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Effective system-of-systems simulation in a VUCA world: lessons learned for design decision-makers

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ABSTRACT: Today, Manufacturing companies are adopting a servitization strategy and Product-Service System model to enhance value and remain competitive. Often, this transition also means to embrace a System-of-Systems (SoS) perspective. Concurrently, companies face challenges with volatile, uncertain, complex, and ambiguous (VUCA) environments. One way to tackle VUCA is to utilize simulation modeling. However, developing SoS simulations can be complex and cumbersome. This paper extracts lessons learned from six case studies to identify effective and ineffective practices in developing simulation models. The analysis has led to nine design principles for more effective simulation modeling. Furthermore, the paper explores simulation techniques for modeling SoS and discusses effective VUCA management. Finally, the paper proposes four future research directions to advance SoS simulation research.

KEYWORDS: system-of-systems, simulation, early design phases, complexity

1. Introduction

In volatile, uncertain, complex, and ambiguous (VUCA) environments, organizations face unprecedented challenges that demand adaptive and robust decision-making frameworks to maintain competitiveness (Taskan et al., 2022). The rise of servitization, transforming traditional product-based models into integrated service-oriented systems, means that the value creation also shifts and becomes more dominant during the operational phase and in the interaction between provider, customer, and environment. This leaves the value creation more sensitive to operational changes and stresses the need to work with the four dimensions of VUCA (Araújo et al., 2021). The transition to subscription-based solutions is not only something we experience in the consumer market (e.g., Spotify and Netflix) but also a transition taking place in the Business-to-Business sector. This trend is often referred to as servitization or the shift from products to Product-Service Systems (Baines et al., 2007). However, this shift demands that the provider not only deliver a product according to specifications but also ensure its value creation through its operational life. Hence, the provider must clearly understand what and how the PSS creates value for the customer (Kuijken et al., 2017). Moreover, PSS solutions seldom operate in isolation but are a part of an ecosystem. A clear example is the Transport-as-a-Service model, which has emerged as a business model in quarry/mining equipment manufacturers, e.g. (Caterpillar, 2021; Komatsu, 2023; Volvo Autonomous Solutions, 2023). The servitization transition means that the design focus shifts from isolated systems to a System-of-Systems (SoS) view. An SoS is a system built from loosely coupled, managerially and operationally independent systems collaborating for a common goal (Kopetz, 2013; Maier, 1998). In SoS, companies need to understand how the combinatory effect of system configuration, environmental constraints, and operational management influence one another. This means that an SoS is evolutionary, with its structures, functions, and purposes being added, removed, or modified as the operations grow and evolve (Jamshidi, 2008). In other words, the complexity and VUCA at large grow exponentially and thus demands on the design team. VUCA is especially relevant for SoS, which is characterized by multiple stakeholders and temporal changes and has more open boundaries, i.e., functions in a complex ecosystem and has extrinsic dependencies.

The interplay between VUCA dynamics and servitization necessitates advanced modeling approaches that can anticipate and adapt to shifting conditions. Simulation models tailored for SoS in early design phases hold significant promise, offering a means to explore potential scenarios, test assumptions, and evaluate trade-offs systematically over entire operational lifecycles. The main purpose of simulation models is to enhance knowledge about the studied context. In a design process, it is essential to frontload the knowledge creation as early as possible (Johansson, 2019). This allows a design team to build knowledge when the design freedom is high and committed cost is low. Knowledge about operational behavior, which can be explicit and tacit, is a cornerstone for the success of an organization working with SoS. The issue of tacit knowledge is that it becomes highly dependent on the people and is difficult to retain within the organization (Wong and Radcliffe, 2000). A countermeasure is then to increase the reliance on explicit knowledge from operational data. Machchhar et al. (2022) performed a literature review that showed that operational data can serve a vital role in understanding the value and knowledge creation in PSS. However, relevant operational data might not be available in breakthrough or disruptive innovation, a pillar for ensuring competitiveness.

