NOVEL APPROACH FOR AUTOMATED AND OBJECTIVE VTOL CONCEPT SELECTION

Victor Zappek, M.Sc.
Graduate Research Assistant

Jonas John, M.Sc.
Graduate Research Assistant

Niklas C. Mueller, B.Sc
Student

Eric Wallner, B.Sc.
Student

Prof. Ilkay Yavrucuk
Professor

Institute for Rotorcraft and Vertical Flight, Technical University of Munich, Germany

ABSTRACT

Selecting the optimal Vertical Take-Off and Landing (VTOL) aircraft concept is a critical and complex step in the design process, as it lays the foundation for the entire development lifecycle. Traditional Concept Selection Methodologies (CSMs) often depend on subjective expert opinions and manual evaluation processes, which are limited in scope and prone to bias, potentially overlooking innovative or unconventional design solutions. This paper presents the Interactive Semi-Automated Reconfigurable Concept Selection Methodology (ISAR-CSM), a novel approach that aims to enhance objectivity, scalability, and efficiency in the VTOL concept selection process. ISAR-CSM integrates a robust database of correlations between VTOL aircraft characteristics and specific design requirements, enabling the automated generation and evaluation of a vast array of potential concepts derived from a generalized VTOL taxonomy. The methodology is anchored by a modified House of Quality (mHoQ) and an Automated Concept Assessment Algorithm (ACAA), which together facilitate the systematic ranking of concepts based on their alignment with predefined mission requirements. A proof-of-concept implementation is provided, demonstrating ISAR-CSM's ability to process a large concept space rapidly, minimize human bias, and identify the most promising designs for further development. The results indicate that ISAR-CSM has significant potential to transform the early stages of VTOL design, though additional refinements and validations are necessary to fully realize its capabilities in practical applications.

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List of Symbols

a_{ij} overall assessment score for concept i related to engineering characteristic j
b upper bound of all correlations c_{kj}
c_{kj} correlation between requirement k and engineering characteristic j
d_{ij} value of engineering characteristic j for concept i
d^*_{kj} ideal value for engineering characteristic j to fulfill requirement k
$f_{k,ij}$ assessment score for concept i related to engineering characteristic j and requirement k
f_{max} highest obtainable assessment score
f_{min} lowest obtainable assessment score
$g_{k,ij}$ weighted assessment score for concept i related to engineering characteristic j and requirement k
i counting variable for concepts
j counting variable for engineering characteristics
k counting variable for requirements
l_j relative importance of engineering characteristic j
m number of concepts in the concept space
n number of engineering characteristics
p_i performance of concept i
r number of requirements
σ_k standard deviation of requirement weighting factor w_k
v_{kj} relative importance of requirement k related to engineering characteristic j
w_k weighting factor of requirement k
z_{ij} normalized assessment score for concept i and engineering characteristic j

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List of Acronyms

ACAA Automated Concept Assessment Algorithm
ACRM Automated Concept Ranking Methodology
AHP Analytic Hierarchy Process
AI Artificial Intelligence

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CSM Concept Selection Methodology
DM Decision Maker
EC Engineering Characteristic
eVTOL electric VTOL aircraft
HoQ House of Quality
IPMADM Interactive Probabilistic Multiple Attribute Decision Making
IRCG Interactive Reconfigurable Concept Generator
IRMA Interactive Reconfigurable Matrix of Alternatives
ISAR-CSM Interactive Semi-Automated Reconfigurable Concept Selection Methodology
LPP Linear Physical Programming
MADM Multi-Attribute Decision-Making
mHoQ modified HoQ
MIGA Multi Iterative Genetic Algorithm
mTOPSIS modified TOPSIS
PCGS Product Concept Generation and Selection
PDF Probability Density Function
QFD Quality Function Deployment
TG Thrust Generator
TOPSIS Technique for Order Preference by Similarity to Ideal Solution
TUM Technical University of Munich
UAM Urban Air Mobility
VFS Vertical Flight Society
VTOL Vertical Takeoff and Landing

INTRODUCTION

Motivation

Urban Air Mobility (UAM)is seen by many as an integral part of the future aviation industry. Industry reports suggest viable and profitable use cases by 2030 [1] and customer perception is generally positive [2]. With the emergence of new high-tech markets comes a boom in new companies and solutions. The aviation and, more specifically, the Vertical Takeoff and Landing (VTOL) market is no different in this regard. New concepts for VTOL aircraft, which will be used for these UAM missions, are presented almost weekly by both established companies and start-ups.

The first and most impactful step for all these companies when designing a new VTOL aircraft is the decision for a general concept. This usually means choosing a layout of lifting surfaces (e.g., wings, rotors/propellers, fans), thrust provider (e.g., propellers, tiltable propellers, turbine engines), drivetrain options (e.g., battery-electric, fuel cell powered, turbine-electric) and other aspects such as landing gear configuration. This process is a classic example from the field of Multi-Attribute Decision-Making (MADM) in systems engineering, which means that the investigated alternatives are evaluated and ranked based on multiple attributes. Several methodologies have been developed in the past with the aim of efficiently evaluating a given concept space for a given design problem, some also specifically for aviation-related design problems [3]. However, none of these are designed to handle the sheer number of possibilities, even at the highest level of a clean-slate VTOL design.

