

A model-driven decision arena: Augmenting decision making in early design

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Abstract

A wide variety of expert competencies, transcending traditional disciplines, are needed to foresee and evaluate the impact of decisions in the conceptual phase of engineering design. Where this previously was a trade-off regarding design and development of the pure physical artefact it is now a complex ambiguity game involving all disciplines touching a solution during its lifecycle, due to the movement towards integrated product-service solutions. Gathering the involved, normally diverse, group of stakeholders in a collaborative setting for design exploration exercises, sharing knowledge and values, is believed to augment decision making ability in early design. A model-driven environment for collaborative decision making is proposed as a solution that potentially may help harvesting these benefits. In this environment stakeholders interact with each other using digital models, model generated information, simulation data and product data collected in the field in order to evaluate design proposals by playing out potential usage scenarios and investigating cause and effect relationships. Initial work on conceptualizing, developing, and testing such an environment is done through a pilot study based on two industrial use cases. The development process iteratively unveils demands and constraints related to the environment. These discoveries go hand in hand with developing an infrastructure regarding both hardware and software as well as required human resources in a functional environment. Fully realizing the envisioned model-driven environment for collaborative decision making entails new ways of working requiring new knowledge as well as technological innovation. In that aspect, environment infrastructure and usage are elaborated on and direction for further research and development is indicated.

Keywords: Model-driven design; Conceptual design; Design exploration; Visualization; Multi-stakeholder; Decision making; Digitalisation

1 Introduction

On today's market even complex products are becoming a commodity. Staying competitive necessitates differentiation other than traditional approaches like superior quality or more efficient manufacturing of the product itself. To face this challenge many companies adopt a strategy where customer perceived value is in focus, often resulting in products being bundled with service offerings, so-called product-service systems (PSS) (Baines et al., 2007). PSS-like business approaches focus on co-developing product and service offerings based on product life extension (often through sharing), and therefore dematerialization of the physical artefacts (Bey & Mcaloone, 2006). The emergence of complex PSS pinpoints the need for multi-domain

evaluations in every aspect of a product's value life. The analysis of such systems, often consisting of many disparate and potentially complicated subsystems, in one integrated model environment is challenging due to lack of resources, knowledge and tools. Current practice is rather to evaluate the sub-systems using stand-alone, domain specific, models. Engineering teams are assigned responsibility for different subsystems. These teams (stakeholders in the system design) are then, without proper steering and coordination on the system level, likely to strive to optimize the subsystem they are responsible for. However, optimal solutions of subsystems are commonly competitive, i.e. optimizing a certain subsystem will likely constrain another subsystem resulting in a suboptimal system level solution. To avoid this, trade-offs on system and subsystem levels as well as conflicting and competing design objectives must be identified and resolved. There is a need for processes, methods and tools, i.e. decision support systems (DSS), to support this endeavour. A DSS may be defined as an interactive computer based system, which help decision makers visualize and utilize data and models to solve unstructured problems (Sprague, 1980). DSS's are categorized by identifying the main architectural component that provides the functionality for supporting decision making (Power, 2002). DSS's based on quantitative models and simulations are referred to as model-driven DSS.

One success factor in engineering design is the ability to make effective and risk-managed decisions in a timely manner. In an era of complex PSS, decision makers are rarely experts on all knowledge domains needed (multi-disciplinary engineering skills, manufacturing, procurement, marketing, sales, maintenance etc) to navigate through the often vast design space. Hence, the quality of design decisions is likely improved by encompassing a broader representation of knowledge and values in the process. A DSS for conceptual design should, therefore, be designed for collaborative decision making, encompassing "Human-in-The-Loop" (HiTL) to capture and reflect preferences of the stakeholder group. HiTL simulation is a modelling framework that requires human interaction (Rothrock & Narayanan, 2011). This allows stakeholders to "shop for a solution" (Balling, 1999). This is important as it increases design freedom considering that formulating design targets and wishes a priori is problematic/dangerous as people in many cases do not really know what they want until they see some potential solution to their proposed problem and are able to get some insight enabling comparison of benefits and drawbacks of competing conceptual solutions. Furthermore, involving the stakeholder group is also likely to improve trust and acceptance of subsequent decisions. Collaborative decision making, ensuring stakeholder involvement in the decision process, has been shown valuable in other areas. One example is participatory integrated assessment deployed in environmental analysis, see for example Salter et al. (2010).