Today, simulation and modeling (S&M) is a well-established approach for virtually testing and evaluating design concepts. Simulations are one of the most common techniques for operational study and building knowledge about a system or when real-world testing is impossible or too expensive (Maria, 1997). Simulations are thus a suitable approach for exploring operational and emergent behaviors. Especially for SoS, where the operational phase is VUCA and multifaceted, simulation is a good method for enhancing understanding (Baldwin et al., 2015). However, developing a simulation model can be a cumbersome task that requires successful integration between multiple stakeholders and disciplines (Lowe and Chen, 2008). The unique characteristics of a SoS, the multi-layer organization, the number of individual systems, and emergent behaviors puts additional stress and complexity on the simulation model (Lowe and Chen, 2008). This means that even though S&M is a good approach for frontloading knowledge in SoS design, it is not an easy task.

This paper takes its stance on the potential of using simulations to manage SoS VUCA and frontload knowledge creation in SoS design. However, the design challenge is to balance all the complexities while being able to develop a simulation model in a reasonable time. This paper draws from multiple case studies to examine the design process for SoS simulation models and how these can be developed effectively while managing the existing complexities. The guiding research question can thus be stated as follows.

How should a simulation model for System-of-Systems design be developed effectively?

The remainder of this paper is structured in the following sections. Section 2 goes through the theoretical framework required for the research topic. Section 3 presents the methodology used for the multiple case study research and illustrates the cases included. Section 4 presents the learnings and derived design principles for effective SoS simulation modeling. Section 5 concludes by setting a future research agenda and reflecting on the study's limitations.

2. Theoretical framework

Systems Engineering has, in recent decades, expanded from looking at a single isolated system to a System-of-Systems (SoS) viewpoint. This can be described as a reaction to the challenging nature of contemporary environments marked by rapid change and interconnectedness, reflecting the need for adaptive, scalable, and resilient solutions (Lechner et al., 2024). A SoS captures multiple independent and dispersed systems that work together to achieve a common goal that cannot be solved by a single system (Walden et al., 2015). A clear example is quarries and mines, which depend on the successful interaction between loading and excavating equipment, load carriers (haulers, bed trucks), crushers, screeners, etc. when performing. Maier (1998) emphasize that five characteristics set SoS apart from the traditional system view: (1) Operational and (2) managerial independence, (3) geographic distribution, (4) emergent behavior, and (5) evolutionary development of the system or components. All these aspects

must thus be considered in the design process of a SoS, something which makes its design a complex task.
Gaspar et al. (2012, p. 146) define complexity as “the amount of relevant information necessary to define a system, including components, interconnections, performance, and scenarios among other perspectives that may be required.” However, in SoS, complexity is added as it encapsulates multiple unique systems that are loosely coupled, exhibit adaptive behaviors, an ecosystem view, and multi-layer dependencies (DeLaurentis, 2007; Lowe and Chen, 2008). A SoS relies heavily on self-organization and emphasizes operational behavior to achieve value creation, which further increases complexity (DeLaurentis, 2007; Keating et al., 2003). Moreover, a single system can internally be structured as a hierarchy, while an SoS is often more organized as a mesh, hindering hierarchal decomposition as a measure to lower complexity (Kopetz, 2013). This means that complexity in SoS cannot be as easily simplified by decomposing and isolating its parts, nor can it be tackled one system at a time. Within SoS simulation and modeling, Kinder et al. (2014, p. 151) state that “the failure of many SoS endeavors can be attributed to the inappropriate application of systems engineering processes, including modelling approaches, within the SoS domain because of the mistaken belief that an SoS can always be regarded as a single large, or complex, system.” This emphasizes that the accuracy of SoS simulations in mimicking real-world behavior is essential to ensure reliability, including all domains in VUCA, all of which are amplified in the system-SoS transition.
Today, simulation and modeling (S&M) are a core part of the design process, regardless of whether it is a single component or a full SoS. Noteworthy, S&M in SoS mainly addresses lowering complexity through a simplified, modeled SoS representation (Lowe and Chen, 2008). For SoS, simulations are also beneficial when emergent behavior and temporal complexities are sought (Fang, 2022). The two main simulation techniques used for SoS are Discrete-Event Simulation (DES) and Agent-Based Simulation (ABS). DES is a top-down approach that focuses on modeling the process, while ABS is bottom-up and tries to replicate the behavior of each system and have them interact with each other (Baldwin et al., 2015). DES and ABS are favorable as they can capture operational and managerial independence of systems and can include VUCA characteristics. Generally, DES emphasizes the events, while ABS addresses the behavioristic characteristics in the studied SoS (Baldwin et al., 2015; Kinder et al., 2014).