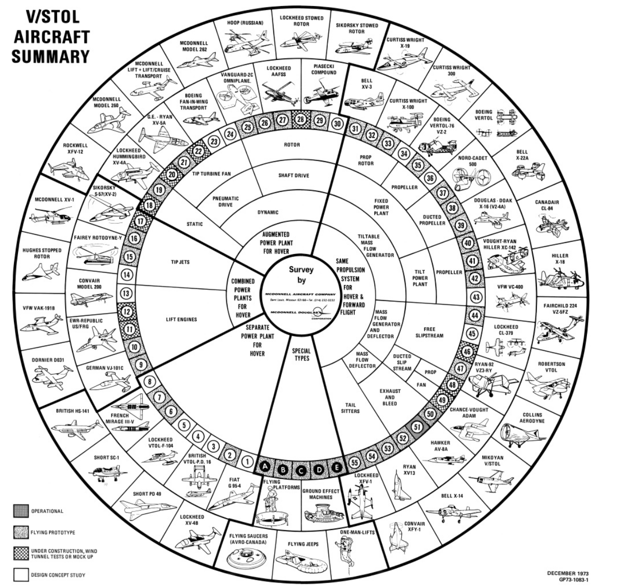


Figure 1: V/STOL taxonomy developed by McDonnell Aircraft Company in the 1960s [4]

In the past, the number of possible aircraft characteristics, hereinafter referred to as Engineering Characteristics (ECs), that make up a concept were far more limited than today. Nevertheless, already in the 1960s a multitude of more complex concepts had been conceived of and collected in the *Wheel of V/STOL Taxonomy* by McDonnell Douglas shown in Fig. 1. With advances in distributed electric propulsion, alternative power sources, such as hydrogen, and more advanced flight control systems, the number of possible combinations of ECs and, thereby also, the number of conceivable concepts has ballooned in recent years. The Vertical Flight Society's (VFS) directory of electric VTOL aircraft (eVTOL) aircraft concepts currently consists of more than 900 concepts and continues to grow at an accelerating rate [5]. The fact that so many concepts have been conceived of and so many more are still being unveiled week after week shows the nearly infinite number of possible concepts that the VTOL space encompasses. Considering all of these possibilities in a mostly manual concept selection is not feasible. The Concept Selection Methodologies (CSMs) presented in the next section can be used to evaluate between 5 to 50 concepts at a time [6].

Another aspect to consider when evaluating possible VTOL concepts is the bias a small group of engineers might introduce when comparing a handful of concepts. One example could be employees of a traditional helicopter manufacturer tending to favor solutions more akin to aircraft they are familiar with. Removing this factor fully from a design step that is not 100% based on physical models is most likely impossible. However, its influence should ideally be minimized by the methodology itself.

These shortcomings are the motivation to develop a new CSM. Its two main requirements which distinguish the new Interactive Semi-Automated Reconfigurable Concept Selection Methodology (ISAR-CSM) from existing methodologies are:

- The methodology must be able to evaluate the complete VTOL concept space
- The methodology should reduce the influence of human bias in the decision-making process to a minimum

It has to be mentioned early on that, perhaps unintuitively, the goal for the ISAR-CSM is not to give a definitive answer to the question *"Which concept is best suited to my VTOL design mission?"*. Rather, the methodology aims to rank potential concept candidates from which a smaller selection can then be investigated in more detail with higher fidelity methods, thereby reducing work in the further process and increasing confidence in the investigated concepts. Taking the results as a definitive answer for a design problem with so many possibilities at such an early stage would overestimate the capabilities of such a CSM.

Current Concept Selection Methodologies

A multitude of CSMs for MADM problems have been developed, as seen in an overview presented by OKUDAN AND TAUHID [6]. In the Paper, they compare commonly used methods and rank them according to scalability and variability, for which a suitable selection was considered for this paper. This selection was made in part using Fig. 2, with the goal being to stay in the most versatile range (higher on the chart) and with the biggest concept comparison space (further to the right on the chart). The selection includes Analytic Hierarchy Process (AHP), Multi Iterative Genetic Algorithm (MIGA), Fuzzy Information Axiom, Yan's Product Concept Generation and Selection (PCGS), s-Pareto Optimization, Linear Physical Programming (LPP), the Interactive Reconfigurable Matrix of Alternatives (IRMA) and Biltgen and Mavris' CSM.

Many of these methodologies implement methods to model and consider the effect of uncertainties of inputs in the decision process. These uncertainties can stem from customers/designers not having a 100% clear picture of the requirements (or their weightings) and from engineers evaluating the concepts not being able to give perfectly conclusive evaluations at such an early design stage. Considering these effects in the design process gives more confidence in the results and was therefore considered as a core requirement for any investigated CSM to base the new ISAR-CSM upon.

Another major factor to consider is the possible complexity of the design space. Due to the high number of possible alternatives involved in the MADM problem of UAM and VTOL aircraft, methods like the AHP are "not suitable to model [these] complexities ... [due to a] lack of flexibility or inability for the hierarchical structure to consider special characteristics of actual scenarios" according to MUNIER AND HONTORIA [7]. Furthermore, AHP does not facilitate modeling of uncertainties. It was, therefore, not considered further in the context of this paper.

The MIGA employs the genetic algorithm's basic principle, akin to Darwin's 'Survival of the Fittest' concept. The attributes (EC values) of a series of concepts are crossed and mutated to develop new possibilities and untried combinations [6]. Each generation, the best-performing combinations are selected and further crossed and mutated. Okudan and Tauhid state that genetic algorithms are useful when handling discrete variables and analyzing remarkably large decision spaces. However, the decision process is not transparent to the decision-maker and finding a clear end point at which an optimum is reached is difficult. Also, MIGA are also computationally expensive and there is no methodology using a genetic approach which can handle uncertainties.

Methodologies using fuzzy logic manage uncertainty in inputs by simplifying the inputs from engineers and customers to more descriptive linguistic terms such as "poor", "fair" or "good" and then mapping a fuzzy range of values to these. The Fuzzy Information Axiom CSM then uses complex, multi-stage calculations to rank and analyze concepts. This application of fuzzy logic uses non-classical mathematics, which lies "outside of the understanding/knowledge set of a typical designer/decision-maker" [6]. Methodologies based on fuzzy mathematics were, therefore, deemed to be beyond the range of comprehension of the user base envisioned for the developed methodology. Additionally, CSMs that contain Fuzzy set theory often necessitate that "criteria ... be mutually preferentially independent" [6], which would be difficult considering that UAM VTOL design requirements can be intertwined, related or even dependent.