This research presents an initial attempt to develop such a DSS realized as a model-driven environment for collaborative decision making focusing on early phase engineering design of complex PSS. This type of decision environment has been successfully deployed within other scientific areas, one example is the decision theatre at Arizona State University, see for example White et al. (2010). The need for such environments in engineering design and initial research towards that has been presented by Rhodes & Ross (2016).

The following chapters present an initial attempt to conceptualize a model-driven environment for collaborative decision making. A procedure based on value-driven design exploration is presented in the following chapter. This is followed by generalized procedural descriptions containing descriptions of the main building blocks of the proposed environment. The generalized procedural descriptions are an abstraction based on the implementation of two industrial use cases, see Panarotto et al. (2017a, 2017b) and Bertoni et al. (2018) respectively.

2 Value-driven design exploration

The design process is essentially about generating products and/or services that satisfy needs in the best way within available means. Unfortunately, these two notions are often both ill-defined and conflicting. Needs are not given in a project fuzzy front end: unveiling them becomes then an integral part of the design process. The notion of ‘available means’ is represented by design constraints, which typically limit the designers’ ability to achieve full satisfaction of the initial needs. Some of these constraints originate from the physical world, some are related to the designers’ perceptions - and interpretation - of the design situation, others are implicit in the representations and processes utilized (Gero, 1994). Designers must then bounce back and forth between problem setting and solving, exploring the design space since an early phase through experimentation to unveil behaviours and constraints.

In modern engineering, design experimentation is seldom a manual process, but rather a process exploiting a number of computerised virtual models. Model-based experimentation (simulation) is an effective means to enabling extensive exploration, so to learn faster (by performing more and earlier iterations) about the characteristics of the best possible design (see: Thomke & Fujimoto, 2000). Systems Engineering (SE) research has stressed the importance of a specific model type to frontload engineering design activities with: the value model (Collopy and Hollingsworth, 2011). This model is expressed as a single objective function that aims at measuring the “goodness” of the design. The resulting value score, expressed in monetary units becomes then the key decision making criterion for the engineering team: the higher is the value, the more successful will the solution be.

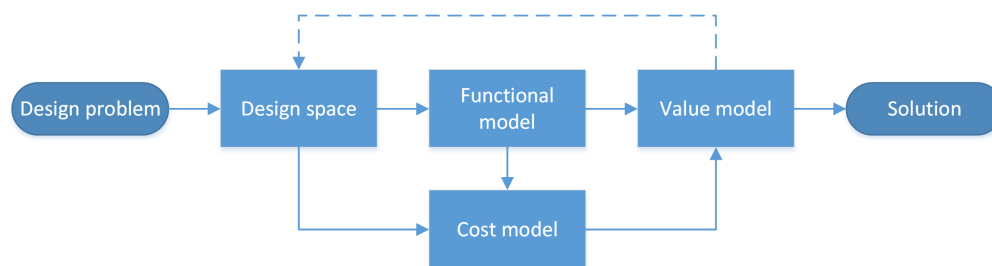


Figure 1. Value-driven exploration scheme.

This Value Driven Design (VDD) approach is explained as a process (figure 1). Once defined, the design space for the specified problem is explored by experimenting with feasible conceptual designs. Functional and cost aspects are assessed at each iteration, unveiling the performance and resource space respectively. The value model is fed with the output of these models to render a value score for the design configuration under analysis. This series of steps is repeated until a satisfactory solution is found. Such a solution might imply identification of areas of significant improvement, new products or even new business models.

3 The model-driven decision arena: Implementation

The envisioned decision arena is a physical location where design decision makers gather to share ideas, knowledge and values to evaluate conceptual designs. Using models, model generated data and data from the field, different conceptual solutions to the posed problem as well as different operational scenarios may be assessed. This transmission from traditional deterministic simulation towards a more probabilistic, evaluating different operational scenarios, is likely to provide more robust solutions. In the arena, the stakeholder group interact with this data using interactive, immersive, visualisations. The group play out different scenarios by manipulating models through graphical user interfaces, enabling also non-expert to actively participate. Another foreseen benefit is that the interaction within the stakeholder

group will start discussions that continues beyond the design exploration session in the arena. The core of the envisioned decision arena is a hybrid model environment with a multi-level model hierarchy. This hybrid environment encompasses, for example, discrete event simulations, finite element simulations, differential equations, algebraic equations and mathematical logic. The main conceptual components of the environment are schematically shown in figure 2. The MDDA server, implemented in Microsoft Excel™, controls interaction, data transfer and execution of all modules in the environment. The functionality of each module is based on sub-modules implemented in different software (clients). The model framework is designed with well-defined interfaces between the server/module/client. This allows models of different fidelity to be used in different stages of a project. Furthermore, this is important to easily change between different projects.