3. Method

This paper is based on collective learning from multiple case studies, based on Yin (2014), that were analyzed in a universalizing comparative study, i.e., aiming to show that different cases follow the same rules (Tilly, 1984). A universalizing comparative analysis is favorable when similarities have been observed between cases, and the aim of explaining these using universal principles is sought (Pickvance, 2001). The case studies stem from different research projects conducted between 2021-2024, some still ongoing. The case studies were selected based on their similarity: all addressing SoS and simulation as an approach to enhance knowledge creation in the design process. Figure 1 presents the design challenge, SoS context, and data collection methods used in each case study. The main difference between them was the design target, where case studies A and B focused on SoS optimization, case studies C and D targeted system design deployed in an SoS, and case studies E and F focused on SoS resilience design. All case studies have been conducted using the Action Research methodology (Avison et al., 1999).
Data collection that was used as input for the comparative analysis came from interviews (I), observations (O), documentation (D), workshops (W), meeting debriefs (M), and demonstrations, both with internal stakeholders (S) and in a public setting (P), e.g., civil servants and citizens. The sampling preceding the data collection was mainly done through an opportunistic sampling approach. Examples of collected data are information about the progress of each simulation model, good and bad learnings of the development, and the participants' (sometimes also external stakeholders) perceived quality and useability of the presented models. The collected data was synthesized using inductive reasoning among research participants to identify common themes concerning simulation model development based on the viewpoint of good and bad experiences. These themes formed the basis for the design principles. Following is each case study summarized.

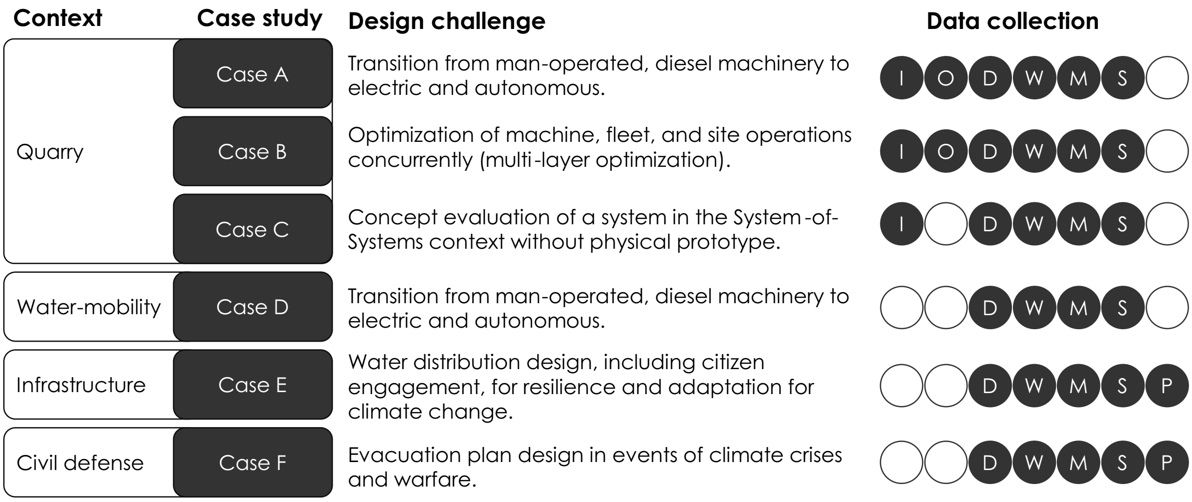

Figure 1. Description of the case studies

Case study A: This study looked at the transition to an electric and autonomous hauling process in an open-pit quarry. The project focused on creating simulation support to assess how this transition could occur and how the value creation shifts from a holistic viewpoint. The simulation model developed in this case study utilized ABS combined with vehicle dynamics models to capture how design choices at subsystem, system, and SoS levels impact the value creation. The simulation tool models the quarry operations from blasted rock to stockpiling. Noteworthy, prior to the final simulation model, a DES model was developed as a design sprint and early demonstrator, but it was later scrapped as the operational complexity grew too big to capture efficiently. More details on the ABS simulation development can be found in (Toller Melén et al., 2024).

