A Modelling Selection Framework for Design Space Exploration in Systems Engineering

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Zusammenfassung: A question Systems Engineers face is how to decide an appropriate modelling effort in the SE process. In the paper we introduce a three-part framework to assist in answering this question, with the goal to reach balanced system designs. The framework bases on two dimensions model scale and model foundation. The second component is a set of heuristics to steer the modelling effort. The third part provides guidelines for model verification and validation.

1 Introduction

Attention in Systems Engineering (SE) is moving towards Model Based Systems Engineering (MBSE), because it promises to improve consistency, integration and reuse in the design process, among others. In industry presently, many projects are not yet model *based* [1], but models play an important – even essential – role. This paper focusses on such use of models in the SE process, in particular the use of models in the exploration of design options and their consequences, often designated as *design space exploration* (DSE). So far, DSE has seen attention in fields like computer science and electronics where *optimization* of design parameters is the main objective. The position of DSE within the larger Systems Engineering process is treated in [2]. The present paper takes a different view, focussing on supporting the systems engineer(s) in planning and conducting a DSE effort. We present a framework for deciding what modelling approach is suitable in DSE situations inside SE.

The paper is organized as follows. First a high-level discussion of models in Systems Engineering is presented. The framework for modelling approach selection and validation in DSE bases on two dimensions for models presented in Sections 3 and 4. These are used in Section 5 for supporting modelling approaches in DSE experiments, and heuristics presented as second component of the framework in Section 6. We then discuss model validity as third component in Section 7. We give an example in Section 8. The paper closes with a discussion, conclusions and future work (Section 9).

2 Different uses of models in SE

Taking the excellent work of Passmore et al. [3] and translating that to the Systems Engineering context, we can distinguish two main uses of models, see Fig.1.

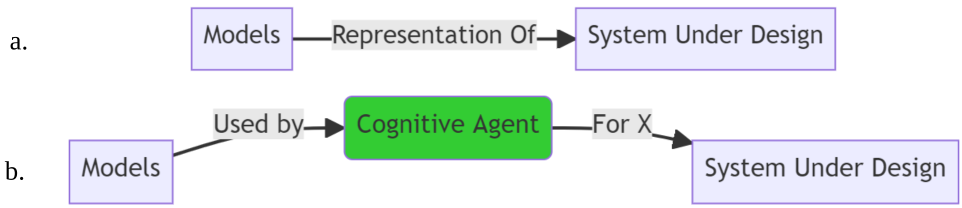


Figure 1. Two different uses of models. In a. the models serve to describe the system under design. In b. models are used to support a cognitive agent (like a systems engineer) to investigate the system under design and its behaviour. “X” stands for *communicating*, *describing* and *exploring*, among others. (based on [3], adapted to the SE context).

MBSE uses models mainly as “single source of truth”; Fig.1a. Yet, humans are crucial “cognitive agents” in SE as shown in Fig.1b where models assist in three ways. Systems Engineers have to (1) communicate continuously. Their communication partners can be from a wide range of backgrounds and with very different roles. To communicate, there should be *common ground* [4] often created using models. Humans can only keep a limited number of concepts in working memory at a time [5]. As a consequence, a systems engineer uses models to (2) organize his/her own thoughts and ideas about the architecture. To support this thinking process, a systems engineer has to use various views on the system under design as it is not possible to show all relevant information in one single picture [6]. Finally, (3) Design space exploration (DSE) is a way to analyse the effect of changing design parameters on the final outcome. The goal is to reach founded decisions for (a set of) design parameters that result in balanced performance metrics for the system. Note that DSE can also support activities (1) and (2).

In engineering, it is common practice to build a model that is gradually increased in resolution and accuracy, ever more precisely representing the System under Design (Fig.1a). In the SE process that takes place early in development, ultimate precision and resolution may obscure the essential trade-offs. The important question that we explore in this paper is therefore how to decide on the appropriate modelling approach for various exploration questions in the Systems Engineering process (fig.1b). We will discuss first the types of models from two views: the *scale* of the model and its *foundation*.