Yan's PCGS method stands out as a potential candidate for the desired application in this project, due to the high number of concepts that can be handled and its versatility, as can be seen in Fig 2. However, as noted by OKUDAN AND TAUHID [6], it requires the decision-maker to have an extensive knowledge of data mining techniques and the fuzzy C-means algorithm. Additionally, the CSM cannot incorporate coupled decisions, which again limits its useful application in the UAM VTOL space.

The goal of the IRMA is not to finalize a design choice, or to objectively compare design choices as in methods such as the AHP and Yan's PCGS, but instead to make designers aware of which design choices could have the greatest impact on concept space limitation.

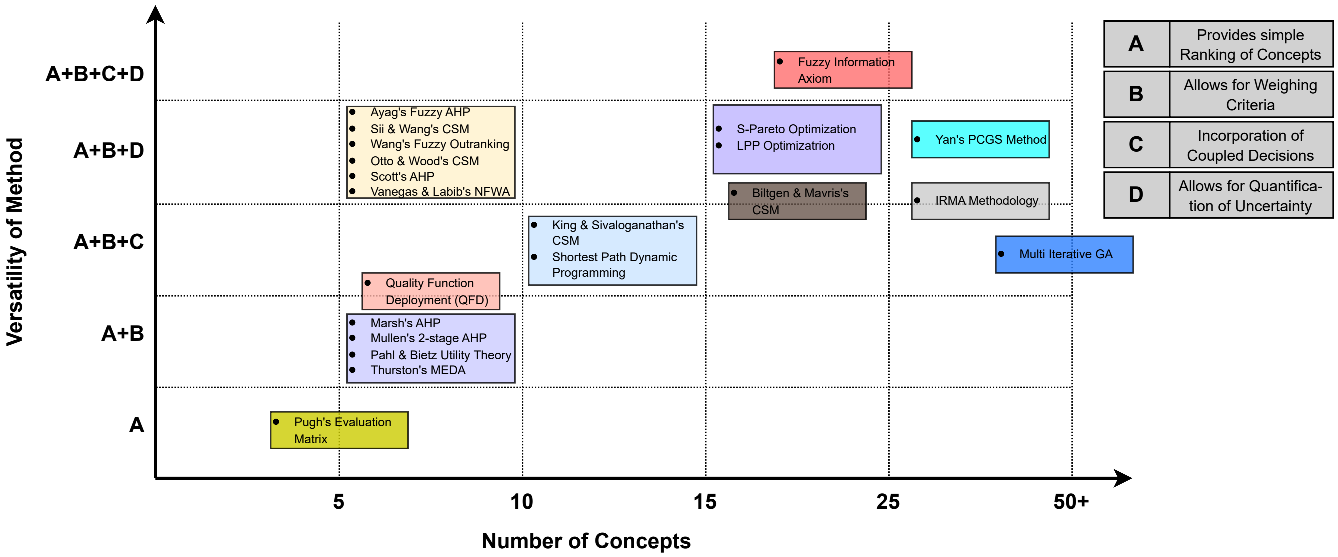


Figure 2: Overview of CSMs from 1980 to 2008 ranked regarding versatility and number of concepts that can be evaluated, by Okudan and Tauhid, recreated from [6]

Additionally, the IRMA allows designers to quickly filter out large numbers of concepts through either a strategic elimination of choices or in a trial-and-error method of design finding; the final concept space size is dependent on how many times the IRMA Process is carried out. According to OKUDAN AND TAUHID, problems with the IRMA involve its time-consuming preparation and execution, inability to take uncertainties into account while not guaranteeing an optimal solution [6].

An additional, valuable CSM to consider is Biltgen & Mavris' CSM. This method, utilizing an Interactive Probabilistic Multiple Attribute Decision Making (IPMADM) method, proposes using a House of Quality (HoQ) matrix, from the Quality Function Deployment (QFD) method, to define correlations between concept design traits (akin to ECs) and customer requirements. These are then used in a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) calculation to find the so-called relative 'goodness' of each concept. This is classed in an n-dimensional space as the smallest euclidean distance to the best possible combination, and the greatest euclidean distance to the worst possible combination of factors. BILTGEN AND MAVRIS use a mixture of visualization tools, and a 'what-if' method of trial and error on-top of a probabilistic environment that plays all 'what-if' games, to add flexibility to the design process and allow designers to understand the design space better [8]. Therefore, through its incorporation of defining correlations between EC and requirements, as well as assigning probability functions to the weightings of requirements, the method enables a large amount of subjectivity to be removed from the decision making process, as well as the ability to rapidly examine large families of concepts [6]. Its limitations include the inability to "quantify coupled decisions" in addition to the use of complex software tools according to OKUDAN AND TAUHID [6].

Considering all of the options listed, a combination of the IRMA method as well as Biltgen and Mavris' CSM is selected as the foundation for the new ISAR-CSM. This is because of the benefits presented by BRICENO ET AL. in [3], which include the coupling of elements in both CSMs. It is possible to reduce the concept space primarily with the system presented by the IRMA, and to evaluate the reduced selection with a system similar to the IPMADM. Yet, neither of these methodologies can handle the number of concepts envisioned for this application and both require manual input for each new design problem. Therefore, modifications and additions have to be made to fulfill these requirements. The structure of the ISAR-CSM is depicted in Fig. 3 and its components are described in detail in the following sections.