Case study B: Similar to the former case study, this one addressed optimizing quarry operations, including all layers, from subsystem to operation management. The optimization utilized value as a guiding principle to identify the optimal solution. This study used the same simulation model as in case study A.

Case study C: The final case within quarries and work machinery looked more at individual systems and how to effectively evaluate different design concepts in an SoS setting. The emphasis was also on the Human-in-the-loop perspective to evaluate how virtual prototypes can shorten design cycles. For this reason, game engines were explored, which theoretically can be seen as a variant of ABS, to gain more realistic simulation environments. The purpose of the simulation was to evaluate a design concept virtually with operator-in-the-loop to capture human-oriented needs without a physical prototype.

Case study D: The case focuses on sizing and optimizing a fleet of passenger ferries in urban public transport through various routing strategies. It explores integrating marine transport with energy storage and power grids, emphasizing energy efficiency, resilience, charging, and land infrastructure. The simulation is constructed in commercial discrete-event simulation software to assess the performance and resilience of the transportation system when facing different types of disturbances. The simulation features two main sections, each corresponding to the (separate) transportation networks on the eastern and western sides of the inner archipelago in Karlskrona, Sweden. The simulation rendered travel times between different destinations and passenger waiting times at the docks - considering an on-demand vs. schedule-based logic - for a service supported by a fleet of vehicles in different scenarios.

Case study E: The case study captured water scarcity and sensitivity in water distribution systems. The project investigated how a water distribution system is affected and can cope with water scarcity because of droughts and the system's resilience from a civil defense perspective. A GIS-based (Geographic Information System) ABS was used to represent households and water plants. The households had probabilistic consumption behavior assigned to mimic the real world better. Additionally, the water replenishment was based on historical meteorological data. The simulation model allowed future "what-if" scenarios to be modeled and used to assess climate resilience based on potential infrastructure investments and behavioral changes due to citizen awareness.

Case study F: This study looked at evacuation planning of neighborhoods and cities in case of climate disasters or civil defense. The case study examined how different evacuation plans and road conditions/ constraints impact the evacuation process. Linked to this, the value drivers for a "good" evacuation were also included. This study used an agent-based traffic simulation tool that can model citizen behavior and transportation. The simulation model aimed to test and evaluate different strategies for evacuation more rapidly than conventional methods, which are often pen- and paper-based.

4. Design principles for effective System-of-Systems simulation modeling

The six case studies resulted in five simulation models; case studies A and B were tackled using the same model. A set of design principles has emerged based on the collected data and analysis thereof. Design principles, in this case, refer to units of learning that support effective simulation development for supporting SoS design. Figure 2 illustrates the links between the case studies, simulation models, and design principles and how they address VUCA. The arrows between the simulation models and design principles indicate which development project was the basis for that principle. The multiple case studies and comparative analysis collectively led to nine design principles.

