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Modularized simulation to manage complex systems throughout the lifetime

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In a time where technological and societal challenges demand rapid innovation, there is a growing need for rapid design of novel, complex systems both in industry and society at large. Managing the underlying challenges and arriving at systems of suitable quality in acceptable time frames, while managing risks and uncertainties requires a structured approach using simulation modelling, i.e. testing, checking, failing and optimizing a digital system is much cheaper and less risky than doing the same on a real system.
We argue that this approach must include modular, lifecycle-spanning and assured simulation models that provide decision support across different phases of the system lifecycle. These challenges are discussed in the paper and solutions are presented. The paper concludes that simulation models are essential for managing the complexity of modern systems. Organizations can build Digital Twins that provide decision support across all lifecycle phases through the application of modularization, co-simulation, different simulation approaches, surrogate modelling, and assurance frameworks. These approaches enable stakeholders to collaborate effectively, reduce risks, optimize time to market and achieve more efficient and reliable operations in complex systems. The paper discusses these elements in detail, proposes solutions, provides examples from our recent work and suggests an outlook into the near future.

Keywords: Simulation, Assurance, Complex systems, Novel systems, Lifecycle, Modularization.

1. Introduction

Technological and societal challenges demand rapid innovation leading to growing need for rapid design of novel, complex systems both in industry and society at large. Some of the main drivers for this growing need are:

Novelty Industries encounter increasing demand to provide solutions for CO_2 reduction, climate adaptation, digitalization and other demanding technical and societal requirements that call for novel solutions. Novel solutions need to path a road into the unknown, where only partial or uncertain information is available. Quality assurance and all risk management activities become a challenging yet more important task due to the lack of knowledge.

Time to market Market pressures demand faster delivery of innovative solutions, driven mostly by capital requirements, but also the need to address pressing global challenges. Time pressure can reach the level that development processes are short-cut, leading at least to major cost increase or even to project failure. There is also the justifiable promise that experimentation and optimisation can be done faster in the digital domain than in reality.

Complexity At the same time, the complexity of systems is increasing, mainly due to increasing system integration and the subsequent increase of sub-system interactions. These interactions can be both local or far-reaching (e.g. cloud solutions). Complexity typically leads to emerging effects, which are hard to predict.

To manage these challenges, a fundamental

question arises: How to design novel, complex systems within sensible time frames and budgets while managing risks and uncertainties? Addressing this question requires a structured approach to simulation modelling. Our proposed solution is the use of various interconnected simulation models as decision support in the design process. A simulation model has always a focus on a limited set of aspects, representing reality well enough to provide decision support in a given use case and -context. However, a single model will often not be sufficient nor feasible to cover all decision-making needs in complex systems. Instead, this paper advocates for the use of modular, lifecycle-spanning simulation models that provide decision support across different phases of system development.

For example, planning an offshore-based wind farm with a novel design of a wind turbine involves multiple simulation phases, which are more challenging as novel designs often introduce new performance characteristics, innovative materials, and unique structural configurations that require thorough assessment. First, to check and optimize the wind turbine it might be necessary to use a high-fidelity fluid-dynamic simulation of a single wind turbine. Next, to optimize the layout of the wind farm it would be recommended to perform a study of multiple wind turbines under varying wind conditions. Given the computational limits, a full fluid-dynamic model is often impractical for this phase, making a more simplified simulation approach necessary. Finally, the investors and the future operators need confidence that the wind farm can be profitably operated and maintained. This requires to simulate many years of wind farm operation in various environmental situations, taking into account technical failures as well as economic market mechanisms in the power grid the wind farm operates in (demand and supply). Obviously, this represents a separate level of detail, which requires its own simulation approach. Each of these phases demand different levels of detail. At the same time there are many elements common to all simulations, such as the wind turbine model, and these common elements should ideally be re-used from one simulation level to the next to ensure consistency and efficiency across all levels.

In the remainder of the article, we elaborate on the issues discussed above: system complexity, integration challenges, time scale differences, cross-phase consistency and computation feasibility. We present solutions for how simulation modelling of systems can be performed throughout its lifetime. Although most discussed solution elements are available, the combination of all elements has to our knowledge so far not been attempted. This implies that only partial use cases can be presented. Thus, the paper should be read as a position paper for our 'Simulation 4.0' commitment.