PROPOSED METHODOLOGY (ISAR-CSM)

Selecting the best-fitting VTOL aircraft concepts at the beginning of a new development is simultaneously an extremely impactful choice with a very large pool of possible options and one with a minimal amount of objective data available. This combination leads to significant challenges facing a new VTOL development, as can be seen from the number of new concepts entering the stage every week and the number of concepts being abandoned at the same time. On the other hand, at its highest level, it is also a design problem with a very similar basic premise for each new development. This makes it uniquely qualified for the development of a gen-

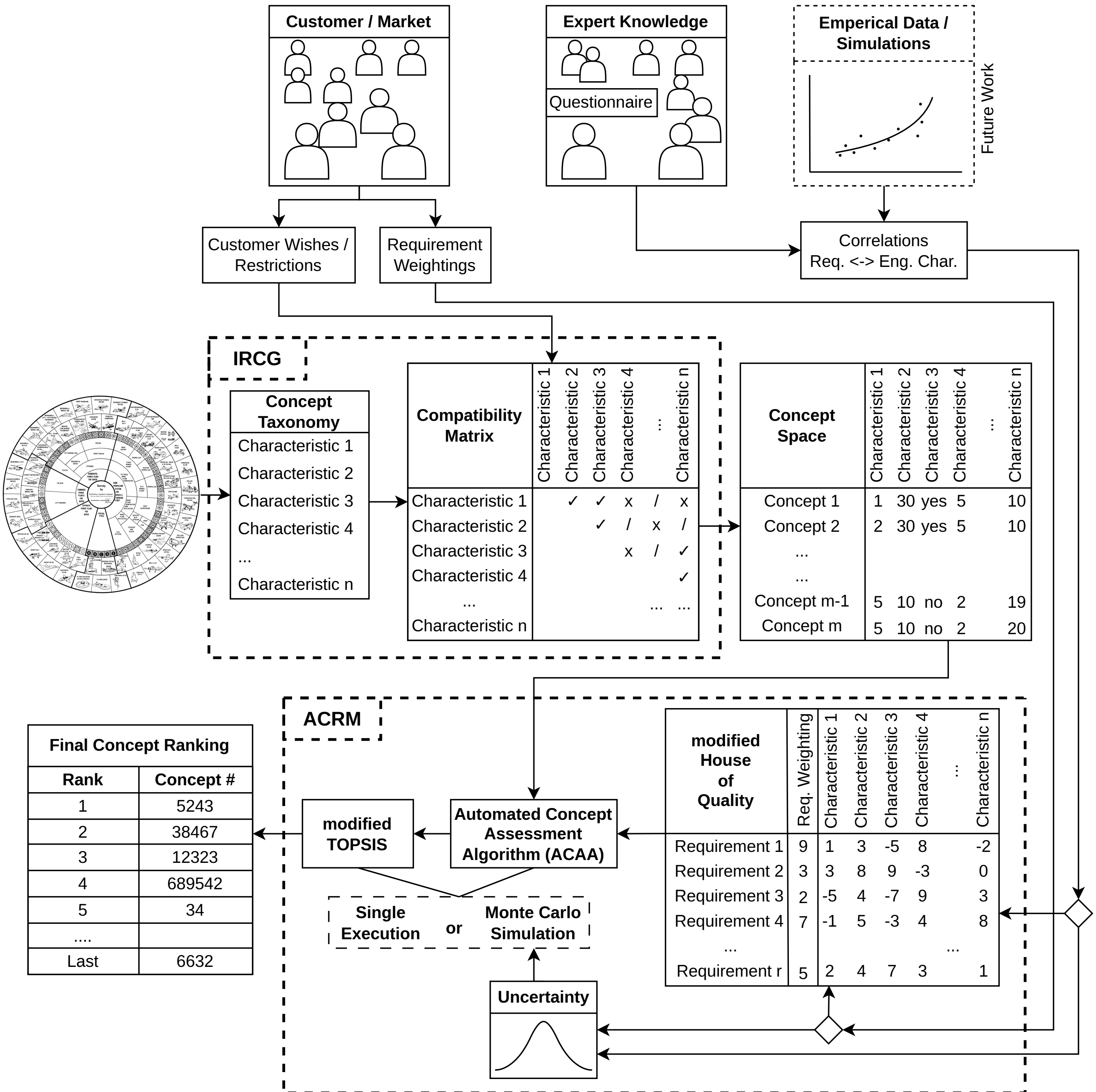


Figure 3: Flow diagram of the Interactive Semi-Automated Reconfigurable Concept Selection Methodology (ISAR-CSM), V/STOL wheel from [4]

eralized CSM which can cover the VTOL developments as a whole.

Based on the review of existing CSMs, a new methodology is developed that automates the concept selection process. The methodology needs to first generate concepts to be evaluated. These concepts then have to be assessed in terms of their suitability to the customer's needs. For this assessment, data is needed that can be used to calculate a goodness score for each concept.

The proposed Interactive Semi-Automated Reconfigurable Concept Selection Methodology (ISAR-CSM) therefore consists of three main building blocks, the Interactive Reconfigurable Concept Generator (IRCG), modified HoQ (mHoQ) and Automated Concept Ranking Methodology (ACRM), shown in Fig. 3. The first block, the IRCG, handles the automatic generation of all evaluated concepts. To generate the concepts, the investigated design problem, in this case VTOL aircraft, is first broken down into a generalized taxonomy. This taxonomy consists of several ECs derived from a review of current VTOL aircraft and existing taxonomies. For each EC, a possible value range is set. From this list of possible EC values, a concept space is created by iteratively combining all possible values with each other. This concept space can include millions of concepts, many of which would not be feasible. Therefore, it is filtered using compatibility data. The result is a concept space comprising many thousand concepts with unique combinations of ECs that the tool deems feasible.