3 Model scale

The scale of a DSE-model can range from a back-of-the-envelope calculation, to full-scale simulations, and beyond. A **back-of-the-envelope** (BotE) calculation is characterised by a strong focus on the essential parameters and/or *figures of merit* [7]. The resulting BotE calculation is brief and simple as it would not fit on an envelope otherwise. Thus it is often wrongly assumed that everyone is able to make one. The contrary is the case: BotE calculations require thorough understanding of the underlying and relevant principles. This implies significant experience in the field. A good BotE calculation is insightful and can communicate to a broad range of cognitive agents (Fig.1b). On the other hand, its range of validity may be narrow as it generally bases on approximations or linearisations. Dimensional analysis can be a good starting point for a BotE calculation. **Simple (analytical) calculations** go beyond the scale of the back of an envelope. They are characterised by a strong symbolic approach, where relations between design parameters are derived, possibly also starting from a dimensional analysis. The relations can be more complex than in BotE calculations, requiring more effort. The process of making these calculations is an important asset, as new insights are formed along the way. The quantification in general happens at the end, when the characteristic relations have been established. Then, many configurations can be calculated and graphically visualised in a spreadsheet program or similar. **(Numerical) simulations** are one step up on the model scale. Here, computer simulation programs like matlab/Simulink, 20Sim, Matcad and SciLab play a role. Instead of defining relations between parameters as in BotE or analytical calculations, the system's state, inputs and outputs are calculated over time, or across frequency ranges. Complex interactions between parts of the system can be modelled, and the resulting behaviour is displayed. Also, evaluating control strategies and fine tuning their design is possible. **Full scale simulations** integrate multiple numerical simulations. Cross-domain behaviour can be modelled to a large extent and with high accuracy and resolution. The result can show emerging behaviour. The effort required for these simulations is extensive. In recent years, due to the low price of computer power, simulations that behave exactly like the system are created as *Digital Twins*. These are among others used at run time of the system to explore future use scenarios. Note that a digital twin in the strict sense is a digital copy of an existing system, but the term appears to be interpreted more broadly nowadays.

4 Model foundation

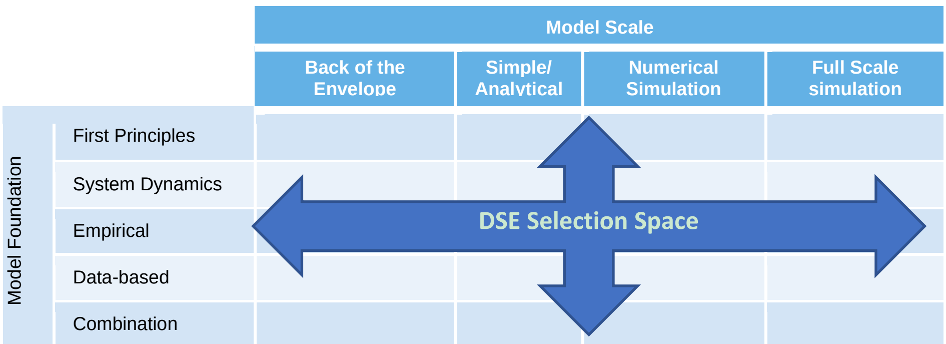
Independent of its scale, a model can be based on different foundations. **First Principles** models base on basic physics like Newton's laws, Bernoulli's principle, and the Lorentz force. This type of model foundation results in a sound reasoning and a scientific underpinning of the model. Yet, the valid range of these principles should be regarded. As a result of how science has evolved into narrow fields, these models may not easily show multidisciplinary phenomena. **System Dynamics**, first introduced by Jay Forrester in the 1950s use causal loop diagrams and modelling of stocks and flows to explore, visualise and simulate behaviour over time of dynamic systems. It can be applied from small scales up to world-scale problems. **Empirical** models, do not use existing well formulated physical principles, but base on experimental data. By setting up and running experiments, the behaviour of a system is explored and made explicit. Related to the empirical models, **data-based models** use data from actual systems. The difference between the two is that data-based models use data from systems in operation, where the empirical models base on data from experiments. The final model foundation is a **combination** of two or more of the ones above. One can think of a model that uses first principles, but requires tuning based on system behaviour via the data extracted from an existing system. Another combination is a system dynamics model where the parameters are based on carefully defined experiments.