2. Modularization and collaboration

Analysis and synthesis represent an old and well-established way of trying to understand systems. Also called top-down and bottom-up analysis it is also the sole method we have to analyse emerging behaviour of complex systems M.A.Bunge (2003). This thinking is directly represented in (simulation) models where components are identified through analysis, and their interactions are then modelled in a way that the system simulation model can represent the system synthesis. Figure 1 visualizes this approach.

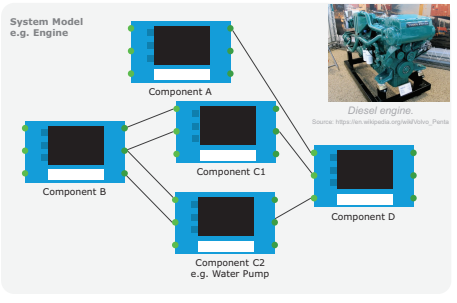

Fig. 1. System model built from component models (from various vendors).

By focusing on modular components, simulation models can better capture and predict emerging behaviours through the interactions of its parts. Moreover, the components of a simulation model often represent physical parts delivered from various vendors. The most natural and feasible way of constructing a system simulation model is thus to honour both functional and ven-

dor boundaries: identifying first the high level functional units and within these units then identifying the parts acquired by (various) vendors. The units on vendor level can then be used as the simulation components. There even is an additional learning in this system design work: if it turns out that the component sub-division is difficult because it generates many cross-connections between components, there might be something wrong with the chosen sub-division, which again indicates that the construction of both the simulation model and the real system will be challenging. The sub-division into components should in such a case be reviewed and optimised.

The usage of vendor-based component models requires also that the intellectual property (IP) of the various stakeholders of a simulation model is protected:

- Vendors cannot be assumed to be willing to share the inner workings of a component model as that often represents the core of their IP, protection of which is crucial to fostering collaboration without compromising proprietary knowledge.
- In high risk applications, where a component model represents critical system functions, it might be necessary that the vendor is assessed in detail by an independent third party. However, most qualification, verification and validation processes should focus on analysing the *observable* behaviour of the model — the outputs generated under specific system states — rather than requiring full access to the internal workings.
- Vendors usually provide user interface specifications to customers. This information is similar to installation instructions, user manuals, safety manuals and other component documentation for physical assets. This is part of any delivery and ensures that users can use a model correctly without needing access to the underlying code.
- Other stakeholders may not get access to the interface information, but might only receive the aggregated results from selected simulation experiments. For example investors may only require high-level results, such as the average profit and its variance, without going into the technical details, which would neither be relevant nor permissible due to confidentiality restrictions. This calls for a fine-grained access rights management within large simulation models.

To enable collaboration within simulation models it is necessary to have an effective protection system in place that ensures each stakeholder receives the necessary information while preventing unauthorized access to sensitive data. Also, as simulation models often operate on interconnected computer networks, cybersecurity measures must be in place.

Co-simulation technology coSim (2025) supports modularization and collaboration within simulation models by allowing different simulation components, often developed by various vendors, to interact in a unified simulation environment. There are open industry standards Modelica (2025), OSP (2025), detailing how component interfaces should be specified and how the simulation code should be packaged to facilitate system model simulations. Though co-simulation represents a versatile way of managing modularization and collaboration in large simulation models, there are especially three challenges:

(1) A tightly coupled system refers to a system in which the behaviour of one component directly and continuously affects another. For example, sub-systems like a crane mounted on a vessel form a tightly coupled system: sudden acceleration of one component creates feedback between connected components, slowing the simulation down to a crawl when not dealt with. Such tightly coupled systems are straight-forward to model if they are *not* split, i.e. modelled as one component, but challenging to model as separate components in a co-simulation setting. On the other hand, the parts may be delivered by separate vendors and may perform widely

different functions, as is evident in our crane-vessel example, justifying and reasoning the split into separate components.

Simulating tightly coupled systems in a co-simulation setting is currently investigated in the SEACo S.Skjong (2021) project. Two promising approaches are (a) coupling the two connected components with a damped oscillator, reducing oscillations between them, and (b) using a PID controller Bennett and Stuart (1996) adjusting control parameters in real time to maintain stability. It is expected that such solutions will at least extend the usage area of co-simulation considerably.