A meaningful evaluation of these concepts requires data. In this case, the data is in the form of correlations between ECs and requirements gathered from engineers. Additionally, weighting factors for the requirements are collected from the customer or a market survey. These are gathered in a matrix similar to the classical HoQ, which is therefore called mHoQ.

The final block is the ACRM, which uses the data from the mHoQ to assess the suitability of the concepts. It is based on a new assessment algorithm which enables the automatic assessment. Its result is then ranked using a modified TOPSIS algorithm. The assessment can be conducted as a single execution or as a *Monte Carlo Simulation* based on the variability of the gathered data in the mHoQ. All of these blocks are described in more detail in the following sections.

VTOL Taxonomy

To enable concept generation, a clear definition of what is to be generated must be developed. Since the goal of the ISAR-CSM is to cater to engineering design problems, it is easiest to develop a so-called taxonomy of the design problem, in this case, the design of a VTOL aircraft. This helps to simplify and unify the descriptive traits of a concept, making generation easier and adds the potential to automate the process.

Taxonomies themselves can help categorize and sort a large data set in a systematic way, and consist of simple traits to help discern unique strings of data from each other. Therefore, when working with a large potential concept space, it is beneficial to discern concepts from each other using easy-to-understand parameters that relate to the fundamental aspects of the design problem. Developing such a taxonomy can be a tedious task, and requires in-depth research as well as trial and error until a robust framework is created. It is useful to start with the most fundamental design elements, trying to keep the definitions as simple as possible. As the taxonomy becomes larger, more and more detail can be added, for example in the form of a hierarchical tree-style diagram. Since developing a taxonomy can be a continuously iterative process, where new definitions or new categories are added when new traits become relevant or meaningful, the IRCG can be scaled.

In the scope of the ISAR-CSM, the developed taxonomy should be constructed to allow direct terminological interfacing with the mHoQ. The usability of terms in the taxonomy as ECs needs to be taken into account. The taxonomy is structured as a tree diagram, with categories, subcategories, and the final branches called taxonomy points. These taxonomy points differentiate individual concepts and should describe a defining trait, not a group of traits. Furthermore, while not all of the taxonomy points need to be defined as ECs, points that are not defined as such will not appear in the mHoQ and, therefore, not be considered in the ranking methodology of the ACRM. For simplicity, taxonomy points will henceforth be synonymous with ECs.

The taxonomy for VTOL aircraft is developed for the implementation of the ISAR-CSM, and is based on existing VTOL taxonomies. Currently, the main VTOL taxonomies referenced in literature is the Vertical Flight Societys (VFSs) Wheel of VTOL [9]. This is originally based on the Wheel of VTOL from the McDonnel Aircraft Company from the 1960s [10], but has been adapted to include newer concepts. Additionally, a new Triangle of VTOL by Lawless and Newman has attempted to redefine the taxonomy, modernizing it so that it can tailor to current issues in classification and certification of VTOLs concepts [11].

Looking at current and upcoming market-players when it comes to new VTOLs concepts, we find Lilium's *Jet*, Archer Aviation's *Midnight*, Volocopter's *Volocity*, Joby Aviation's *S4*, and Airbus's *Racer* or *H135* Helicopter to name a few. The first four concepts, of which most have entered sub or full-scale testing already, are good examples to compare to find definitive traits of VTOL aircraft designed for UAM applications. When looking at all six side-by-side, it is noticeable that their propulsive system setup is unique to every concept. Each has its own approach to solving the engineering problem of vertical and horizontal flight, but critically also contain more

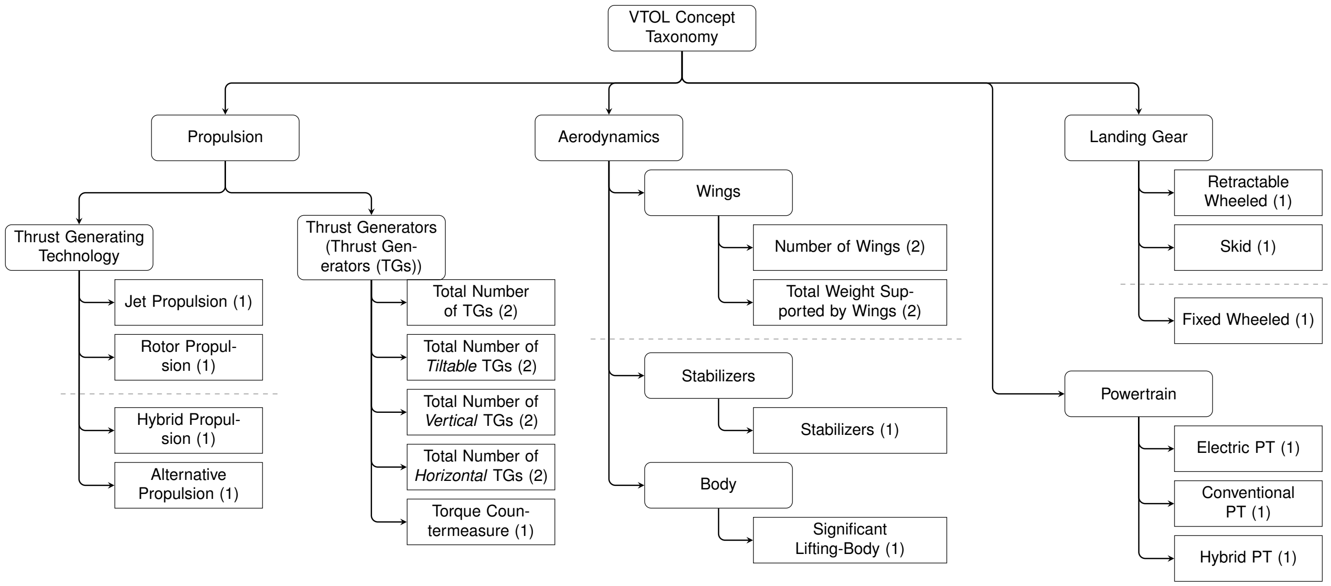


Figure 4: Overview of the created VTOL taxonomy for the IRCG, dotted line denotes taxonomy used for proof-of-concept implementation

subtle differences, such as different landing gear set-ups and some employing the use of aerodynamic surfaces. The first four examples listed currently run on battery-electric propulsion, yet Joby is also experimenting with hydrogen-electric, so the method of powering electric motors varies. Airbus' examples run on conventional turbines or newer hybrid turbines in the Racer's case, so alternative powertrains are also a key difference.