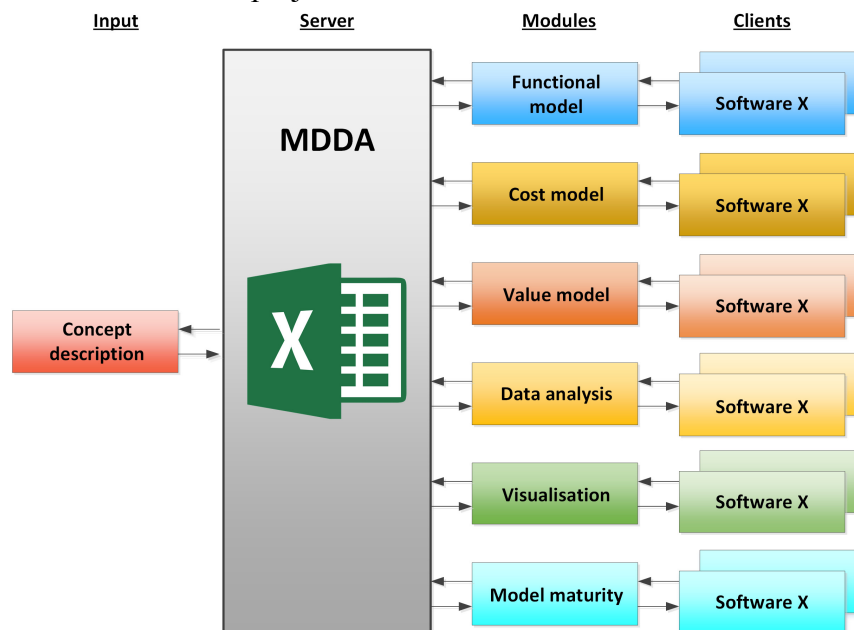


Figure 2. Framework for implemented multi-model structure.

Input to the MDDA server is a description of a conceptual design containing information about system hierarchy, geometrical data, contextual data, envisioned operation scenario, etcetera (define design problem stage of figure 3). The concept description is, to a large extent, digitally stored in a CAD model. This CAD model is feature based and parametric, i.e. it is defined by dimensional, geometric and algebraic constraints. Generating and through computational methods evaluate and compare all feasible conceptual solutions in the current design space is rarely a practical solution. Furthermore, in an extreme case, if an optimal solution was stumbled upon early on in an exploration endeavour the ability to recognize that is lacking unless comparative studies are conducted. The MDDA server implements an automated Design-of-Experiment (DOE) tool for the exploration of the design space. DOE is a technique for choosing a limited set of data samples in the design space with the goal of maximizing the amount of information produced (Giunta et al., 2003).

When the CAD model is created, design parameters intended to be selectable as design variables in the DOE are defined. After importing design data from the CAD model, a list containing all selectable variables are automatically generated in a GUI and the user may define which of them to include in the DOE study. The next step is to define a usage scenario and choose the parameters to be varied in the study. After that all variables and their bounds are set, an appropriate sampling technique to generate the experimental plan is selected and the experiment is executed. When the experiment is executed, associated attributes for all concept variants in the DOE generated experimental plan are predicted and stored in a database.

Relevant data is then retrieved from the database and analysed. Finally, results are presented. Simulation models need near to real-time performance regarding execution time to enable simulation of new scenarios during a decision meeting. In most cases, this is not attainable. If so, thorough design space exploration needs to be performed before hand, generating and saving design data that at a later point can be scrutinised in a collaborative manner. The modules used in the described workflow is presented in the following sections.