(2) Global component connections, such as the connection of global environmental states to several component models in a system, represent a challenge in co-simulation approaches, as these introduce a huge amount of output-input connections, tend to be difficult to manage and might slow down the simulation considerably. For example wind, waves and current (which are inter-dependent) might influence a vessel (in principle at all outer points), the crane load (influenced by wind forces), the wind sensor (which reports the wind speed and direction with some noise to the control system) and the propulsion system (influenced by waves and current). Meaning, highly correlated data must be synchronised and dispatched to potentially many sub-systems at all times and at all relevant points in space. In general it must be assumed that such global influences are not uni-directional but also bi-directionally influenced by the simulation components in turn, like the vessel propulsion changing the waves and currents around the vessel, which often need to be taken into account to reach the desired accuracy.

It is important to provide an efficient solution for global influences and hopefully at the same time treat the global data provider as a co-simulation component. This challenge is also currently addressed in the SEACo project S.Skjong (2021).

(3) Scalability issues can arise when multiple high-fidelity component models interact. While there are always simulation feasibility limits as function of (at least) the type of model and desired fidelity it is also observed that co-simulation offers the possibility to parallel-process components in a large simulation, even on separate machines, thus extending the limits of feasibility.

In summary, modularisation provides a practical solution for the management of complexity, by breaking down systems into smaller components. It improves stakeholder collaboration by protecting vendor intellectual property and allowing the integration of various models. Co-simulation provides additional support for this approach by facilitating the interaction of component models in a unified simulation environment, despite challenges such as globally influenced systems and tightly coupled systems that are subject of current research projects.

3. Modelling throughout the lifecycle

Decision support from simulation models might be desired in several phases of a system's lifecycle, from early design to long-term operation, and with a focus on challenges from various stakeholders. A true digital twin S.Boschert et al. (2016) should provide such decision support. The challenge arises as each lifecycle phase comes with unique requirements and questions to be answered, that require different modelling approaches in terms of focus, time scale, and level of detail. The construction and maintenance of such models can become time consuming and expensive and it is necessary to make use of as many synergies as possible.

Modularization, again, is a key enabler to this, as it allows for a separation of responsibilities, not only in the physical but also in the digital domain. A digital value chain is established, mirroring or "twinning" its physical counterpart. The stakeholders and their contractual relationships remain the same; where responsibility is distributed in the physical domain, it is also distributed in the digital domain C.Rostock et al. (2025).

Component models form the main artefacts in this digital value chain. Their maintenance

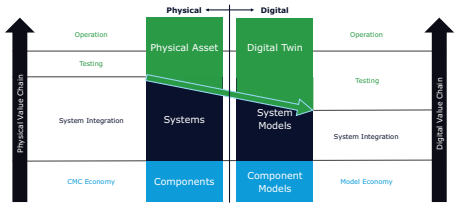

Fig. 2. Emergence of a digital value chain (right), mirroring the physical value chain (left) into the digital domain. Trust gets aggregated along the value chain from component level to system level and eventually the asset level.

throughout the lifecycle hence is key. We distinguish four key types of simulation models and how they address different lifecycle challenges.

3.1. *Basic continuous time simulation*

The first phase of modelling typically begins with basic continuous time simulations to analyse individual components. These simulations provide decision support for properties such as structural strength or hydrodynamic performance, which are essential during early design stages. For example a new type of wind turbine for an offshore environment might call for structural strength simulations and estimates on maximum wind speed at which the turbine should be turned out of the wind. Such simulation is typically performed as continuous time simulation either as hydrodynamic simulation or specialised higher-level codes. In any case, the time scale is in the range of seconds and involves running sensitivity analyses across various wind scenarios.

3.2. *Environment continuous time simulation*

After optimizing a single component, the next step is to simulate component performance in an expected environment, adding interactions with other components inside the common, shared environment. Placing a wind turbine within a wind farm introduces wake effects, where turbines influence each other's performance. Simulating these interactions is necessary to optimize turbine placement and account for dominant wind directions. For this simulation type, the time scale might be similar to the former single-turbine case, but scaling detailed hydrodynamic simulations to an entire wind farm is most often computationally unfeasible. As the turbine is the same as in the single turbine case, surrogate models can replace the single turbine by using prior data from the basic continuous time simulations. Surrogate modelling is an old technique and was previously called e.g. Response Surface Modelling RSM (2025). With the advent of AI, surrogate modelling can become more efficient and in fact potentially safer, as techniques exist to quantify the *uncertainty* of the estimations at any point in a multi-dimensional search space.

