A MORPHOLOGICAL ANALYSIS OF METHODS FOR CONCEPTUAL AIRCRAFT DESIGN UNDER UNCERTAINTIES

V.T. Todorov[1], D. Rakov[2] & A. Bardenhagen[1]

[1]Technical University of Berlin, Institute of Aeronautics and Astronautics, Marchstraße 12-14, 10587 Berlin, Germany
[2]Blagonravov Institute of Engineering Science, Russian Academy of Sciences, Malyi Kharitonievskiy alley 4, 101000 Moscow, Russia

Abstract

The globally defined goals for emission reduction and energy-efficiency in the aeronautical domain stress the necessity for the implementation of disruptive technologies as well as innovative aircraft concepts. In order to guarantee the goals' fulfillment, this should be achieved by assuring their reliable operation while accelerating their development cycle and entry into service. Therefore, novel conceptual design methods should be introduced, which handle challenges such as a) lacking deterministic/test data on emerging technologies; b) the generation and assessment of novel aircraft concepts which might be left out of scope; c) the impossibility to define or solve optimization processes for complex conceptual design problems. These challenges are targeted by the Advanced Morphological Approach (AMA), which decomposes the design problem into functional or characteristic system attributes, each corresponding to a number of technological implementations. Currently, the AMA assesses disruptive configurations based on expert evaluations and yields a qualitative solution space. Hence, potential methodological improvements are sought in order to increase the informativeness of the resulting solutions at this early conceptual design stage. In the context of the AMA, this work fills the methodological gap of elaborating the steps for the definition of conceptual design approaches in a structured way, which still largely depends on professional experience and brainstorming. After identifying the main stages of the AMA process, promising approaches and tools have been selected, potentially able to contribute to the AMA enhancement. Then, the AMA itself was used to assess and select promising combinations of these methods. A sensitivity analysis with the ANOVA statistical test and multiple visualizations of the solution space allowed to elaborate potential approaches for the further methodological development. Major identified contributors were the application of Bayesian networks for the system modeling and probabilistic parameter estimation, knowledge elicitation with the IDEA protocol. This structured way can be used as a guideline to elaborate and justify the form of complex conceptual design methods and mitigate numerous development iterations.

Keywords: conceptual aircraft design, structured methodology development, Advanced Morphological Approach

1. Introduction

The requirements for drastic emission reductions and efficiency increase of civil aerial transport have reached the levels of regional and global policy. Such are formalized in the FlightPath 2050 framework [1] established by the European Commission, envisaging CO2 and NOx reduction of 75% and 90% respectively. While a great effort is invested in the optimization of established civil aircraft technologies, a report suggests that even an optimistic timeframe of these activities might not satisfy aviation's contribution to the Paris Climate Agreement of 2015 [2]. Such estimations stress the necessity for development and implementation of disruptive technologies and innovative aircraft concepts. In order to guarantee the fulfillment of the goals, disruptive technologies should be introduced by assuring their reliable operation while accelerating their development cycle and entry into service. In its turn, novel

conceptual design methods should be brought forward, which are able to address challenges such as a) lacking deterministic/test data on emerging technologies; b) the generation and assessment of novel aircraft concepts which might be left out of scope with conventional design methods; c) the impossibility to define or solve optimization processes due to the lacking data and/or the complexity of conceptual design problems [3].
These aspects constitute the main focus of the Advanced Morphological Approach (AMA), which serves as a method for the conceptual design of complex, unconventional engineering systems. While the AMA can be generally used for product design in various domains, the development focuses on its application in the conceptual design of civil aircraft. As an extension of the classical Morphological Analysis (MA), the AMA is initiated by decomposing the design problem into functional or characteristic system attributes, each corresponding to a number of technological implementations (referred to just as "options" henceforth). In a next step, the options are evaluated according to relevant criteria, which allows the generation and visualization of a solution space.
The current development stage of the AMA implements qualitative technology assessment, which is especially suitable for the evaluation of technological options with few to no statistical data. This implies the option evaluation on a qualitative scale, resulting in a solution space depicting the relative positions of the design solutions, without quantification of any physical properties, design parameters or mission performance. In order to improve the reliability of the approach, the next aim is to increase the level of precision for the assessments of the generated solutions and quantify the uncertainties.

Current objectives

The current paper aims to identify development scenarios for the extension of qualitative aircraft conceptual design methods under the conditions of lacking data, with focus on the AMA. In the future, these should go beyond purely qualitative technology evaluations and account for the 1) interactions between selected technologies; 2) quantification of uncertainties; 3) approximation/modeling of the technological impact on global system performance; 4) transparency and avoidance of black box models. Based on the experience with the AMA development, an overview of potential tools in Aircraft design as well as suitable statistical and participative approaches, this work aims to suggest potential scenarios for conceptual design methodologies dealing with lacking data.
In this context, the main targets of the current work are:

1. To outline the dominating uncertainty types and their specific aspects in the domain of conceptual aircraft design;
2. The identification of the main steps of conceptual design with lacking data with focus on the AMA;
3. The identification of existing approaches to fulfill these steps;
4. The morphological overview and analysis of these, resulting in their relative comparison according to criteria such as uncertainty level, transparency, etc.;
5. Selection of promising tools to fulfill the AMA improvement goals.

2. Methodological background

The defined objectives require the presentation of the AMA and similar methods, as well as the classification of uncertainties, which will be outlined in this chapter.

2.1 Advanced Morphological Approach

The general workflow of the AMA is depicted in Figure 1. The concept of MA is used to decompose design tasks into functional attributes as well as their alternative technological implementations (options) [3]. These are summarized in a morphological matrix (MM). Based on qualitative expert evaluations of each option according to given criteria, an exhaustive solution space is generated by combining these into possible solutions. The solution space is then visualized and allows its further exploration.