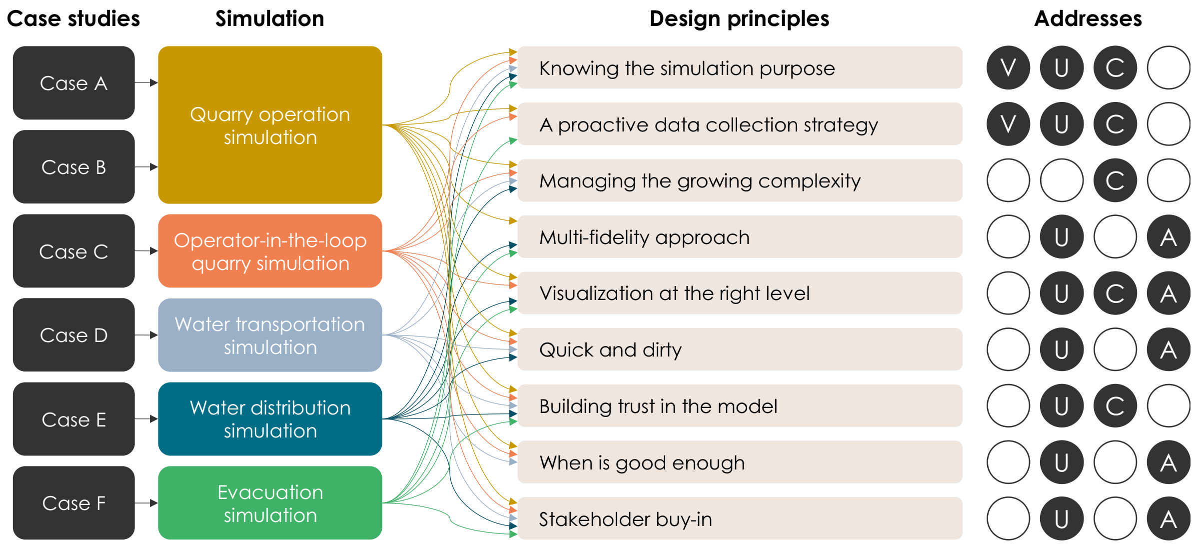

Figure 2. Proposal of design principles for effective System-of-Systems simulations

Examination of Figure 2 shows that the case studies and simulation models contribute to multiple design principles with significant overlaps indicating generalizability. The design principles "Knowing the simulation purpose," "Building trust in the model," and "Stakeholder buy-in" were recognized from all case studies, indicating their criticality for successful SoS modeling. Moreover, at least three simulation model developments could reference each design principle. For the remainder of this section, each design principle is described in more detail, including their capability to assist with the VUCA challenges.

Knowing the simulation purpose: The saying "garbage in, garbage out" is just as true for simulation models. If the purpose is unclear or ambiguous, it is easy to develop a sub-optimized simulation model or incapable of providing relevant information, especially in a multi-stakeholder context. Focusing discussions on value earlier led to better stakeholder alignment regarding the knowledge gaps to be filled by the simulation. Additionally, simulation models developed from a needfinding exercise performed better and achieved higher maturity. For instance, case studies A and B required five iterations of simulation models before one was developed that tackled what the stakeholders "actually" wanted to see, not what they initially said they wanted. SoS are complex and, therefore, resource-intensive to model. Having a clear understanding of the simulation model's purpose helps steer the resources to where they provide the highest value. Hence, this design principle can support the management of volatility, uncertainty, and complexity by properly disseminating the operational scenario, contributing to stakeholder alignment, and identifying potential constraints. The more effort you have spent on problem space dissemination, the better the simulation model can capture it. However, it is not possible to tackle ambiguity as these are unknown unknowns.

A proactive data collection strategy: A simulation model can generate vast amounts of synthetic operational data, slowing simulations down, taking unnecessary memory space, and causing information overload. For instance, the evacuation simulation required ca 175 MB per scenario, while it was found in the quarry simulation model that six data points were required to describe one scenario (excluding visualization data). In general, cases where the required data collection was discussed and identified early in the development process simplified the post-processing and were often better at supporting decision-making. It was also found that keeping the collected data "raw" was better as the refinement process often changed in later stages, e.g., stakeholders asked: "What if we calculate using this approach?" or "Can we get the specific queue times per station?". Using raw data allowed these requests to be addressed immediately without remodeling the simulation. Ultimately, knowing how data links to the value creation is essential for setting up a data collection strategy, much in line with data-value research (Machchhar et al., 2022). Case studies where the value creation was explored also led to more precise data collection strategies. Knowing which data to collect supports volatility, uncertainty, and complexity management as you ensure that the necessary data for their dissemination is present.

Managing the growing complexity: An SoS adds an additional layer to the simulation model, which renders complexity due to increased variety and intra- and inter-layer dependencies (Haberfellner et al., 2019). Hence, it is essential that the simulation model deal with this growing complexity. Figure 3 maps the simulation models based on addressed SoS size and complexity. For case studies A and B, the initial DES simulation model had to be abandoned (marked with an asterisk), and a new ABS model was created as the complexity became too great. DES is generally considered a simple modeling approach as it can model state changes as "black boxes," hence disregarding the internal system states (Baldwin et al., 2015). Controversially, this means a loss of information that might be required to properly capture certain complexity.