5 Framework Part I: Model selection space

The model scale and model foundation span a DSE model space along two independent axes as visualised in Table 1. While it seems logical to combine BotE with first principles, or data-based with full scale simulation, there are also less obvious combinations. For instance create a relation between vehicle weight and battery capacity based on existing electric vehicles on the market (data-based), to use the relation in a BotE calculation to explore options for a new electric vehicle.

With the modelling space explicit in Table 1, it becomes easier to decide on the appropriate approach for a design space exploration effort. Depending on the goal of the DSE and the availability of data, test rigs, and understanding of the underlying physics, one can decide for the model foundation (the rows in Table 1). The model scale (the columns in Table 1) should be decided upon based on the available time and capacity versus required accuracy and resolution. As a rule of thumb one can say that the upper left corner in Table 1 is mostly useful to explore, create understanding and communicate the principles, whereas the right hand side results in more accurate results that can be implemented in the system under design.

Table 1: Model scale and model foundation as two independent views on Design Space Exploration models. While the table suggest distinct transitions, in most cases these are more gradual.



6 Framework Part II: Model selection heuristics

The second part of the framework is a set of heuristics. As a help for planning and managing the modelling effort, the COMBOS method [8] provides guidelines that can be reused for design space exploration modelling. The essence of the 11 heuristics in [8] adapted to the current framework can be summarized as:

1. Only model if there is no quick alternative
2. The system engineer is responsible
3. Couple operational views to other views
4. Visualize in different views
5. Modelling serves knowledge creation
6. Consider system behaviour and structure
7. Clearly define the goals of the modelling
8. Define stop criterion for modelling
9. Consider system states and transitions
10. Communicate results concisely (on A3)
11. Avoid going in too much detail

7 Framework Part III: Model validity

Because “All models are wrong, some are useful” (George Box), an explicit check on the fit-for-purposeness of any model should be done. Figure 2 shows the model and data flow in Design Space Exploration: starting from reality, we come to a set of design parameters. Reality is abstracted (link #1) into a conceptual model that describes reality in a set of relations. Next, the Conceptual Model is translated (#2) into a Computerized Model in order to do the calculations and facilitate (#3) the DSE. The desired result of the DSE is (#4) a set of Design Parameters that deliver balanced system performance. For the data in the model, we see that Reality is source to (#5) Data and (#9) Scenarios (also indirectly via Data, #6) that are used (#8 and #10) in the DSE. Note that often the scenarios represent situations not yet materialised into reality, which result in engineering challenges. In the case of Empirical and even more so Data-driven models, the Conceptual model may be less prominent, and the Data is directly translated (#7) into a Computerized model.

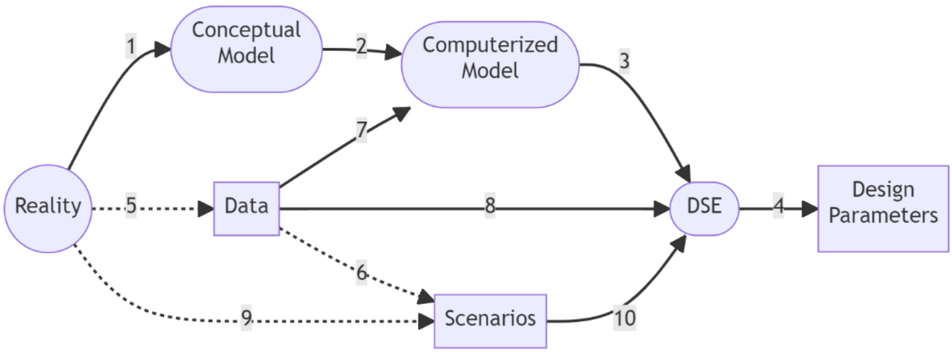


Figure 2. The modelling flow in context of a Design Space Exploration (DSE) effort. The links are numbered for easy reference from the text.

For every link in Figure 2, the modeller and systems engineer need to validate the usefulness and verify correctness. Sargent discusses verification and validation of simulation models in [9]. We will treat how that source relates to Figure 2, using the numbered links.

