will prioritize societal goals beyond job creation and growth, and respect environmental boundaries [17]. To support these goals, Industry 5.0 requires novel digital enablers to be developed.

The challenges and opportunities in this regard pertain to the following.

4.5.1. Digital Twins: from experimental surrogates to process governance

One of the important digital intelligence capabilities within the scope of circular systems engineering is the Digital Twin [102], the real-time, "live" digital representation of physical assets. Digital Twins are key enablers of the Digital Thread in a variety of roles ranging from the design phase to post-life.

Complex systems require complex design models to be developed before the systems get realized. Digital Twins can act as safe and affordable digital surrogates of physical systems enabling experimenting with them [103]. Systems subject to digital twinning are usually well-instrumented cyber-(bio)physical systems, a trait that allows for the data-based synthesis of design models [104]. Once deployed, Digital Twins can act as data ingestion proxies to keep models updated. This allows human stakeholders to rely on systems design documents as the single source of truth when observing and analyzing operational systems. Digital Twins are also well-positioned to govern end-to-end processes [15], contributing to important operational goals, such as adaptive control and predictive maintenance [105].

However, Digital Twins are no silver bullet in fostering more sustainable systems engineering practices. Tzachor et al. [64] report multiple challenges that might prevent Digital Twins to support sustainability goals. The level of digital maturity (or the lack thereof) often hinders proper data management, sometimes to the point where real-time data may not be available or is of poor quality. By McKinsey's industry digitalization index [106], particularly challenged are agriculture, construction, and healthcare – three sectors strongly linked to sustainable development through precision agriculture, smart cities, and more patient-oriented health systems, respectively. The feasibility of adopting Digital Twins is also far from being trivial [107], and it is usually a challenge outside of well-developed countries. Furthermore, modeling and simulation of systems with social elements is a wicked problem [108], and studies on applying Digital Twins to social problems are currently lacking.

While research mostly focuses on sustainability *by* Digital Twins, it is important to acknowledge that Digital Twins themselves need to be sustainable to support larger sustainability goals. Bellis and Denil [14] report four important sustainability challenges of Digital Twinning: energy consumption, modeling effort and complexity, the ability to evolve with the physical twin, and the deployment of the twin architecture within organizations. Predictive methods and better design automation are key to alleviating these issues.

4.5.2. Synthesis of Digital Twins

The development of Digital Twins is hindered by the complexity of systems subject to digital twinning. The crucial role of Digital Twins in circular systems engineering necessitates devising novel methods for their efficient and rapid synthesis. Such a rapid synthesis mechanism can be, for example, the component-based synthesis of Digital Twins, especially in relation to the ISO 23247-2 reference architecture for manufacturing-oriented Digital Twins. While other classification frameworks exist [109], they usually do not provide such details as standardized frameworks. Nonetheless, they can be used in the ideation phase of developing Digital Twins, or to communicate with stakeholders.

Component-based service synthesis methods have shown to be particularly well-suited for AI-based automation [110, 111]. Extending these methods to the realm of Digital Twin services is a direction to be investigated. To further improve the composability of Digital Twins, variability support [112, 113] for Digital Twins can be developed. Closely related preliminary work has been done in the field of simulator synthesis [114]. Finally, to tackle the challenges of siloed environments and leverage the benefits of Digital Twinning, interoperability mechanisms of Digital Twins are to be developed [115]. Interoperability allows loosely coupled Digital Twins to scale up into hierarchies of integrated Digital Twins. On a related note, extra-functional properties—such as security [116], reliability [117], and performance [118]—of such Digital Twin hierarchies must be prioritized.

4.5.3. Digital Ghosts

Among the many roles of Digital Twins, the one that helps bridge gaps across Digital Threads and acts as a surrogate for a retired physical twin, is of particular importance. We refer to these Digital Twins as *Digital Ghost*s, the representations of systems that do not exist. The retirement of systems does not necessarily mean they stopped playing a role in the overall value chain of an organization. Quite the contrary – circular systems engineering requires effective value retention across lifetimes. To support this, Digital Ghosts act as surrogates for retired physical systems. They allow easy access to the history of the system to support the reuse of knowledge. Such access should go beyond simple analytics and allow for complex scenarios such as experience replay [119] and interactions with the surrogate model through the metaverse [120].

Digital Ghosts can also act as surrogates of physical systems or components that *should* exist but were never realized in the first place. While in the previous scenario, a Digital Ghost is of a descriptive nature ("How would the real system behave?"), here, it is more of a prescriptive nature ("How should the real system behave if there was one?"). An immediate application area of Digital Ghosts are power grids that are known to be susceptible to instability as modern power generators associated with renewable energy are introduced to the grid [121]. In such scenarios, Digital Ghosts can be used to control, analyze, and experiment with the emulated grid, and to create appropriate sources of synthetic inertia [122].

Currently, no methods and tools exist that are optimized for the challenges associated with Digital Ghosts. Particularly, there are opportunities in researching efficient knowledge representation and retrieval, the specificities of creating digital counterparts of virtual (non-existent would-be) systems, and the potential in synthesizing physical twins from prescriptive Digital Ghosts.

4.6. Methods and algorithms: the role of AI

Given the immensely complex nature of sustainability, modern artificial intelligence and machine learning methods will inevitably make their way into the toolbox of circular systems engineering. Such trends have been identified in numerous domains, e.g., affordable and sustainable energy[5], AI for climate change [105], and AI4Good[6]. The abundance of data along the Digital Thread makes such directions feasible.

The challenges and opportunities in this regard pertain to the following.