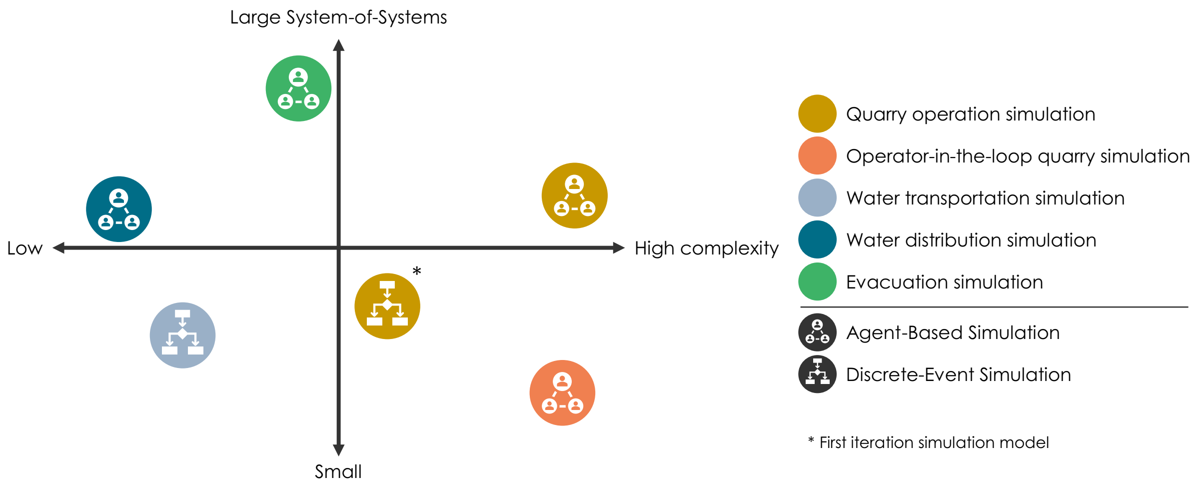

Figure 3. System-of-Systems complexity in developed simulation models

Generally, it was found that DES was well suited for SoS with low complexity, as in the water transportation case. Creating a simple SoS was tedious for ABS, but it managed the growing complexity much better. It was not found that opting for an ABS model straight off was the better choice as the early development stages were also about building knowledge about the simulation model and DES models can be developed more rapidly than ABS. The simulation technique was also based on tool availability, such as the evacuation simulation that fitted well with an existing, niched simulation tool. Generally, it was found that proactively working with complexity and multidisciplinary settings is a key to success.

Multi-fidelity approach: A strategy that proved useful early on was adopting a flexible system fidelity approach, a system referring to constituent systems of the SoS. Fidelity refers to the level of detail in the system representation, spanning from basic lookup tables to advanced dynamics models. This means that each constituent system can have different fidelity levels depending on the required granularity. In the quarry example, the wheel loaders and haulers were of significant interest (high fidelity) to the stakeholders, while the crusher was not (low fidelity). A similar case was seen in the water transportation study, where it was discovered that increasing fidelity did not impact the results, as both significantly increased computational demands, pointing toward a too-high fidelity. A good approach was to identify the significance of a system on the value creation and match the fidelity to that. It was also useful to start with low fidelities for all system models, progressively increase when needed, and investigate its potential impact. This managed the simulation model to better balance the trade-off between accuracy and model efficiency. This approach restrained the simulation models from growing too complex and resource-consuming, which meant they could be more easily deployed in uncertain and ambiguous environments. By minimizing the computational demands with a given complexity, it is easier to allow the exploration of the unknowns.