The common trait among the taxonomies named above is the classification of concepts into their thrust generation set-up. Either the type or way the power-plant is used to generate thrust for hover, or the set-up of propulsive devices is looked at. Therefore, a main component for differentiating VTOL concepts in the developed taxonomy is the order and use of TGs in a concept, which has been included under the *Propulsion* category. To represent the current trend in the industry to produce battery-powered VTOLs compared to the currently widespread usage of helicopters driven by conventional piston engines or turbines, a *Powertrain* category was added to differentiate the method of powering the propulsion system on board. In addition to this, the UAM VTOL market currently has several concepts that rely on additional lifting surfaces to assist in cruise flight, so an *Aerodynamics* category was added. Finally, a *Structural* category was created to account for structural elements of a VTOL, like the landing gear setup. A full overview of the taxonomy can be seen in Fig. 4, where a dotted line separates what was implemented into the proof-of-concept implementation.

Two types of taxonomy points / ECs are defined for different kinds of features:

Boolean (Type 1) - A Boolean EC that represents a technological choice or feature choice, taking the value *1* or *0*. This can represent either an additional feature being present or not or a choice between different mutually exclusive features. The latter requires appropriate compatibility settings which are explained in the next section.

Range (Type 2) - An EC that can take on a range of values that have been predefined. The upper and lower boundary, as well as the spacing of possible values, greatly increases the number of concepts that exist in the concept space, so the useful valid range needs to be carefully considered.

Concept Generation

Once the taxonomy for the engineering design problem has been created and consolidated, the IRCG is used to create the concept space. This is done by cycling through the developed taxonomy and creating the entire span of all combinations of possible values for each taxonomy point. This span is very large, and also full of irrelevant, illogical concept designs. To limit this, the entire concept space is filtered using predefined compatibilities and customer-set limitations. To do this, a few key distinctions and classifications are made, regarding the ECs as well as compatibilities.

The ECs are defined in a table with their respective chosen parameters, which can be seen in the example below. The full descriptive name of the EC is put in place of the simplified, indexed list presented here, and the *Fixed* value denotes an EC whose value has been fixedby the Decision Maker (DM). This is akin to the Kill-Switches used by ENGLER ET AL. in the IRMA [12]. Furthermore, two types of compatibilities have been defined for the IRCG. As seen in the IRMA method by ENGLER ET AL.,