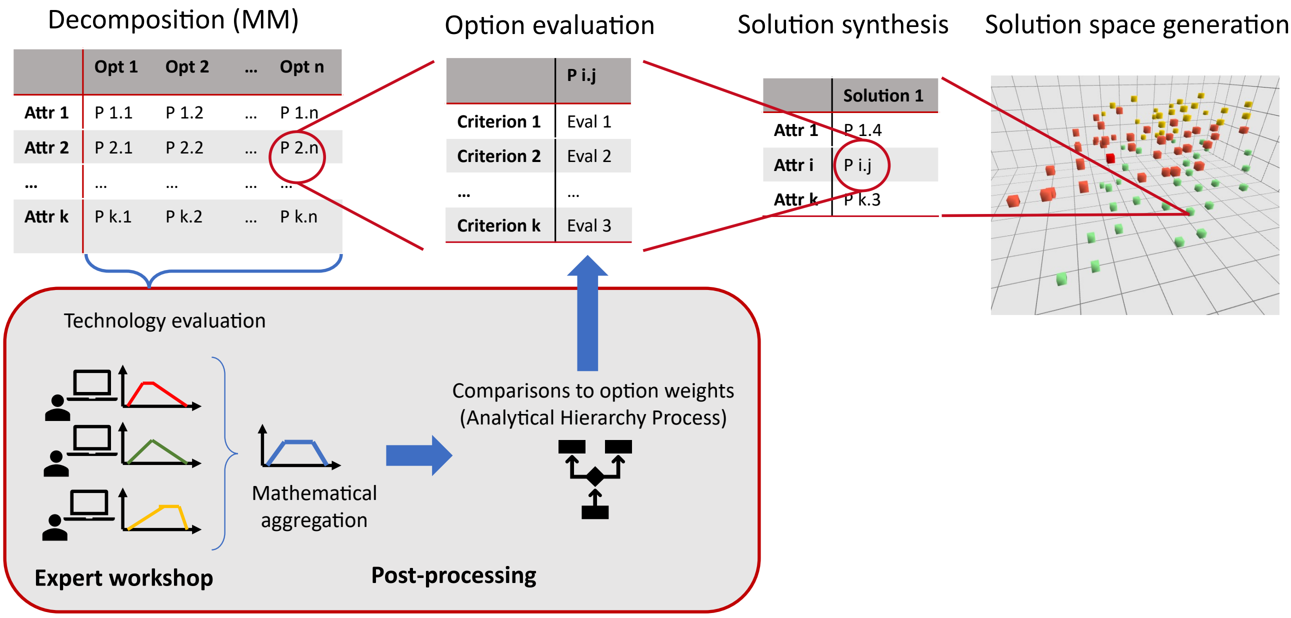


Figure 1 – Workflow of the Advanced Morphological Approach. Adapted from [4]

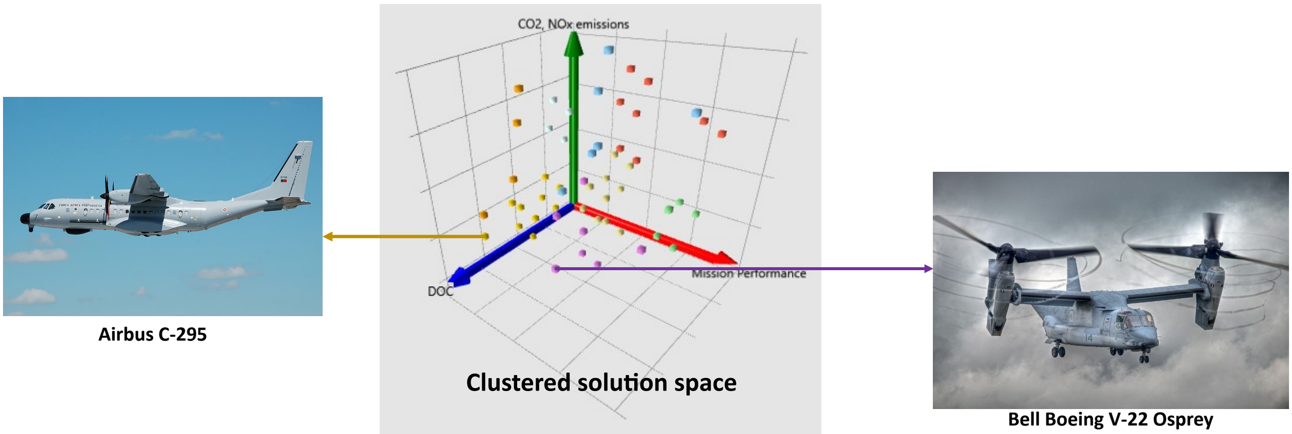


Figure 2 – Generated solution space and reference aircraft of the search and rescue aircraft design use case. Different colors represent solution clusters. Source: [5]. Aircraft image sources: [8, 9]

The main advantages of the AMA include a) the generation and consideration of unconventional aircraft concepts, which may be neglected; b) handling of voluminous solution spaces; c) possible consideration of disruptive technologies with limited test data. The AMA is being continuously enhanced and has been applied to several aircraft conceptual design use cases: 1) search and rescue aircraft [5]; 2) wing morphing architecture [6] and 3) regional air transportation in France. The resulting solution space for the search and rescue aircraft design is shown in Figure 2, including the positioning of reference (existing) configurations along the qualitative axes, representing Direct Operating Cost (DOC), mission performance, as well as CO2 and NOx emissions. The current state of AMA development includes the modeling of uncertainties with fuzzy numbers, the derivation of technology evaluations from expert opinions via mathematical aggregation and the Analytical Hierarchy Process (AHP) [7], elaborated structure for expert workshops and questionnaires [6], as well as sensitivity analysis by means of analysis of variance (ANOVA) statistical tests [4].
Currently, the AMA offers qualitative evaluation of technology options based on structured expert workshops. However, it still does not incorporate the potential interactions of the technological options within the design solution. This requires the consideration of deterministic system and component parameters to a certain extent, which involves significant uncertainties and represents a challenge in the early conceptual design stage.

2.2 Conceptual design stages with focus on the AMA

The selection of methods and tools to use in an improved version of the AMA requires the identification of main conceptual design process tasks, which will be handled in the following subsection. These will be then further expanded and completed, allowing to offer a more detailed step-by-step description of the AMA.

Key tasks of the AMA

As a classical method implying system analysis (SA), AMA's key elements are decomposition, analysis and synthesis of the engineering solution. The SA helps to understand the complexity and interrelationships between the elements of the system, identify problem points, optimize processes and improve the functioning of the system as a whole. The decomposition step requires the breakdown of a system into its component parts or subsystems in order to study their functional characteristics and interactions. Subsequently, analysis stands for the study of each subsystem or element in order to determine its level of efficiency, performance, shortcomings and possible improvements. Finally, synthesis is the combination of all system components into an integral structure with optimal characteristics that meets the requirements and tasks.
The decomposition stage gives a general idea of the system and involves the execution of certain actions:

- Study and evaluate the capabilities and limitations of the system, as well as determine the main functions and goals of the system, take into account the influence of various factors.
- Select appropriate methods and tools to break down the system into simpler components and decompose the system into its component parts and determine their relationships.
- Describe development trends, uncertainties of various kinds
- Conduct a requirements analysis and determine what changes need to be made to improve the system.

The system at this stage is treated as a "black box". The following main types of engineering system decomposition exist:

- Decomposition by functional elements: The system is divided into individual functional elements that perform specific functions.
- Decomposition by subsystems (structural decomposition): A system is divided into parts that interact with each other through certain types of connections.
- Decomposition by management hierarchy: the system is broken down into management levels, from the highest level of strategic management to the lowest levels of operational management.
- Decomposition by time and space: The system is broken down into separate temporal and spatial segments to facilitate analysis and understanding of the system functioning.

Each of these types of decomposition can be used depending on the specific conditions and goals of the system analysis.

Main steps of the AMA conceptual design process

Based on the previously described tasks, this subsection aims to complement these in order to obtain main steps of the AMA as a design process.

1. **Knowledge/expertise/data source identification**

   The character of the design process is highly influenced by the type of available data and its quantity - be it measurement data, empirical estimations or expert knowledge. Further considerations might be:

   (a) Data source identification

   (b) Identification of necessary data quantity
   (c) Data availability, known unknowns, etc.

2. **System decomposition - MM**

   As an integral part of the AMA, the system decomposition is summarized in a MM. However, the question how to obtain the criteria, the attributes and their options remains open. Possible approaches are:

   (a) Brainstorming
   (b) Work domain analysis [10, 11]
   (c) Architecture design space graph [12]

3. **Analysis - Knowledge modeling and performance inference**

   In order to obtain the performance of the options for the criteria, it is necessary to model these dependencies. This requires a balance between precision/informativeness of the estimations and innovativeness/lack of data on novel technologies. Potential approaches to model the knowledge and infere the option performance could be:

   (a) Multi-criteria decision-making (e.g. the Analytical Hierarchy Process)
   (b) Rules for expert systems
   (c) Bayesian inference (Bayesian networks)
   (d) Surrogate modeling
      i. Linear Regression
      ii. Neural networks, etc.