Visualization at the right level: Visualization of the simulation result is an important communication tool. However, the requirements for detail and realism varied depending on the user. The preference often depended on the specific stakeholder's purpose of the simulation, e.g., a 2D animation was enough for quarry site managers, while vehicle specialists wished for realistic 3D visualizations. In the water distribution case, an interactive VR headset was used to visualize the results, which was a good approach for achieving citizen/stakeholder engagement, while a 2D map was enough for decision-makers. Case study C with Human-in-the-loop had the highest demands, where tactile feedback was even wished. Based on this, the selection of visualization techniques varied between the contexts and even between the stakeholders. It is, therefore, beneficial to assess the potential of using multiple visualization techniques to cater to more needs. By having dedicated visualization for each stakeholder, the efforts could be spent on understanding how they interpreted the data and, through that, potentially spot uncertainties and ambiguity aspects. Moreover, good visualization made it easier to see unexpected behavior and events from a stakeholder perspective, further strengthening the ambiguity efforts.

Quick and dirty prototyping: The early design phase is often characterized by ambiguities and uncertainties, including the design of a simulation model. Stepping away from a rigorous design process and opting for quick and dirty prototyping can be a good avenue to promote the thinking process, stimulate creativity, and encourage dialogue (Gómez and Lopez-Leon, 2019). Quickly generating simple simulation models allowed stakeholders to rally around something, accelerating stakeholder alignment and the needfinding process. Case studies E and F (among the later research projects) adopted this to test whether the conceptualized simulation models tackled the design challenge correctly or not. The first prototypes did not completely fulfill their purpose. Still, they only took approximately one working week each to develop, which is quick for a SoS simulation model compared to the other more mature models. Moreover, the SoS was often difficult to grasp theoretically, and the initial prototypes assisted in uncovering the uncertainties and unknown unknowns (ambiguity) more easily.

Building trust in the model: One of the most important questions asked by participants in the case studies was, "Can we trust the data?" Simulation models that had not been verified were often seen as far less trustworthy. However, there is not necessarily a direct correlation between accuracy and trustworthiness as long as the model's purpose is explicit (Johansson et al., 2017). It was deemed fine to have simulation models that were crude and holistic as long as they aligned with the aim and were communicated. This change of perception was observed in case study B when the accuracy was announced before a demonstration. When the participants expected rough estimates, they tended to trust the results better. Being able to show at a general level how the simulation model was developed, i.e., increasing transparency, was another key factor in creating trust for the results. Trust is especially an issue in uncertainty and complexity as it might be hard to validate the models with experts, and the simulation becomes more of a black box. By dividing the SoS model and building trust in each part, the trustworthiness could increase despite the presence of uncertainty and complexity.

When is good enough: Linking to the previous design principle, the balance between capability and development efforts in a simulation model is important to consider. One participant in case studies A and B often rhetorically stated, "Is 10% accuracy okay, or is a fifth decimal required?" A good measure for enough detail was when the different scenarios started to deviate in value creation. The main goal of a simulation model in all case studies was to compare different scenarios, not to get exact values for each specific scenario. The simulation model should, hence, be good enough to allow this comparison to be done. From a capability perspective, an iterative approach was found most useful. This means that the first iteration only addressed the core functionality and more capabilities were added progressively for each iteration. Trying to add too many features directly often led to time overruns and larger rework demands later, mainly due to more complex models that were harder to remodel. The quarry simulation model experienced this issue, eventually leading to a complete remodel. Finding a good enough level lets you capture and predict futures within a reasonable timeframe. It was determined that is was a trade-off between modeled complexity and efforts to understand what is unknown, both uncertainty and ambiguity.

Stakeholders buy-in: A critical factor for guaranteeing a simulation model's success was stakeholders' commitment and buy-in. Simulation models with a clear commitment could also more easily be co-created with stakeholders, which led to higher maturity in the end, case studies A, B, C, and D. Those that failed to get buy-in early on often froze and eventually halted in maturation, case studies E and F. At the same time, having a successful model can be a way to get stakeholder buy-in (Johansson et al., 2017). This highlights that it can be a good strategy to narrow the scope in the first iteration of the simulation model to quickly get success and hence increase the likelihood of stakeholder buy-in. The main benefit from stakeholder buy-in was the willingness to co-create and support the development process. This connects well with the view of value co-creation and value co-production as drivers for success (West et al., 2018). Moreover, an active stakeholder commitment made exploring the simulation results easier and exploiting the cause-and-effect of emergent behaviors, making it a good principle for dealing with uncertainty and ambiguity.