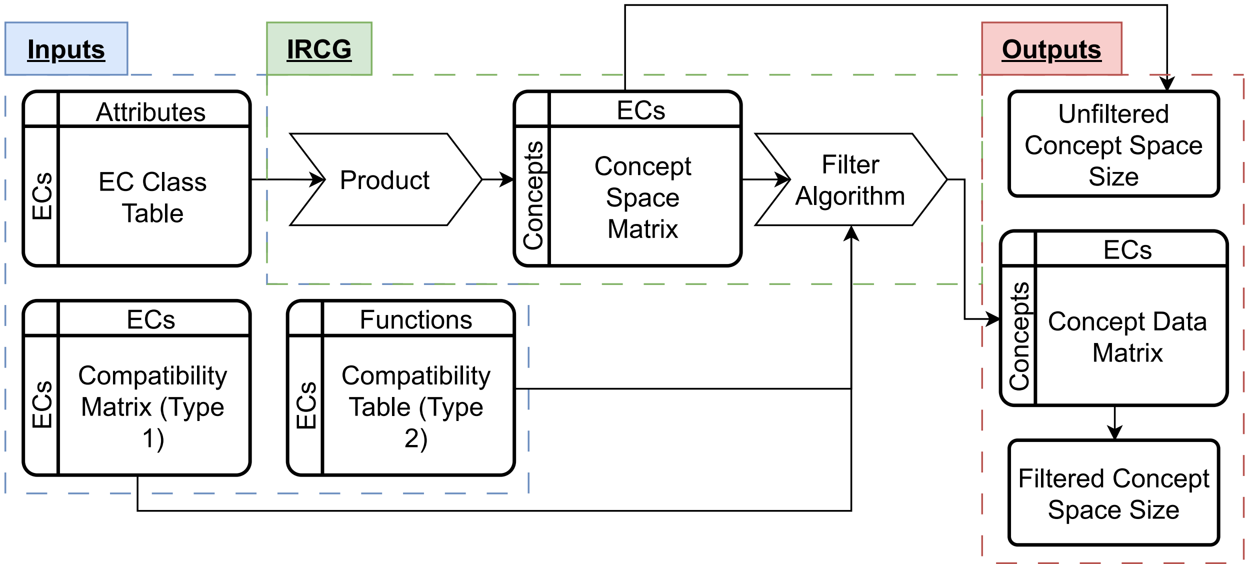


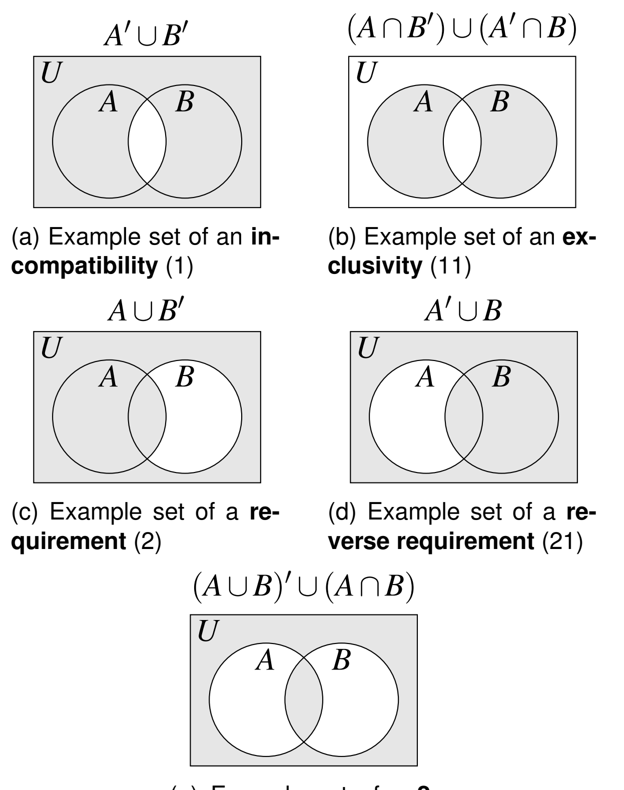
Figure 5: Flow diagram of the Interactive Reconfigurable Concept Generator (IRCG)

Index	Name	Type	Fixed	Max	Min	Step
1	EC_1	1	0	-	-	-
2	EC_2	1	1	-	-	-
3	EC_3	2	0	0	5	1
4	EC_4	2	0	0	15	5
⋮	⋮			⋮		
n	EC_n	1	0	-	-	-

Table 1: Table showing the useful information for the EC class, so that it can be effectively implemented

the first compatibility type (known as the compatibility matrix, or type 1 compatibility) is set through a matrix. All defined ECs are placed against each other, so both the columns and rows correspond to an EC. The matrix is then filled out so that each position in the matrix is given a specific compatibility value, corresponding to the EC of the row to the EC of the column. In the IRMA by ENGLER ET AL., there are three possible values that any non-diagonal position in the matrix can take on; compatible (0), incompatible (1), and required (2). This has been extended in the IRCG so to include cases critical to the complete description of logical interactions between ECs, based on set theory seen in Fig. 6.

In the current implementation it is possible to define a compatibility, two types of incompatibilities (Fig. 6a and 6b) as well as three types of requirements (Fig. 6c, 6d and 6e). A final value is reserved for blocking the diagonal of the matrix, as no EC can be evaluated against itself. This enables a more thorough description of logical interactions between the ECs, and, more crucially, simplifies the matrix filling process, which was otherwise very time-consuming for a large taxonomy due to the



(a) Example set of an **incompatibility** (1)

(b) Example set of an **exclusivity** (11)

(c) Example set of a **requirement** (2)

(d) Example set of a **reverse requirement** (21)

(e) Example set of a **2-way requirement** (22)

Figure 6: Representation of type 1 compatibilities (possible inputs in type 1 compatibility matrix), where the shaded area shows the valid domain.

double filling required across the whole matrix. The type 1 compatibility matrix is created as seen in Eq. 1, where the values entered are in relation to the Venn diagrams.

$$\begin{array}{c}\text{Type } 1\\ \text{Compatibility}\end{array} = \begin{array}{cc} \begin{array}{ccccc} \text{EC } 1 & \dots & \text{EC } j & \dots & \text{EC } n \end{array} & \\ \begin{bmatrix} a_{11} & \dots & a_{1j} & \dots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \dots & a_{jj} & \dots & a_{jn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \dots & a_{nn} \end{bmatrix} & \begin{array}{c} \text{EC } 1 \\ \vdots \\ \text{EC } j \\ \vdots \\ \text{EC } n \end{array} \end{array} \tag{1}$$

The second compatibility type deals with more complex interactions between ECs. Some possible formulations of type 2 compatibilities can be seen in Table 2. In the propulsion category listed in the taxonomy above, the relationship between thrust generators is defined akin to the third row in the table. The *Total Number of TGs* (EC_3) is equal to the sum of each *directional TGs* (EC_{4-6}), so that when filtered, all concept combinations where the sum does not equal to the total are removed from the concept space.

Index	Equation
1	$EC_1 = EC_2 \cdot \frac{K}{EC_3}$
2	$EC_1 < EC_2 - EC_3$
3	$EC_3 = EC_4 + EC_5 + EC_6$
$\vdots$	$\vdots$

Table 2: Type 2 compatibility table

Compatibilities are defined through a mixture of inputs, but mainly with the guidance of experts in the field after the taxonomy has been developed. Workshops to assist the filling in of the compatibility matrix and of the compatibility table can be very helpful and effective. It is possible to develop empirical relationships between ECs. For the Proof-of-Concept, a small focus group with people involved in the project, including the taxonomy developers, was created, and compatibilities were set.

Once the taxonomy is complete and robust, and all inputs have been defined, the IRCG takes all information and starts to create concepts. The concept space is created as a product function of all possible input values for every EC. Once this space is created, it is passed over to the filtering algorithm, which uses the compatibility inputs to reduce the concept space to only include feasible options. At the end of this process, the *Concept Data Matrix* $D_{m\times n}$ is returned, which consists of m concepts with n ECs each. Even though this matrix contains only the data for the feasible concepts, it can still include hundreds of thousands of concepts, potentially even millions. The elements are d_{ij}, with $i = 1,...,m$ and $j = 1,...,n$. The value d_{ij} can either stand for the quantity of EC j for concept i or represents a Boolean value. In case EC j is not implemented in concept i, d_{ij} is set to *0*, otherwise d_{ij} is defined as *1*. An overview of the data-flow for the IRCG can be seen in Fig. 5.