4. **Analysis - Knowledge elicitation** Data for the component performance estimations can be obtained from various sources - e.g. measurements, empirical approximations or expert knowledge. Since the AMA focuses on the last source in order to allow the consideration of unconventional or disruptive technologies, this part will handle the necessary steps to elicit knowledge from experts and the necessary post-processing, such as:

   (a) Elicitation protocols and formats
   (b) Uncertainty modeling
   (c) Questionnaire format
   (d) Knowledge aggregation

5. **Structural synthesis - idea generation**

   This step implies the creation of design solutions by combining different options. This process can also be defined as the "idea generation" step from the idea management process [13]. Namely, it allows the creation of innovative concepts through unconventional designs, which represents one of the main advantages of the AMA. In this context, one could address the following aspects

   (a) Generated part of the solution space – exhaustive, with selection, etc.
   (b) Clustering algorithm – K-Means, DBSCAN, etc.
   (c) Clustering type – crisp, fuzzy, etc.

2.3 Uncertainty classification

Numerous classifications of uncertainties exist in literature, which are often defined for the various discipline domains such as economics, policy, engineering, etc. [14]. In order to model the uncertainty within the AMA process, some uncertainty types have already been discussed in reference [7]. However, since the conceptual design process (also the one implemented with the AMA) vastly relies on decision-making among technologies and configurations, it is necessary to obtain an overview of potential uncertainty types in this context. Such an overview has been provided by French [15] in the context of multiple criteria decision-making methods, which is summarized in the following[15]:

- Knowledge of the external world
  - Stochastic or aleatory (physical randomness)
  - Actor (behavior of others)
  - Epistemological (lack of knowledge)
- Modeling and analysis error
  - Judgmental (misjudgments in model definitions)
  - Computational (inaccurate calculations and mistakes)
  - Modeling error (imperfect fit of the real world)
- Internal uncertainties about ourselves
  - Ambiguities
  - Value, social and ethical
  - Depth of modeling

This extended overview underlines the complexity of the overall conceptual design process and the importance of the thorough selection of methodological tools.

2.4 Overview of potential methods and tools to fulfill the AMA improvement goals

The experience with the AMA development has shown that the core step responsible for the introduction of more information to the design solutions is the approach used for system modeling. For this reason, the current section will briefly present the most prominent ways to model complex system configurations and their performance at the early design stages.

The Analytical Hierarchy Process (multi-criteria decision-making methods family)

The AHP has established itself as an integral member of the multi-criteria decision-making (MCDM) methods family. Similar to other MCDM algorithms, the AHP serves to assess and compare alternative concepts or actions by considering a complex system of criteria [16, 17]. The AHP does so by intuitively structuring the alternative actions and the criteria into separate hierarchy levels, connected by the logical dependencies between the elements of different levels. An example of such a hierarchy used for the conceptual design of wing morphing architectures [4] is exhibited in Figure 3. Detailed explanation of the AHP, its integration into the AMA and improvements are outlined in [7, 4].

Expert systems

As a part of artificial intelligence (AI), expert systems (ES) represent knowledge-based systems built upon human reasoning and aim to solve complex problems of a given field in an automated manned [18, 19, 20]. Typically, such an approach consists of the following elements: knowledge base, inference engine, knowledge acquisition, explanation facility and user interface [18]. Such configurations allow not only the elicitation of knowledge on a given set of technologies or actions, but also make inferences on new inquiries based on a set of rules programmed in the knowledge base. Among the main characteristics of ES are: increased problem-solving performance comparable or better than human experts, large domain knowledge base, transparency and explanations of the decision-making process, ability to update the knowledge base [18].

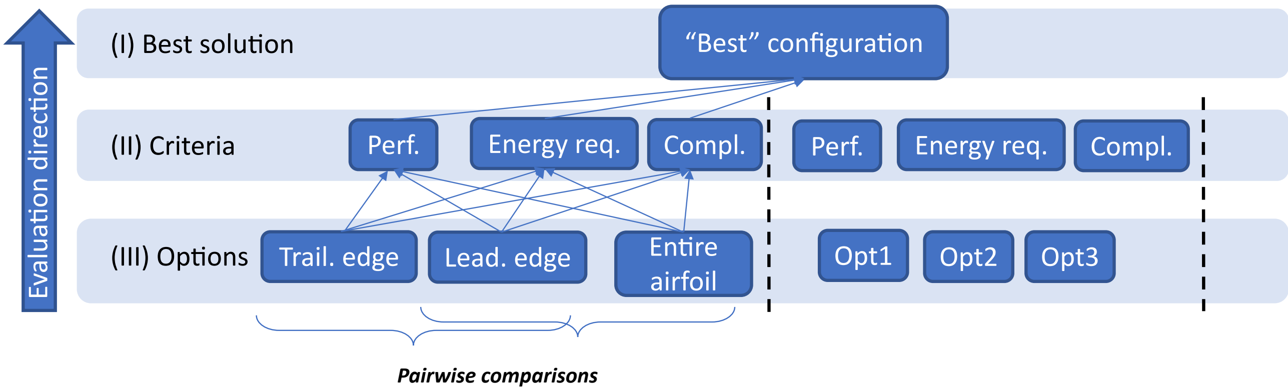


Figure 3 – An example of a hierarchy used for the conceptual design of wing morphing architectures with the AHP. Source: [4]. Abbreviations: perf. - performance; energy req. - required energy; compl. - system complexity; trail. edge - trailing edge; lead. edge - leading edge; opt. - option.

The ES definition already reflects certain similarities to the way AMA uses expert knowledge. In particular, the inference rules of ES may be potentially used in the system modeling stage of the AMA. As stated in [4], the knowledge-based character of the AMA aims in a way to become similar to a full-scale ES. An example in the aeronautical domain is the ES development tested on the condition-based maintenance of aircraft systems [21].

Surrogate modeling

A surrogate model (SM) represents a statistical model which reflects the dependencies "between inputs (i.e., model's adjustable parameters) and outputs (i.e., the performance measure of the simulation model)" [22] of a given system. SMs are used to approximate the results of higher-order models, especially when the operations within these models are complex, computationally expensive, could not be described analytically or traditional optimization techniques are not applicable [23]. For instance, SMs could be used to achieve a faster overall estimation of an aircraft wing design, instead of directly applying high-fidelity numerical methods [24]. The current advancements of machine learning (ML) approaches from the AI domain have expanded the availability of algorithms such as linear regression (LR), random forests, Gaussian processes and artificial neural networks (ANNs) for surrogate modeling purposes [22, 23].