4.6.1. Automated inference of simulators

Simulators are key tools in the general systems engineering toolbox. With the complexity of modern systems reaching unprecedented heights, the simulators of those systems become unfeasible to develop manually. Spiegel et al. [123] show that identifying assumptions even in simple models, such as Newton's second law might be infeasible. Horizontal challenges stemming from models situated at different levels of abstraction, vertical challenges stemming from inappropriate abstraction mechanisms, and scalability challenges stemming from the increased search friction due to the abundance of information further hinder simulator composability and component reusability [124].

[5] `https://sdgs.un.org/goals/goal7`

[6] `https://ai4good.org/`

The benefits of neural network augmented simulators are being re-discovered [125], although Recurrent Neural Networks have been used already decades ago to augment simulators [126]. Reinforcement learning is gaining popularity in digital twinning settings due to the reliance on real-time interactions instead of voluminous historical data for training purposes. The sensors and actuators of cyber-(bio)physical systems that are subject to digital twinning allow learning agents to interact with the system and learn through trial and error within reasonable safety boundaries. Such directions have been explored, e.g., by David et al. [127] and David and Syriani [104]. These directions highlight new research opportunities in applying AI for simulator construction.

4.6.2. Human-machine collaborative design

The design of complex systems requires a collaborative effort between stakeholders of different disciplines, often in real-time. Augmenting AI agents with collaborative mechanisms promotes AI to a teammate from being a mere tool [81]. Machines excel in problem-solving situations when information overload and ambiguity hinder collaborative design—two traits sustainable systems engineering clearly exhibits. Machine collaborators can improve design and analysis, e.g., by effectively identifying reliable, accurate information [81]. Such support is highly desired in an array of domains, such as automotive design [128], material design space exploration [94], and principled network design [79].

Substantial effort has been dedicated to developing mixed-initiative interfaces in the field of Human-Computer Interaction [129]. Mixed-initiative interaction refers to an interaction strategy in which each agent (human or machine) contributes what is best suited at the most appropriate time [130]. Human-AI collaboration can be seen as the next step in this paradigm that, with the advent of generative and conversational AI agents [131], has the potential to disrupt current systems engineering processes that rely on the human to orchestrate AI agents.

4.6.3. Sustainable systems by sustainable AI

While the impact of AI on systems engineering is immense and AI is set to unlock previously unprecedented opportunities, especially in sustainable systems engineering, it is important to note that the cost of such directions might easily defeat the purpose [16]. Training AI/ML models is a particularly resource-demanding endeavor, especially in terms of energy. The experiments by Strubell et al. [132] report a staggering 270 tonnes of CO_2 emission for training a large NLP model with neural architecture search [133], equivalent to the lifetime emissions of five cars. Google's AlphaGo Zero generated 96 tonnes of CO_2 over 40 days of research training[7], equivalent to the lifetime emissions of two to three cars [132, Table 1].

Clearly, to support the sustainability ambitions of circular systems engineering, AI itself must become sustainable. This will require researching and prioritizing computationally efficient hardware and algorithms [132], and better tools to assess the environmental impact of AI [134, 135], and proper legal, societal, and technical frameworks to govern and enforce sustainable AI practices [136, 137].

5. Conclusion

As sustainability is becoming a first-class citizen in modern systems, our systems engineering methods need to be revised to support sustainability ambitions. In this paper, we have defined circular systems engineering, a novel paradigm for systems sustainability. Circular systems engineering is a digital technology-centered, actionable implementation of sustainability ambitions; a systems engineering paradigm of developing and operating systems in sustainable ways, including retaining a substantial portion of their value after service time, preferably over numerous circles (lifetimes).

While the idea of circularity has been around for decades and has been generally recognized as a desirable direction for humankind's overall sustainability and innovation endeavors, systems engineering is yet to adopt sustainability as a governing principle. With the looming paradigm shift from a technology-focused Industry 4.0 towards a value-focused Industry 5.0, systems engineering now has a rare opportunity to promote sustainability to a first-class citizen. We believe circular systems engineering can be a guiding principle along this road.

To drive the adoption of circularity principles and instigate future research, we have derived prerequisites for circular systems engineering, defined a maturity model, and identified key challenges and opportunities. Researchers and practitioners can use

[7] https://inhabitat.com/mit-moves-toward-greener-more-sustainable-artificial-intelligence

the paradigm to steer their sustainability-themed research and development activities and to identify the modeling, simulation, and digital transformation goals appropriate to the level of sustainability maturity of their organization.

Call to action

Promoting sustainability in systems engineering practices is our joint responsibility. While we kept our discussion focused on systems engineering and intentionally refrained from making links with the most pressing contemporary societal issues, such as drastic climate change [138], systemic inequity and poverty [139], and depleting natural resources [140], we must acknowledge that humankind faces immense challenges that seem to be insurmountable within the current governing frame of thinking. We need to revise our current ways of coexisting with our environment and with each other.

Elevating sustainability to a leading principle in systems engineering, while it might seem a minuscule improvement in the grand scheme of things, will go a long way as it will render the next generation of our systems more environmentally friendly and more useful for society at large.

We invite professionals in systems engineering, computer science, and all adjacent domains; academic researchers, industry organizations, and technology transfer entities to contribute to the vision of circularity in systems engineering through research, development, and knowledge dissemination. We encourage professionals to apply the paradigm of circular systems engineering in their projects, to open discussions about its limitations and benefits, and to inspire others to follow suit. We are in a prime position to pave the way for sustainable systems engineering practices. Circular systems engineering might be the paradigm we need for it.

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