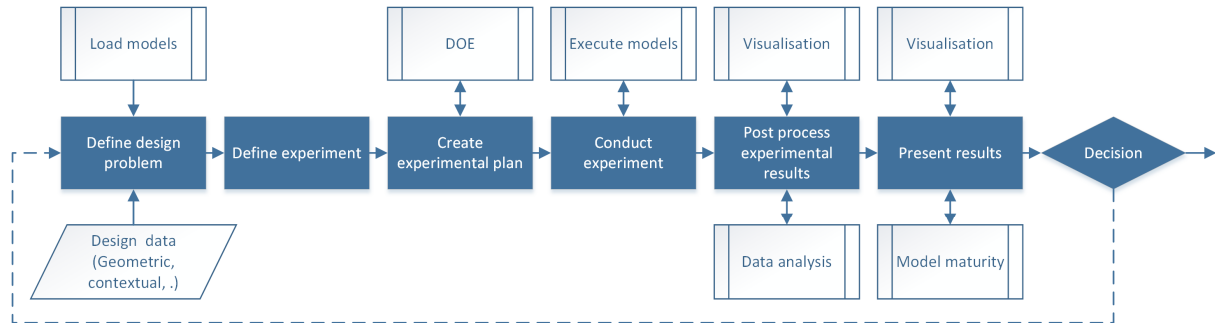


Figure 3. Schematic workflow of MDDA.

3.1 Functional model

Exploration of the performance space requires reliable information/data regarding design attributes, for example, structural behaviour and physical performance of a proposed design. Functional as well as non-functional attributes may be derived directly from the CAD model. Functional attributes might, for example, be mass of a component or system, used either directly or as a proxy to perform a function. Non-functional attributes might, for example, be estimates of the CO2 footprint caused by manufacturing the proposed design assessed based on material selections and assumed generic manufacturing flows for the components and sub-systems. Other performance attributes such as for example energy consumption, are evaluated through engineering models. These models might take the form of differential equations, algebraic equations, or mathematical logic. In the case where attributes are derived from engineering models, most data needed to populate those models, such as geometric and technical descriptions of the major sub-systems and components, are attained from the CAD model of the studied design concept.

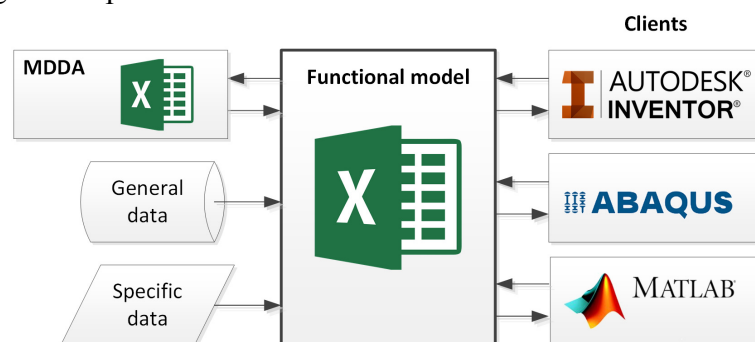


Figure 4. Example of functional model set-up.

Figure 4 shows an example of functional model set-up. The functional model module (refer to figure 2) is implemented in Microsoft Excel™. The module controls and interacts with a number of other software (CAD, FEM, numerical computing platform etcetera), here referred to as clients, running specific models needed to assess different aspects of the studied concept. The functional model module is controlled by the MDDA server as previously described.

3.2 Cost model

Literature (e.g., Fabrycky and Blanchard, 1991) highlights that cost must be an active rather than a resultant factor throughout the system design process. The cost analysis module aims at quantifying the economic gains (and the losses) of a new concept compared to a baseline design. The analysis is based on a Total Cost of Ownership (TCO) equation (1), which distinguishes two main cost families - Ownership (OW) costs and Operating (OP) costs. The main cost types upon which the TCO model in the Decision Arena is built are further described in Table 1.

$$TCO = \sum_{i=1}^n \frac{(DPC+FINc+OH)+(Ec+Lc+Sc+Mc+Rc+Lc+P\&F)}{(1+r)^i} + \frac{(DCc-RV)}{(1+r)^n} \quad (1)$$

Table 1: Main cost items in the TCO model.