Bayesian networks

The estimation of system parameters based on uncertain input can be approached by employing Bayesian inference. Bayesian statistics is a paradigm stating one could obtain a more accurate estimate of an event, state, or parameter of a given system by updating their own prior uncertain beliefs about the system with incomplete data on the systems components or events [25]. The base for such inferences is a system model (in particular: directional acyclic graph), which incorporates variables representing the system elements and their influences on each other depicted by arrows. The variable uncertainties are modeled as probability distributions and their relationships could be stated as mathematical expressions. Along with the model, one requires their initial belief/knowledge about the system in the form of variable uncertainties (designated as "priors θ") as well as data on certain system variables obtained from observations, measurements, calculations, etc., designated "y". The output of Bayesian inference are the posterior distributions (named "posteriors"), which reflect the updated beliefs. The mentioned elements of this inference concept are connected with the Bayes' theorem. In other words, the posteriors are the probability p($\theta|y$) of the priors θ given the data y. Since the calculation of the posteriors for multiple variables cannot be conducted analytically, the state-of-the-art method to solve such problems are Markov Chain Monte Carlo (MCMC) algorithms such as Metropolis-Hastings or Hamiltonian Monte Carlo. [25]

3. Methodology

Since the aim of the current study is to conduct a morphological analysis of methods and tools to integrate into the AMA, the methodology follows the main steps of the AMA itself, as shown below. These will be explained in further detail within the following subsections.

1. Morphological matrix
2. Knowledge modeling with the AHP and defined criteria
3. Option evaluation via developed SEJE approach
4. Solution space generation, visualization and analysis

3.1 Morphological matrix

The MM for the current study is based on the main steps of the AMA presented in Section 2.2 . Three main sections of attributes have been identified, which categorize the tasks of the AMA design process - system decomposition and modeling, knowledge elicitation , as well as knowledge aggregation and solution space generation. In order to improve readability, the MM is presented in the thematically separate Tables 1-3, although these are all considered as a single MM in the current work. This selection aims to combine both older stages of the AMA development as well as potentially new tools, with focus to introduce quantification of physical parameters and account for uncertainties. Although the Tables reflect thorough research in these directions, these are not presented as exhaustive outlines of all possible design approaches and could be further extended.

Table 1 – MM on system decomposition and modeling

Attribute	Option 1	Option 2	Option 3	Option 4	Option 5
Data sources	Statistical data	Prospective technology research	Expert knowledge	Hybrid	
System modeling	AHP	Bayesian networks	Linear Regression	Neural networks	Rules for expert systems
Definition of the system model	Pre-defined	Elaborated with experts			
System decomposition	Brainstorming	Work domain analysis	Architecture design space graph		

Table 2 – MM on knowledge elicitation

Attribute	Option 1	Option 2	Option 3	Option 4
Elicitation protocol	Classical model	SHELF	Delphi	IDEA
Elicitation format	Remote	Individual interviews	Interactive group	Individual evaluations and group discussions
Uncertainty modeling	None	Intervals	Fuzzy numbers	Probability distributions
Technology evaluation	Separate (each option)	Pairwise (compare 2 options)		
Interaction of attributes	None	Qualitative	Quantitative	

Table 3 – MM on knowledge aggregation and solution space generation

Attribute	Option 1	Option 2	Option 3	Option 4
Aggregation type	None	Mathematical	Behavioral	Mixed
Mathematical aggregation	None	Arithmetic mean	Geometric mean	
Evaluation aggregation	No weighting	Weighted for expertise	Weighted for uncertainty	
Results discussion and reevaluation	No	Yes		
Solution space generation	Exhaustive generation (all options)	Exhaustive generation with selection	Inexhaustive generation with selection	

3.2 Knowledge modeling with the AHP and criteria

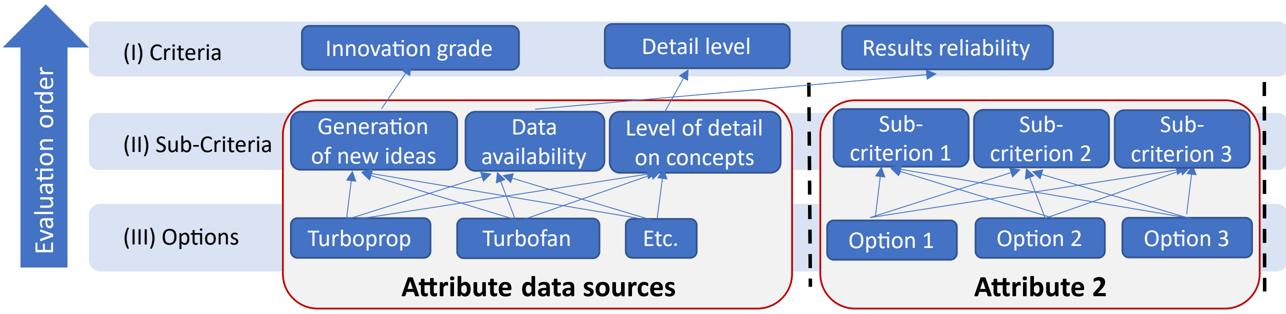


Figure 4 – A general schema of the hierarchy including the MM options, criteria and sub-criteria

The evaluation of the options is conducted by selecting three global evaluation criteria with corresponding sub-criteria, which are also attribute-specific. This assessment system is structured in a hierarchy and resolved via the AHP, which is integrated into the AMA as described in [7]. Figure 4 yields the main schema of the elaborated hierarchy. The lowest level number three contains the alternative options, which are evaluated according to the attribute-specific sub-criteria from level two. In a next step, these sub-criteria are then assessed regarding the global criteria in the top level. The entire set of criteria, sub-criteria and their corresponding attributes are exhibited in Table 4. The global criteria in the top level reflect the defined directions of the desired AMA improvement, namely the increase of solution innovation grade, the detail level on solutions, as well as the reliability of the results.

Table 4 – Defined criteria and the attribute-specific sub-criteria

Attribute	Sub-criterion	Global criterion
Data sources	Generation of new ideas	Innovation grade of solutions
	Enough available data	Results reliability
	Level of detail on concepts	Detail level of solutions
System modeling	Precise representation of relationships	Results reliability
	Detail level on components	Detail level of solutions
	Level of uncertainty quantification	Detail level of solutions
Definition of MM, criteria	Innovation grade of solutions	Innovation grade of solutions
	Consideration of all aspects	Results reliability
	Detail level on technologies and criteria	Detail level of solutions
System decomposition	Detailed representation of the system	Detail level of solutions
	Use of innovative components	Innovation grade of solutions
	Consideration of all relevant system aspects	Results reliability
Elicitation protocol	Bias reduction	Results reliability
Elicitation format	Evaluation objectivity and bias reduction	Results reliability
	Multidisciplinary considerations	Results reliability
Uncertainty modeling	Bias reduction	Results reliability
	Grade of uncertainty quantification	Results reliability
	Grade of uncertainty quantification	Detail level of solutions
Technology evaluation	Bias reduction	Results reliability
Interaction of attributes	Precise representation of relationships	Results reliability
	Quantification of interaction contribution	Detail level of solutions
Aggregation type	Bias reduction	Results reliability
	Multidisciplinary considerations	Results reliability
Type of mathematical aggregation	Bias reduction	Results reliability
Type of mathematical aggregation	Multidisciplinary considerations	Results reliability
Extent of solution space generation	Generation probability of innovative solutions	Innovation grade of solutions
Extent of solution space generation	Generation probability of the optimal solutions	Results reliability
Evaluation aggregation	Multidisciplinary considerations	Results reliability
	Bias reduction	Results reliability
Results discussion and reevaluation	Multidisciplinary considerations	Results reliability
Results discussion and reevaluation	Bias reduction	Results reliability

3.3 Option evaluation via developed SEJE approach

The necessary evaluations defined in the hierarchy have been obtained from the subjective opinion of one of the authors, which is based on their experience with the AMA development and the thorough research on its further extension. For this purpose, they answered a structured questionnaire, which was developed during previous work [6, 7]. An exemplary question is shown in Figure 5. They