1. How well does the conceptual model represent reality *for the issue at hand*? The validation needs to check whether all *relevant* phenomena have been included, and in the right way, and that no irrelevant effects are included. Reviewing the conceptual model with experts is a proper technique.
2. Is the conceptual model correctly implemented in a computer model? This involves checking the code and running verifications.
3. Is the computerized model up to the job of the DSE? So, is the model accurately enough for the DSE, and what is the sensitivity of the DSE to inputs to the model?
4. Similar to the validation in #3: what is the sensitivity of the output to the underlying assumptions in the model? (#3 and 4 belong to operational validation as defined by [9].)
5. Is the data extracted from reality an accurate representation of reality? Questions to address relate to the way the data is obtained, sample size, and procedures etc.

6. Is the way data is used to formulate use scenarios for the system under design (SUD) appropriate? Scenarios basing on existing operational data will most likely lead to improvements in performance, not completely new operational modes.
7. What data to use in (i) big-data type of models to find relations, or (ii) to tune or calibrate the computerized model, or (iii) to check the model performance? Once data has been used for purposes (i) or (ii) it cannot be used anymore for checking (iii).
8. What data not used for other purposes (like 6, 7) can feed the DSE directly? Checks relate to accuracy, reliability and resolution of the data used.
9. and 10. How well can understanding of reality and existing scenarios give inspiration for new and innovative use scenarios? In case there is no clear information yet about such new use scenarios, it is hard or even impossible to validate them.

8 Example

The author was involved in development of a scanning device for the semiconductor industry in the past. Very early in the design process, crucial design parameters had to be set like scan speed and acceleration. These parameters (and some others) have a significant impact on the dimensions of the scan table, measurement systems and therefore the complete machine size. This illustrates (see heuristics 3 and 4) how quantification of functional behaviour impacts the physical implementation. In addition to fixing the design parameters, goal was to explore how the various parameters affect the mentioned dimensions. Referring to Table 1, the most appropriate approach was first principles in combination with Back of the Envelope and Simple/Analytical calculations.

After pages full of analytical calculations (this was in the time when powerful symbolic calculators were not widely available), the relations between inputs and outputs could be analysed symbolically. Consequently validation was performed by frequent auditing these by the author and colleagues. The computerized model implementing the symbolic relations in spreadsheets to also get numerical result was validated by running a number of test cases that were benchmarked with data of an existing system.

The results were a.o. that larger acceleration results in more throughput, potential lower accuracy and smaller table size. Longer settling time improves accuracy, but yields larger table and machine sizes and lower throughput. Consequently, the systems engineers decided for a balanced set of parameters for settling time, field length, scan speed and acceleration.

9 Discussion, Conclusions and Future Work

Even outside of Model Based Systems Engineering (MBSE), models play an important role in SE to support a human – a cognitive agent (Fig.1b) – in communication, making the architecture explicit and documenting it for future use, and for Design Space Exploration (DSE), the subject of this paper. While often the approach for a DSE emerges gradually, more explicit decision making on the scale, foundation and validation of the models is desired. The framework of this paper is developed to aid in planning and managing a DSE in SE.

Part 1 of the framework is the space of model scale and foundation shown in Table 1. Together with Part 2 – a set of heuristics – the systems architect(s) and modellers are assisted in making an informed decision on an efficient and effective modelling effort. Explicit verification and validation of the model and the DSE experiments and the data used are required. The model flow in Figure 2 allows for an explicit audit of each modelling step, completing the third and final part of the framework.

The use of data should be planned carefully so that the available dataset(s) can be partitioned in parts for model calibration/tuning and for model validation. In cases where only limited data is available, the pressure to use all for calibration and tuning may be high. Then the result is a finely tuned model whose validity cannot be shown.

The example shown is illustrative in how the framework can be applied but in reality the situation in the example gave rise to the questions addressed in the framework. In its present form, the framework is presented to students in a course on electric vehicle system design, where a model has to be created to come to a balanced design for the EV. Monitoring of the framework use is planned for the next run of the course.

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