Figure 3 illustrates the use of a surrogate model instead of a complex and computationally expensive simulation model. The simulation model produces high-fidelity results, which are used to train and validate the surrogate model. Once validated, the surrogate model efficiently predicts the quantity of interest (e.g., wake interactions in wind farms), while also providing an assessment of uncertainty for these predictions.

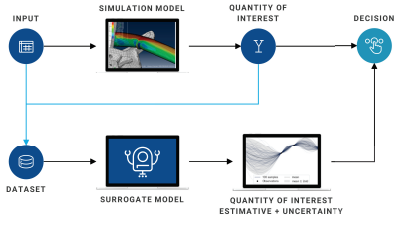

Fig. 3. Surrogate model with uncertainty built from a simulation model.

The projects RaPID Ferreira (2025) and OptiStress S.Skjong (2023) address these issues and motivate with promising results.

3.3. *Extended continuous time simulation*

Some lifecycle phases require simulations over longer time scales, where running high fidelity models becomes impractical. One common application is a training simulator for (future) operators of the system. The simulator needs to cover minutes or hours while the high fidelity component models might cover milliseconds. Surrogate models can be made to cover this gap delivering the

correct level of detail and making the simulation feasible.

Another example for extended continuous time simulations are operation fragments with special challenges, like the docking manoeuvre of a novel vessel type in a narrow harbour. It is interesting to note that surrogate models are already common practice with respect to manoeuvring simulations of vessels. The related surrogate models are not necessarily produced through AI, but often ”conventionally” through parametrization from experiments or hydrodynamic simulations, where results get turned into a lookup table or a response surface, which then serves as surrogate.

3.4. *Discrete event simulation*

Projects need investors and they want to reduce uncertainty with respect to the return of investment. This issue concerns time scales of typically years, and in addition the uncertainty is often taken into account as random combination of many possible outcomes, like weather situations, component failure and repair, etc. Random combination of scenarios further increases the required simulation time as the results must be provided as statistical measures which should be statistically significant. The type of simulation performed for such simulations, therefore, is typically discrete event simulation Banks et al. (2025), which is well-established and done as standard analysis for many long-term performance studies. Discrete event co-simulation is unfortunately not well established and represents a lack for this promising simulation technique. Still, in principle there are no issues for the extension of co-simulation techniques towards discrete event simulation. Having extended co-simulation towards discrete event simulation, the challenge is that existing component models must be further generalized to furnish the focus area of the event-based simulation. For example, a new type of electric, battery-driven vessel might have been simulated with respect to short and medium time issues, but the owner wants to know whether the planned route can be fully operated with the designed batteries and the available charging facilities in expectable weather situations. For such a simulation, requirements on fidelity and accuracy are lower: Often it is sufficient to get a good estimate of the average power consumption in a given environment and weather situation. The average power consumption can be calculated from the hydrodynamic model for typical en-route situations. Such a high level surrogate model can then be used in the anticipated event-driven simulation. In such a simulation, any major change in operation or weather (e.g. sailing direction wrt. the wind direction) would generate an *event* at which the total energy consumption (so far) gets updated using the *previous* required propulsion power, followed by calculating the *new* required propulsion power valid for the next period, i.e. until the next discrete event is triggered. Model efficiency requires a way to specify the essential variables for a surrogate model, so that the surrogate model can (automatically) be created from the higher-detail continuous time model.

3.5. *Model updating*

With the desire to model a system throughout the lifecycle, the issue of changing data, concepts and solutions throughout time arises, potentially rendering models invalid or even obsolete. Consequently, model metadata like input data to all models, model documentation, and model tests must be kept updated, requiring careful planning, active follow-up and smart solutions. For example, the model documentation source should be built into the models themselves, so that changes and documentation go hand in hand. Also, there should be an (automatic) possibility to determine the impact of modifications throughout the reality and the various system models A.Benventiste et al. (2015).

In summary, modelling throughout the lifecycle requires different simulation approaches tailored to specific phases. Continuous time simulations provide detailed decision support at shorter time scales, while discrete event simulations address long-term performance and uncertainty related to that. The use of surrogate models is necessary to enable the re-use of detailed simulations within higher-level simulations, enabling analyses across various time scales.