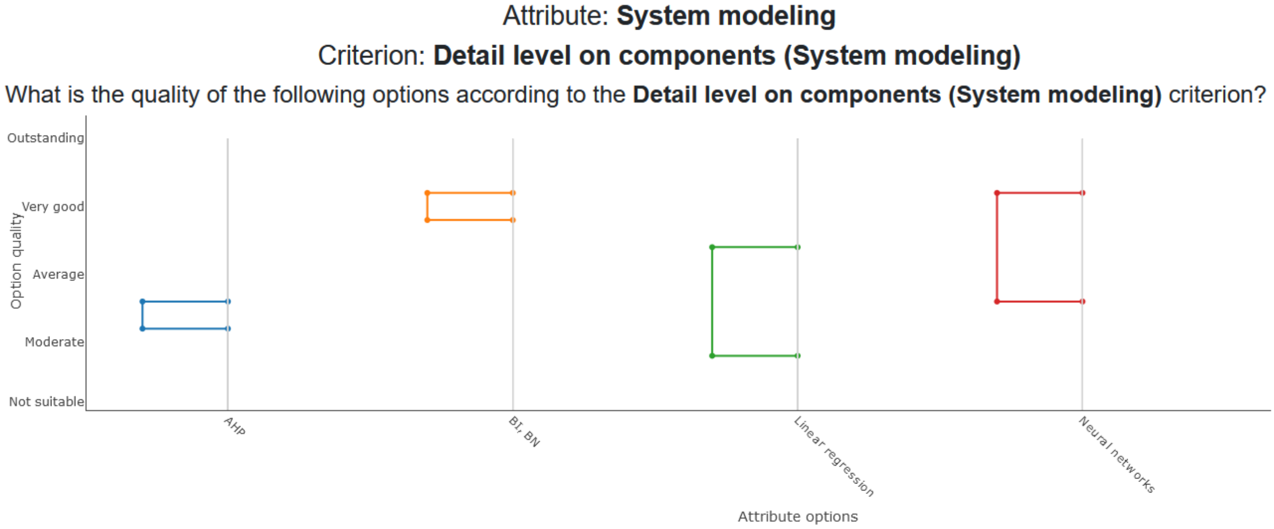


Figure 5 – An example task from the developed questionnaire. The expert entered the upper and lower qualitative interval boundaries for the evaluation of each option according to the criteria.

were asked to evaluate how good the options of each attribute were according to the sub-criteria by entering a range on a qualitative scale from "1.Not suitable" to "9.Outstanding". According to the defined hierarchy in Figure 4, the questionnaire started with the evaluations of the options (level 3) regarding to the sub-criteria (level 2). The second questionnaire part implied the assessment of the sub-criteria in reference to the global criteria.
The post-processing of the results comprised of the application of the AHP algorithm, allowing to obtain the option weights for the global criteria. Contrary to the previous AMA applications, only a single expert was asked to give their evaluations instead of a broader panel with multiple participants. Therefore, no results aggregation was required from different decision-makers.

3.4 Solution space generation and analysis

The MM, the criteria and the global option weights were used as input to the AMA software, developed by the authors. This information was used to generate and visualize the solution space by combining the attribute options. The solutions were clustered with the OPTICS algorithm (Ordering Points To Identify the Clustering Structure) [26] implemented as part of the scikit-learn library [27] in the Python programming language.

4. Results

4.1 Solution space

The morphological space of all option combinations based on the MM from Section 3.1is 16588800, which is equal to the permutation of the option count in every attribute. In order to reduce the computational effort, 100000 solutions have been generated, out of which 50000 with the highest total score were selected. The further removal of impossible option combination results in 5403 rational solutions, which are visualized in Figure 6. Each data point represents a solution, containing a certain combination of options. The three-dimensional diagram spans over the global criteria "Innovation grade of solutions", "Results reliability" and "Detail level of solutions". The solutions are colored according to their 28 designated clusters, while the gray ones have remained unclustered due to the parameters set with the OPTICS algorithm. The cluster number X marked in brown is located the furthest from the coordinate system origin and therefore demonstrates best qualities regarding all three criteria.

4.2 Sensitivity analysis and trends

The AMA software allows the study of criteria score sensitivity against the changing options within the attributes in two ways - the conduction of ANOVA statistical tests and the application of color

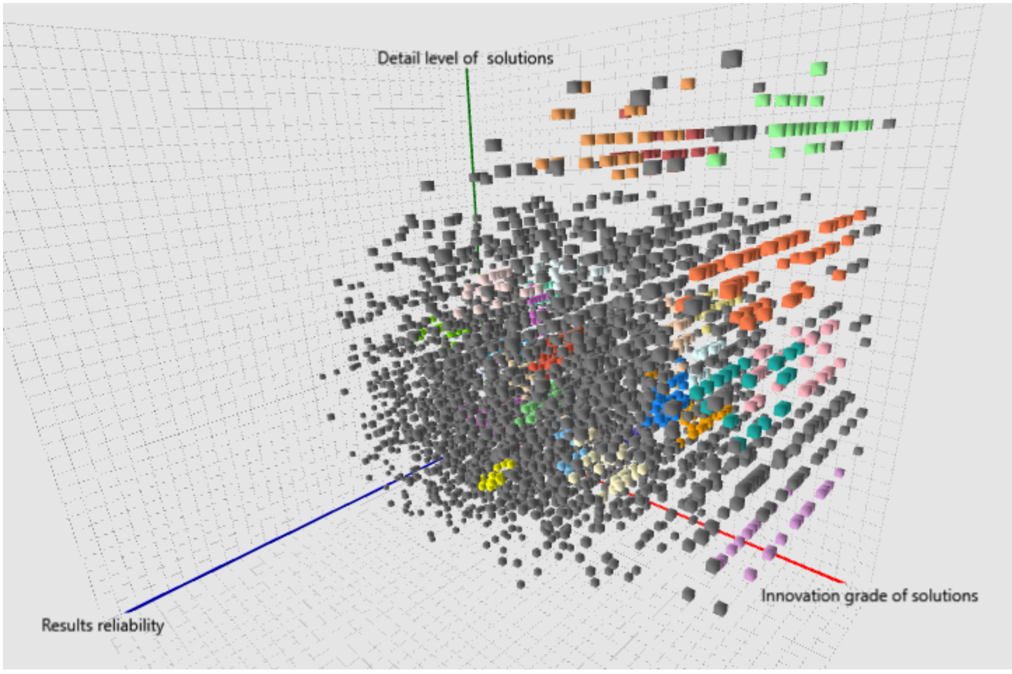
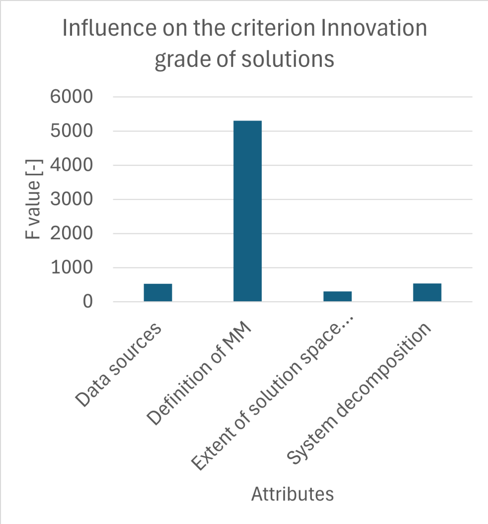