DPc: Depreciation cost	Capitalization of the acquisition cost over the lifecycle.
FINc: Financial cost	E.g., interest on loans and taxation reduction.
OH: Overheads	E.g., training, recruitment and insurance costs.
DCc: Decommissioning cost	For the hardware, only if it is not sold second-hand.
RV: Resale value	For the hardware, only if it is sold on the second-hand market.
Ec: Energy cost	Proportional to the energy used during the entire lifecycle.
LC: Labour cost	Proportional to the human labour needed to operate the system.
Sc: Setup cost	E.g., preparation and inspection of the hardware.
Mc: Maintenance cost	E.g., labour, consumables and downtime/opportunity cost.
Rc: Repair cost	E.g., labour, spare parts and downtime/opportunity cost.
Lc: Logistic cost	E.g., transportation, storage and other costs.
P&F Penalties and fees	E.g., quality-, delay-, accident- and environmental-related costs

Populating the equation requires the development and executions of a set of sub-models for performance analysis. Two main models in the decision arena are the lifecycle performance model and the manufacturing model. The first predicts the accumulated usage cost during the lifetime of the hardware as a function of different operational scenarios. Value lifetime refers to the time whilst a product is disposed due to by the customer perceived inferior performance, functionality or appearance compared to alternative products available on the market (Umeda et al., 2007). Energy consumption, needed man-hours for conducting tasks according to the given operational scenarios, etc. are all inputs to the lifecycle performance model. This also calculates maintenance costs, which may depend on selected design features, components and assembly structures as well as on the operational scenario.

The manufacturing model is a key component to calculate acquisition and depreciation cost. The model makes use of geometrical data from CAD, such as for example, number of components in a system (affecting assembly cost), estimated mass (affecting manoeuvrability), component size, driving for example machining time based on material thicknesses, circumferential length etcetera. Engineering models linked to the functional module might also be used. An example of such a model might be a weld analysis, where necessary weld throat thickness is estimated considering required component life, geometric description, and load case. Predicted weld throat thickness affects time required for the weld operation and possibly also feasible welding techniques, both having a direct effect on manufacturing cost.

3.3 Value model

Focusing only on costs drivers reduction leads to false perceptions of ‘value’ and does not enable a sound judgement to be made during the design of an engineering product (Price et al.,

2012). Value extends further beyond cost, to encompass the evaluation of 'ilities' proposed by McManus et al. (2007), and more intangible factors, such as brand acknowledgement, aesthetics or sustainability impact (Steiner and Harmor, 2009). For instance, while increasing the engine power of a vehicle leads to better performances and reduced operational cost, it also results in increased production of CO₂, reducing its appeal among potential buyers.

The decision arena proposes two complementary approaches to capture value aspects beyond cost and technical performances. It is possible, on one end, to quantify all aspects of value in monetary terms, so that they can be more easily traded-off with more traditional requirements. Monetary units are convenient, practical and universally understood metrics for value, and are beneficial in the design process to stress the potential success of investments (Kipouros and Isaksson, 2014). This quantification process in the decision arena is driven by the implementation of Net Present Value (NPV) and Surplus Value (SV) from the VDD literature (see: Price et al., 2012). Quantification presents several challenges, mostly in terms of data availability and trustworthiness of the monetary models. A complementary approach is that of adopting a more qualitative approach, with the aim of assessing the "goodness" of a design for a given set of value-related criteria. The introduction of a Multi Criteria Decision Analysis (MCDA) module is then seen as a pragmatic approach to account for value aspects in the decision process which are hard to quantify with precision in economic terms (and that might mislead decision makers).

The value criteria for the MCDA exercise are derived from a framework that considers customer and provider perspectives separately. The definition of value criteria is guided by the equation proposed by Lindstedt and Burenius (2006), which defines customer value in the broad perspective of 'gains' vs. 'pains', and describes it in terms of 'main', 'additional', 'supporting' and 'unwanted' functions. The Feasibility-Viability-Desirability (FVD) from Design Thinking research (Leavy, 2010) and the Triple Bottom Line (TBL) model (see: Willard, 2012) help in detailing the nature of such gains and pains. Analytical Hierarchical Process (AHP) is used as principal method to rank-weight the value criteria. TOPSIS, VIKOR, ELECTRE and PROMETHEUS are main approaches in the engineering toolbox to qualitatively assess the value of solutions in an early stage. The decision about what method shall support the MCDA exercise is driven by considerations on team size, experience with MCDA and information availability. More advanced methods such as Concept Design Analysis (CODA) (Eres et al., 2014, Bertoni et al. 2018) are applied when the team needs to better capture the rationale behind the assessment, and to document richer lessons learned that can be exploited in future projects.