5. Discussion and conclusions

Capacity around methods and tools for future scenario planning, simulation, and visualization to effectively address SoS environments. At the same time, there is a crucial need to foster a culture of learning and experimentation, supporting organizations in exploiting modeling and simulation capabilities to promote systems thinking and innovation. The lessons learned described in this paper provide a baseline for conducting SoS simulation modeling. As the design shifts from a single system to SoS, the consequences of VUCA and, thus, the requirements for proper simulation and modeling increase. Forecasting demand fluctuations, responding to disruptions, and utilizing simulation support to foster knowledge sharing across multiple stakeholders to proactively address ongoing and evolving VUCA effects are essential for companies to stay competitive. Based on this, a broader set of research questions or 'tracks' to be followed by companies to improve their ability to use simulations in the context of VUCA environments is proposed.

The first track emphasizes the need to strengthen 'modeling' as a discipline, identifying methods, tools, and practices needed to develop and expand simulation models capable of supporting critical decisions in dynamically shifting environments to support directly in the operational phase. An SoS simulation model can serve well in the design process, but as an SoS is not static and evolves over time, the ability to support the design process beyond the initial deployment is paramount. However, this requires the simulation model to be developed to seamlessly extract operational data and assess potential futures, effectively moving towards what is known as a Digital Twin. In VUCA environments, utilizing simulation models throughout operational life can drastically adapt and enhance the value creation. More knowledge of this transition is needed.

The second track focuses on how to develop, set up, use, and validate SoS simulations aimed at exploring vast design spaces and testing innovative strategies for complex, adaptive systems in uncertain environments. The aim should address existing gaps in multi-level hardware simulations for detailed system representation, hybrid methods for modeling system-environment interactions, and techniques for managing high-dimensional data to ensure transparent predictive analysis. Additionally, going beyond simulation models as SoS representations for operational assessments to operational synthetic training environments can be a promising path for expanding the useability of SoS simulations. This should also include investigating the possibility of quantifying VUCA aspects to understand better how to combat them in early SoS design stages.

The final track aims to wrap up the discussion concerning collaborative and distributed decision-making to co-create value. Innovation engineering faces challenges today in balancing exploration and exploitation due to the absence of standardized approaches for integrating multidimensional value factors from desirability to sustainability and more in rapidly changing contexts. Simulations can support these decisions, but further studies on how to design them for this purpose are needed. VUCA adds complexity to the simulation modeling, and the multi-stakeholder environment stresses this further. There is a need to understand how to effectively design simulation models for VUCA environments and collaborative decision-making beyond what this paper has found.

The final track addresses how the simulation models can be leveraged using emerging technologies. Two of the case studies looked at using more immersive visualization approaches by deploying Extended Reality. The introduction of Extended Reality has transformed how users can experience information and virtual environments. It is believed that decision-making can be enhanced further by more effectively visualizing the different operational scenarios. Another rapidly emerging technology is AI. SoS are complex to describe and evaluate. Being able to lower complexity by utilizing Generative AI is interesting to investigate.

Finally, some limitations in the study exist. Even though this is a multiple case study, the application domain is limited and thus impacts the generalizability. Further, the studies have focused on early design stages, and the design projects linked to the case studies have yet to be completed and introduced to operations. Once this is done, the effectiveness and success of simulation models can first be properly evaluated. Finally, the results are based on qualitative data, which includes risks of biases and misinterpretations. Including six case studies and their cross-examination adds some rigor to the results but does not mitigate them completely. There is also the risk of bias in the analysis and data collection for the comparative study.
In conclusion, transitioning from a product-centric to a PSS perspective and rising demands on civil defense push organizations to shift their design view from system to SoS. However, this shift also means challenges of volatility, uncertainty, complexity, and ambiguity. This paper draws on learnings from multiple fields to determine how simulation models for SoS can be designed more effectively. The hope is that the nine design principles can help simulation teams develop quicker and more accurate models that can support the SoS design process.

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