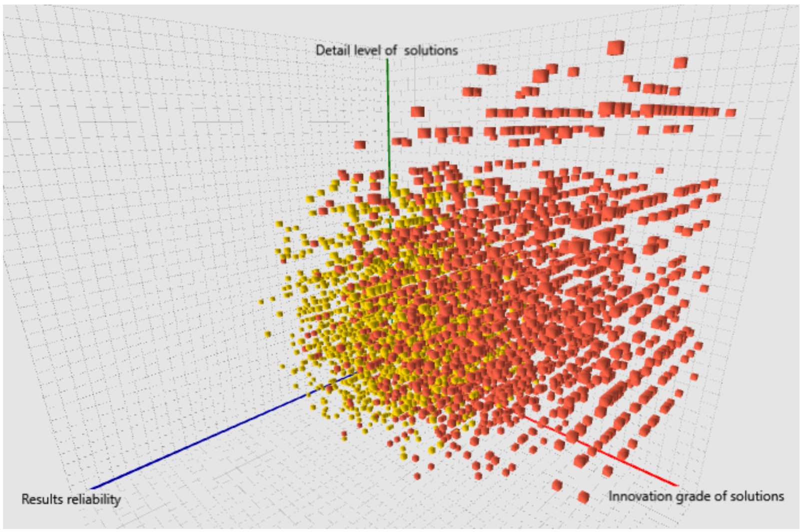
Figure 6 – The clustered solution space, containing 11045 rational solutions and their position for the three global criteria "Innovation grade of solutions", "Results reliability" and "Detail level of solutions". The colors represent different clusters.

mapping to solutions with different options. The application of ANOVA tests in the AMA is described in further detail in Reference [4]. After having confirmed the fulfillment of the ANOVA assumptions, its main output is expressed in the so called F value, which stands for the sensitivity in the solution criteria scores (the output) against the variation of options within a single attribute (the input). Figures 7a, 7c and 7e showcase this indicator for the three main criteria, accompanied by solution space visualizations confirming these estimations. Attributes, which are not shown in the F value diagrams, do not influence the respective criteria. In particular, one can see the option distribution of the attribute "Definition of MM and criteria" in Figure 7b, which exhibits the clear separation of the design space into solutions implementing the options "Elaborated with experts" (red) and "Pre-defined" (yellow). This is supported by the highest F value of this attribute in the Figure on the left, stating the highest influence compared to the rest of the attributes.

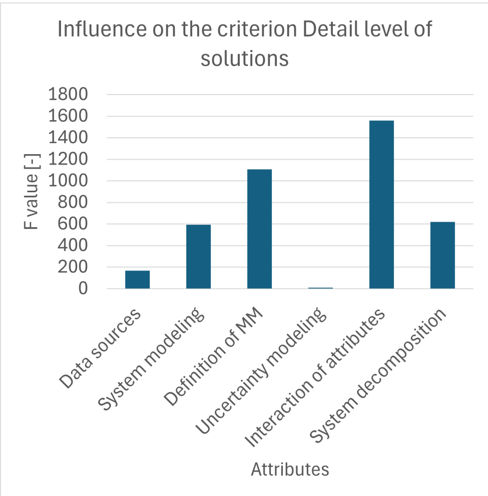
Furthermore, Figure 7d depicts the option distribution of the attribute "System modeling". It involved methods such as the AHP, BN and different types of surrogate modeling, hence influencing the information detail level on the resulting solutions from this conceptual design approach. This is reflected in the figure, indicating BNs (shown in red) as a method yielding most information on solutions, justified by the quantification of uncertainties. The worst option in this context is the AHP (solutions in yellow), which relies solely on qualitative comparisons of technologies. Although this attribute resulted only in the fourth highest F value for the sensitivity of solution detail level (Figure 7c), its options are highly linked with certain implementations of attribute interactions and system decomposition approaches - for instance, a BN implies quantitative technology interaction.



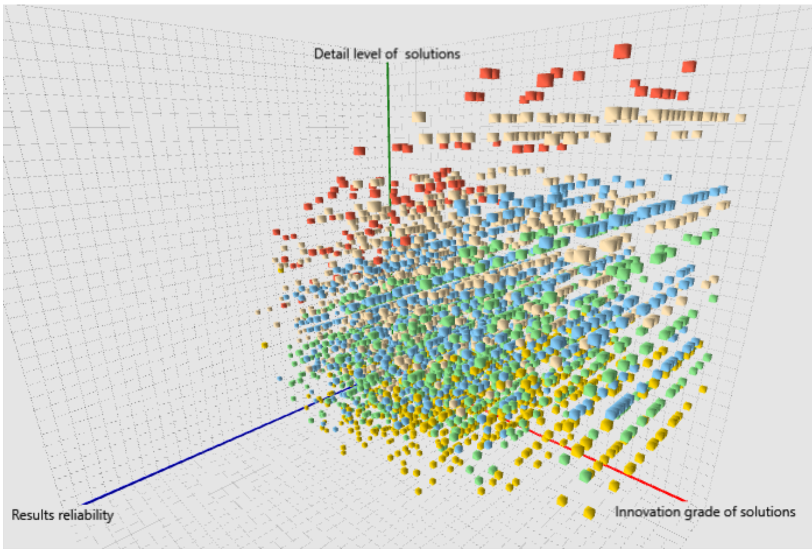
(a) Sensitivity analysis of the score for Innovation grade of solutions against the different attributes.



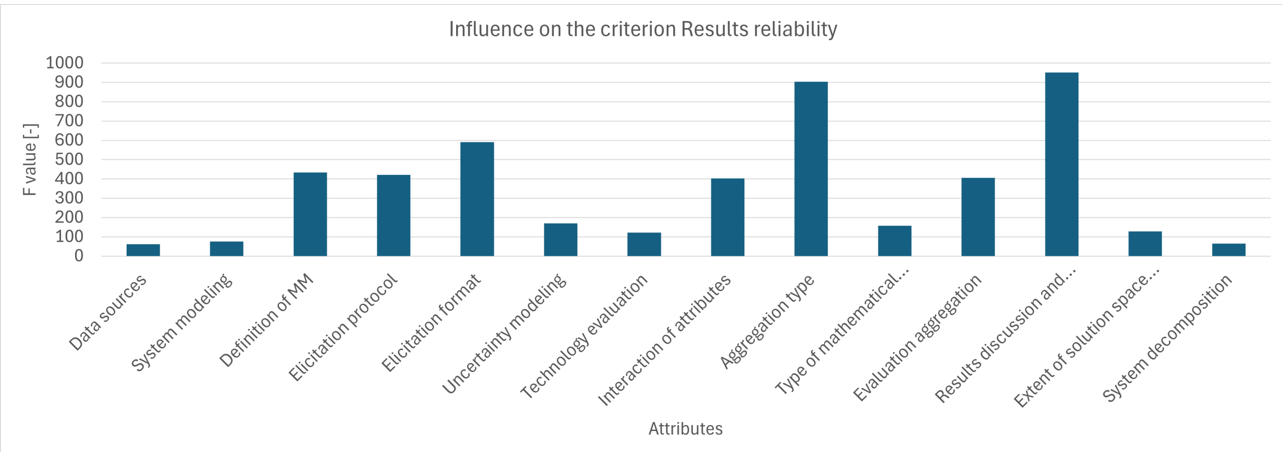
(b) Distribution of options from the attribute "Definition of the MM". Red - Elaborated with experts; yellow - pre-defined.