3.4 Data analysis and visualisation

Design exploration activities may generate an abundance of data. The generated data contains a complex hierarchy of attributes, ranging from the top level attribute of value down to basic functional attributes of the concept design. To understand how attributes on different levels is affected by system/sub-system/components or on a more detailed level relates to component features is imperative to explore cause and effect relationships. Such analysis is based on "variation" among and between data samples. A general method for this is analysis of variance (ANOVA), see for example (Myers et al., 2016). Such methods allow to predict the trends in the simulated response data, i.e. determine the relationship between design variables (factors) affecting a process and the output (response) of the studied process.

However even if the outcome of the data analysis stage contains necessary information to support sought decision, it is still hard for a diverse group of stakeholders to navigate through and make sense of the generated data. A key enabler of exploration and negotiation in a multi-stakeholder decision scenario are constructs and practices aiding interaction with model generated data. A major challenge is the analysis of very large sets of generated data. The

analysis process of this data, potentially incomplete and inconsistent, requires human judgment to make the best possible evaluation in the face of high uncertainty. Visualisation that provide capability to contrast and compare results are therefore crucial.

Among examples of deployed, commonly available, visualisation techniques are scatter plots, parallel coordinates, radar charts and histogram plots. Other visualization constructs that facilitates negotiation in a multi-stakeholder decision scenario are tailor made for the environment, such as the approach adopted by Bertoni et al. (2013), who develop a lifecycle value representation approach connecting qualitative value scores (based on a 9-point scoring system) to the actual CAD representation of the product under analysis. Value scores are mapped to a colour scale to highlight areas that are negatively or positively affected by new designs.

3.5 Model maturity and impact

For a group of stakeholders involved in a decision scenario, a very important issue is trust, i.e. trust in models and model generated data in order to feel comfortable making a decision. Uncertainty, the absence of certainty, or knowledge – about unknowns, in decision scenarios are normally high and the ability to understand limitations of used models is crucial. Due to the abstract nature of models, which becomes even more pronounced in a hybrid multi-model environment, it is therefore important to inform decision makers of maturity and impact of models used in a specific decision scenario.

Model maturity level (MML) depicts a distance, or compromise, between the actual (i.e., current value) and ideal certainty level to be expected from the model. Similarly, as with other maturity constructs in literature, MML is envisioned to follow a levels-scale, from low to high maturity. Impact is included to add an additional dimension to assessing uncertainty. The idea is to have a dimension that represents a spread of different modelling situations and contexts, where two different contexts might render the same model sufficient or insufficient. For instance, a high impact-level means that the aspect that is modelled is critical for the product, and thus the model needs to produce results with high chance of certainty. Stakeholders are then advised to approach with caution. On the other hand, a low-level means that the potential impact is negligible and thus there is not a need for further scrutiny or improved development in relation to this topic. Previous research (Johansson et al., 2017) presents an attempt to visualise and bundle meta information about model maturity and impact in a specific decision scenario with the model.

4 Conclusions and future work

The paper presents initial findings related to the development of a model-driven environment for collaborative decision making in early engineering design. The MDDA necessitates new ways of working and requires new knowledge as well as technological innovation. A generalized usage description of the MDDA is presented, containing needed functionality mainly regarding software but to some extent also hardware. Presented procedures are a generalised abstraction based on the implementation of two industrial use cases.

Importantly, the main ability of the MDDA is not only to facilitate decision makers in exploring the design space using models, but also to support negotiation in the cross functional team, so to facilitate the sharing of tacit, contextual knowledge about the product/service being designed. Due to the complex nature of design problems combined with the vast amount of data generated in proposed design exploration scheme, data analysis and visualization are key success factors in realizing the MDDA. In this spirit, the paper presents and discusses visualization constructs that facilitates negotiation in a multi-stakeholder decision scenario. The emerging research field of visual analytics holds promise to help in this aspect.

Future research work will focus on issues related to validating both the physical environment and the proposed decision making process. A major activity concerns testing decision scenarios in the proposed environment with practitioners. Efforts will also be put into further standardising model interfaces and simulation procedures in order to attain a versatile environment able to encompass new scenarios and design problems with limited efforts. Another recognised challenge in operating the MDDA is to populate models in early stages of engineering design due lack of trustworthy data. This might be mitigated by advances in data mining and related research fields. An identified hinder in developing the MDDA is the general lack of interoperability of simulation software. Integration is in many cases realized through in-house developed code.

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