4. Model assurance

As simulation models may be used for high-consequence decisions, be they economically- or safety-critical, the applicability, accuracy and reliability of these models must carefully be evaluated to ensure that decisions are based on trustworthy outputs. Figure 4 illustrates the four possible outcomes when comparing simulation results with real-world behaviour:

- True Positive: The simulation correctly predicts a feasible outcome, leading to a viable solution.
- True Negative: The simulation correctly identifies an infeasible outcome, preventing unnecessary effort.
- False Positive: An infeasible solution is incorrectly considered viable by the simulation, resulting in high-risk scenarios. Either the fault is found during field trial and leads to expensive late system change or the problem is not even found during field trial leaving the potential of a hazard at a later time.
- False Negative: A feasible solution is incorrectly rejected by the simulation, leading to missed opportunities and unnecessary costs, which is not desirable. One might treat this category as less critical than 'False Positive', but from a societal point of view it might be retorted that a model not working for real situations is not desirable.

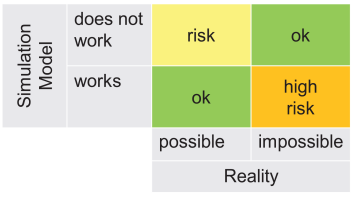

Fig. 4. Modelling risk

It is thus clear that a balance between the desired confidence in a model and the effort put into the quality of model must be established. We suggest that a model risk analysis with respect to 'the model fooling the user' in mind (see above) is performed during the conceptual modelling phase. The risk level translates then into the confidence put into the model and into related efforts with respect to modeller capabilities and model assurance activities.

Risk is still often depicted as a function of likelihood and consequence, but we argue it is impossible to estimate the likelihood with which a simulation model will fail. To resolve this problem and to honour the more modern definition of risk as "Effect of Uncertainty on objectives " ISO31000 (2018) we suggest to use a set of *uncertainty shaping factors* and relate these to the consequences arising from a model failing to assess the risk. Uncertainty-shaping factors include e.g. simulation model issues like size of models, novelty and complexity of a model.

As uncertainty is an important issue, it is also important that the system models analyse and inform uncertainty. That implies that the model uncertainty should be known for all stakeholders. Model uncertainty can be assessed through various means, but not least through sensitivity analysis. Simulation models have the nice feature that experiments are cheap and safe, at least compared to field experiments. As explained, modern surrogate modelling techniques allow uncertainty estimates, and within discrete event simulation, the direct inclusion of uncertain quantities is a natural ingredient. Beyond that, the main challenges for uncertainty are probably knowing what may be uncertain, addressed by the system model risk analysis and informing uncertainty Bles et al. (2019).

Assurance of Simulation Models is addressed in the DNV Recommended Practice DNV-RP-0513 Rostock et al. (2021). This recommended practice outlines a structured approach to verifying and validating simulation models to ensure their accuracy and reliability. In summary, model assurance is essential to help organizations reduce modelling risks and improve trust in model-based decision-making.

5. Conclusion

Simulation techniques have reached a level of maturity to constitute a backbone of Digital Twins

and provide decision support to users of complex systems during all phases of a system's lifecycle. Simulation allows organizations to analyse, optimize, and predict system behaviour across a wide range of time scales, from seconds to years, using various simulation types tailored to specific lifecycle phases.

Cooperation among stakeholders in simulation of complex systems is essential to a successful implementation of a digital twin. **Modularisation** allows for models to be kept manageable and adaptable, while **co-simulation** technologies enable the integration of components from various vendors and support IP protection by enabling the integration of black-box models from different vendors, where only the necessary interface specifications are shared. By implementing access control mechanisms and a fine-grained rights management, stakeholders can collaborate effectively while maintaining a professional balance between openness and IP protection.

Surrogate models can be used to generalize detailed models across different time scales and larger models. The time scales covered with suitable (surrogate) models reach from seconds to many years, substantially reducing computational demands. Trust in decision support systems heavily relies on the confidence placed in the underlying models. Therefore, it is essential to perform model **assurance** activities. The models must be verified and validated according to the risk identified for and associated with their use (through risk analysis).

In conclusion, simulation models are essential for managing the complexity of modern systems. Organizations can build Digital Twins that provide decision support across all lifecycle phases through the use of modularization, co-simulation, different simulation approaches, surrogate modelling, and assurance frameworks. These approaches enable stakeholders to collaborate effectively, reduce risks, optimize time to market and achieve more efficient and reliable operations in complex systems.

Most solution elements discussed in this paper are already existing, but must be combined in suitable ways to achieve the goals. More research is needed to achieve automated creation of surrogate models based on high fidelity models, and the inclusion of discrete event techniques into the co-simulation paradigm.

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