(c) Sensitivity analysis of the score for Detail level of solutions against the different attributes.



(d) Distribution of options from the attribute System modeling. Red - BN; beige - rules for expert systems; blue - ANNs; green - LR; yellow - AHP.



(e) Sensitivity analysis of the score for Results reliability against the different attributes.

Figure 7 – Sensitivity analysis of the main criteria against the attributes.

The reliability of AMA results is mostly influenced by the attributes Results discussion and reevaluation, as well as Aggregation type (Figure 7e). This is justified by the fact that both reflect the level of interaction within the expert pool, e.g. whether a behavioral aggregation through discussion would increase the technology assessment objectivity or a simple mathematical aggregation should be performed.

4.3 Reference solutions and Pareto front

Reference solutions represent known designs (in this case: methodologies), which are also projected in the solution space and serve as references . The reference solutions defined in this work are the methodological approaches used in previous AMA development stages, which are described in Table 5. In order to identify the most promising tools to improve the AMA process, the solutions forming the Pareto front are visualized as well, as shown in Figure 8 (in red). It also highlights the section of the diagram which contains the reference solutions (yellow rectangle), positioned in a closer proximity to the diagram origin compared to most generated points.
Therefore, the solution space exhibits the improvement potential of the current AMA state, which could be accomplished by suggestions in the Pareto front (marked in red). The most significant improvement suggestions are for alternative approaches in system modeling and attribute interactions, such as Bayesian Networks which yield more information on design solutions through quantitative estimations and uncertainty considerations. Furthermore, probability distributions are also estimated higher along the axis "Detail level of solutions" due to the uncertainty quantification of quantitative system parameters.

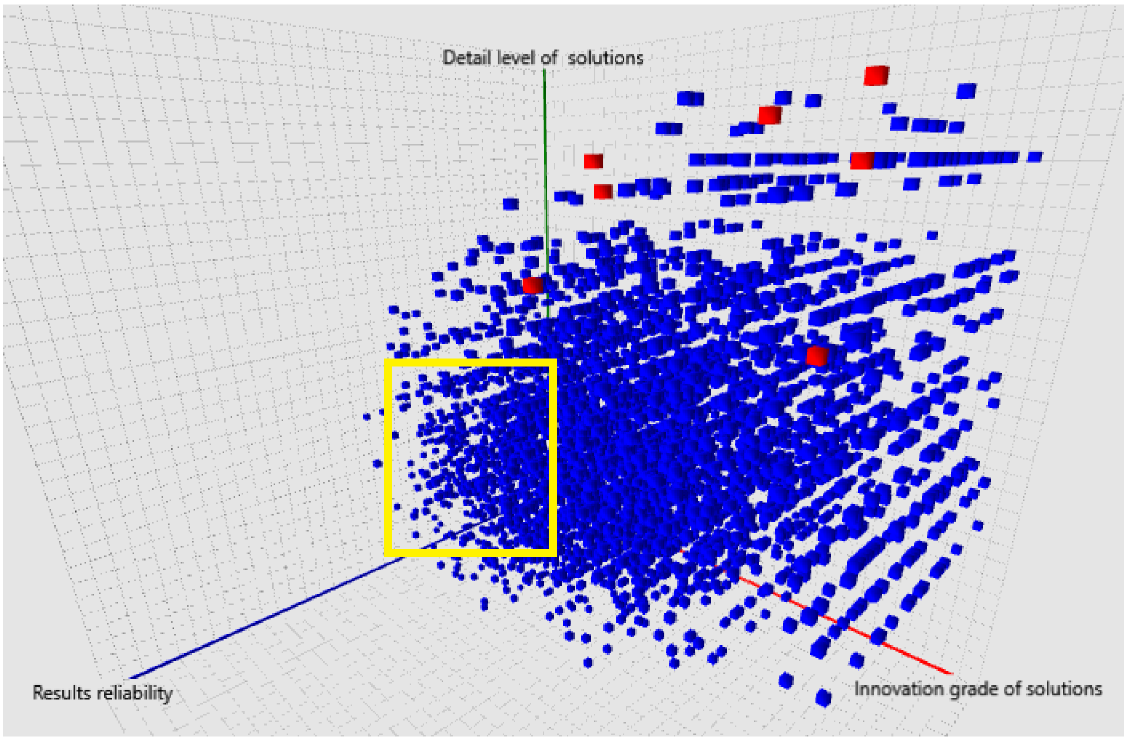


Figure 8 – Location of the Pareto front solutions (red) and the area containing the reference solutions (yellow rectangle).

Table 5 – Selected options in the reference solutions

Attribute	Use case 1	Use case 2	Use case 3
Data sources	Expert knowledge	Expert knowledge	Expert knowledge
Knowledge/system modeling	AHP	AHP	AHP
Definition of the system model, criteria, etc.	Pre-defined	Pre-defined	Pre-defined
Elicitation protocol	Delphi	SHELF	IDEA
Elicitation format	Remote	Individual evaluations and group discussions	Individual evaluations and group discussions
Uncertainty modeling	Fuzzy numbers	Fuzzy numbers	Intervals
Technology evaluation	Pairwise	Separate	Separate
Interaction of attributes	None	None	Qualitative
Aggregation type	Mathematical	Mathematical	Mixed
Evaluation aggregation	No weighting	Weighted for expertise	Weighted for uncertainty
Results discussion	No	Yes	No

5. Conclusions

The development and consideration of certain concept ideas in aircraft and engineering design in general has relied to a large extent on the designer's experience, existing products and statistical data. The main challenge of this established approach is the limitation of the solution space to known configurations thus challenging the exploration of unconventional technology combinations. This had been addressed earlier by the introduction of the AMA to decompose problems via MA and synthesize a more extensive amount of designs in a visualized solution space. Since the consideration of disruptive technologies required their qualitative assessment due to their lack on historical data, the AMA yielded somewhat limited information on the configurations in its initial development stages, based solely on qualitative comparisons of the solutions. In order to augment the solution informativeness, further approaches and tools were sought to enhance the existing AMA.

The complexity of the AMA process and the diverse character of its stages required a thorough analysis of potential improvements. The further design process development required decisions to be made on matters such as handling of system modeling, social interactions during workshops, uncertainty modeling, and aggregation of expert knowledge. The analysis complexity suggested the use of AMA itself to pave the way to its own further development.

After a thorough research, the potential alternative implementation of different AMA steps were summarized in a MM, containing three attribute groups: system decomposition, knowledge elicitation, as well as knowledge aggregation and solution space generation. The options were qualitatively evaluated according to appropriate criteria from the categories innovation grade of solutions, detail level of solutions, and results reliability. By considering incompatible option combinations, a solution space has been generated, limited to 5403 solutions for purposes of computational efficiency and visual comprehension. Subsequently, sensitivity analysis via the ANOVA statistical test has been conducted, yielding the influence of varying options within the attributes on the solution criteria scores. These results have been justified by multiple visualizations, showcasing the distribution of options in the solution space.

The Pareto front and the sensitivity visualization of the attributes have shown that the main drivers for the increase in solution information is the system modeling via Bayesian networks or similar rules for expert systems, which implies quantitative attribute interactions, as well as uncertainty modeling via probability distributions. On the side of solution innovation, main contributors are system decomposition (both advantageous options are here work domain analysis and the architecture design space graph) and the involvement of experts for the definition of the MM. Concerning the results reliability, these are mostly improved by the IDEA and SHELF elicitation protocols. The contributions of the

other attributes are considered, however less significant.
These findings help draw the conclusion on the future development of a more informative, innovative and reliable AMA or similar design processes. This should involve the probabilistic estimation of quantitative design parameters and their connection within the system modeling with Bayesian networks, in combination with expert knowledge elicitation. The layout of the BN could be obtained by applying work domain analysis. The elicitation of the values and uncertainties of the parameters could be conducting via the IDEA protocol in combination with some aspects of the Classical Model. Considering the complexity of the AMA design process, the current work serves as a structured scientific justification for the further AMA developments. Apart from that, the study fills the methodological gap of the structured elaboration of the definition of conceptual design approaches, which aims to improve the justification of selected tools and reduce numerous iterations of methodology development.

6. Funding

This research was funded by Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) grant number 443831887.

7. Contact Author Email Address

mailto: vladislav.t.todorov@tu-berlin.de

8. Copyright Statement

References

[1] European Commission. Directorate General for Research and Innovation. and Directorate General for Mobility and Transport. *Flightpath 2050 :Europe's vision for aviation : maintaining global leadership and serving society's needs.* Publications Office of the European Union, Luxembourg, 2011.

[2] The Shift Project and SUPAERO DECARBO. Pouvoir voler en 2050: quelle aviation dans un monde contraint? (Flying in 2050: what future for aviation in a constrained world?). Technical report, March 2021.

[3] A. Bardenhagen and D Rakov. Analysis and Synthesis of Aircraft Configurations during Conceptual Design using an Advanced Morphological Approach. Bonn, November 2019. Deutsche Gesellschaft für Luft- und Raumfahrt - Lilienthal-Oberth e.V.

[4] Vladislav T. Todorov, Dmitry Rakov, and Andreas Bardenhagen. Sensitivity Analysis and System Attribute Importance for Conceptual Aircraft Design with the Advanced Morphological Approach. *Aerospace*, 10(7):608, June 2023.

[5] Vladislav T. Todorov, D. Rakov, and A. Bardenhagen. Improvement and Testing of the Advanced Morphological Approach in the Domain of Conceptual Aircraft Design. Bonn, 2022. Deutsche Gesellschaft für Luft- und Raumfahrt - Lilienthal-Oberth e.V.

[6] Vladislav T. Todorov, Dmitry Rakov, and Andreas Bardenhagen. Structured Expert Judgment Elicitation in Conceptual Aircraft Design. *Aerospace*, 10(3):287, March 2023.

[7] Vladislav T. Todorov, Dmitry Rakov, and Andreas Bardenhagen. Enhancement Opportunities for Conceptual Design in Aerospace Based on the Advanced Morphological Approach. *Aerospace*, 9(2):78, February 2022.

[8] A. Pingstone. Portuguese air force casa c-295, 2014. URL: `https://commons.wikimedia.org/wiki/File:Portuguese_Air_Force_C-295_arrives_RIAT_Fairford_10thJuly2014_arp.jpg`. Accessed: 17.11.2022.

[9] P. Gronemann. Bell-boeing v-22 osprey at the 2012 royal international air tattoo, 2012. URL: `https://en.wikipedia.org/wiki/File:V22-Osprey.jpg`. Accessed: 17.11.2022.

[10] Robert R. Hoffman and Gavan Lintern. Eliciting and Representing the Knowledge of Experts. In K. Anders Ericsson, Neil Charness, Paul J. Feltovich, and Robert R. Hoffman, editors, *The Cambridge Handbook of Expertise and Expert Performance*, pages 203–222. Cambridge University Press, 1 edition, June 2006.

[11] Gavan Lintern. Tutorial: Work Domain Analysis. Tutorial, 2016.

[12] Jasper H. Bussemaker, Pier Davide Ciampa, and Bjoern Nagel. System Architecture Design Space Exploration: An Approach to Modeling and Optimization. In *AIAA AVIATION 2020 FORUM*, VIRTUAL EVENT, June 2020. American Institute of Aeronautics and Astronautics.

[13] Stefan Kohn and Stefan Husig. Development of an empirical-based categorisation scheme for CAI software. *International Journal of Computer Applications in Technology*, 30(1/2):33, 2007. Number: 1/2.

[14] Daniel P. Thunnissen. Uncertainty Classification for the Design and Development of Complex Systems. Newport Beach, California, USA, 2003.

[15] Simon French. Reflections on 50 years of MCDM: Issues and future research needs. *EURO Journal on Decision Processes*, 11:100030, 2023.

[16] T. Saaty. *Decision-Making. Analytic Hierarchy Process*. Radio i Svyaz, Moscow, 1993.

[17] Shu-Jen Chen, C. L. Hwang, and Frank P. Hwang. *Fuzzy multiple attribute decision making: methods and applications*. Number 375 in Lecture notes in economics and mathematical systems. Springer-Verlag, Berlin ; New York, 1992.

[18] K.P. Tripathi. A Review on Knowledge-based Expert System: Concept and Architecture. *IJCA*, 4(Special Issue on Artificial Intelligence Techniques - Novel Approaches & Practical Applications):21–25, 2011.

[19] Madjid Tavana and Vahid Hajipour. A practical review and taxonomy of fuzzy expert systems: methods and applications. *Benchmarking: An International Journal*, 27(1):81–136, September 2019.

[20] Ali Ahmed Mohammed, Kamarudin Ambak, Ahmed Mancy Mosa, and Deprizon Syamsunur. Expert system in engineering transportation: a review. *Journal of Engineering Science and Technology*, 14(1):229–252, 2019.

[21] Alexandre Sarazin, Jérémy Bascans, Jean-Baptiste Sciau, Jiefu Song, Bruno Supiot, Aurélie Montarnal, Xavier Lorca, and Sébastien Truptil. Expert system dedicated to condition-based maintenance based on a knowledge graph approach: Application to an aeronautic system. *Expert Systems with Applications*, 186:115767, December 2021.

[22] Chen Wang, Qingyun Duan, Wei Gong, Aizhong Ye, Zhenhua Di, and Chiyuan Miao. An evaluation of adaptive surrogate modeling based optimization with two benchmark problems. *Environmental Modelling & Software*, 60:167–179, October 2014.

[23] B.A. Williams and S. Cremaschi. Surrogate Model Selection for Design Space Approximation And Surrogatebased Optimization. In *Computer Aided Chemical Engineering*, volume 47, pages 353–358. Elsevier, 2019.

[24] Spyridon Kilimtzidis and Vassilis Kostopoulos. Static Aeroelastic Optimization of High-Aspect-Ratio Composite Aircraft Wings via Surrogate Modeling. *Aerospace*, 10(3):251, March 2023.

[25] Timo Koski and John M. Noble. *Bayesian networks: an introduction*. Wiley series in probability and statistics. Wiley, Chichester, 1. publ edition, 2009.

[26] Mihael Ankerst, Markus M. Breunig, Hans-Peter Kriegel, and Jörg Sander. OPTICS: ordering points to identify the clustering structure. *ACM SIGMOD Record*, 28(2):49–60, June 1999.

[27] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.