In contrast to the methodology presented by BILTGEN AND MAVRIS [8], this matrix contains no subjective assessment scores since the assessment is performed automatically by the Automated Concept Assessment Algorithm (ACAA). ECs with no quantitative data available, such as *Powertrain*, for instance, can easily be implemented by breaking them down into their respective types and by assigning them Boolean values. The EC *Powertrain* can therefore be split into, for example, *Electric Powertrain*, *Conventional Powertrain*, and *Hybrid Powertrain*, resulting in three new ECs. The concepts are then assessed according to the respective Boolean values.

Negative values for d_{ij} are not very common. For the sake of completeness, however, this case is also taken into account in the following, since the ACAA as well as the modified TOPSIS (mTOPSIS) are able to deal with different signs of d_{ij}. The general *Concept Data Matrix* $D_{m\times n}$ is displayed below.

$$D_{m\times n} = \begin{array}{cc} \begin{array}{ccccc} \text{EC } 1 & \cdots & \text{EC } j & \cdots & \text{EC } n \end{array} & \\ \begin{bmatrix} d_{11} & \cdots & d_{1j} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{i1} & \cdots & d_{ij} & \cdots & d_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mj} & \cdots & d_{mn} \end{bmatrix} & \begin{array}{c} \text{Concept } 1 \\ \vdots \\ \text{Concept } i \\ \vdots \\ \text{Concept } m \end{array} \end{array} \tag{2}$$

$$\text{with } d_{ij} \in \mathbb{R}\ \forall\ i, j$$

Correlation of Characteristics and Requirements

Based on the *Integrated Product and Process Development Methodology* presented by SCHRAGE [13] in 1999, BILTGEN AND MAVRIS [8] combine the so-called QFD technique with a MADM methodology, the TOPSIS. The QFD-element mainly utilized is the HoQ. It connects the requirements the product shall fulfill with ECs used to define a concept. This is done by describing the relationships between each EC and each requirement in a matrix. By combining these values with predefined weighting factors for every requirement, a relative importance can be calculated for every EC. Hence, it is possible to determine the importance of each EC for fulfilling the requirements. [8, 14]

The general structure of an HoQ is displayed in Fig. 7. The approach to building the HoQ is explained in great detail by HAUSER AND CLAUSING [14]. However, BILTGEN AND MAVRIS [8] use a simplified version of the HoQ, such as presented by GOLDBERG ET AL. [15]. This simplified HoQ utilizes only the core elements, which are essential to determine the importance of each EC. These elements are marked in yellow in Fig. 7.

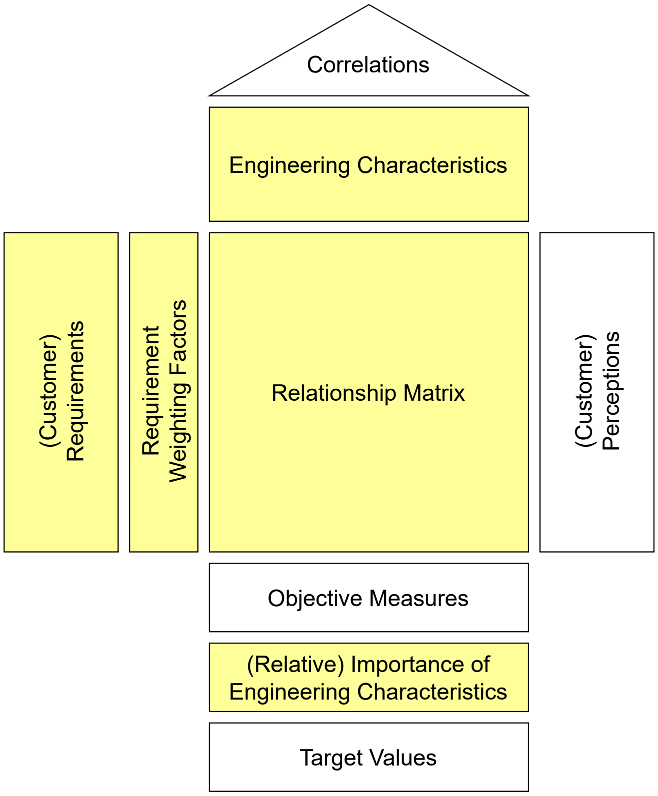


Figure 7: Original version of the HoQ, based on [14], elements marked in yellow are used in the simplified version of the HoQ, based on [15]

The main steps to build the core elements of the HoQ, as described by HAUSER AND CLAUSING [14], are listed below:

1. Determination of requirements through market research
2. Determination of the weighting factors for each requirement through customer survey
3. Determination of the ECs through literature research
4. Determination of the relationships between requirements and ECs through expert knowledge

The structure of the mHoQ, introduced in this paper and used for the ACRM, is similar to the HoQ. The main goal is to connect requirements with ECs to calculate the importance of each EC for the concept evaluation process. However, the challenge lies in the preceding concept assessment. The original HoQ only considers relationships between requirements and ECs, meaning only positive values in the *Relationship Matrix*. Therefore, no statement can be made whether more or less of an EC is considered as *better* with regard to a specific requirement. However, a completely automated concept assessment based on the HoQ is only possible if the preferred direction for each EC is defined beforehand. The most obvious approach is to allow negative values to describe the correlations between the requirements and the ECs. Consequently, the *Relationship Matrix* is replaced by a *Correlation Matrix*. This matrix should not be confused with the *roof* of the original version of the HoQ depicted in Fig. 7, which contains correlations between the ECs. However, these correlations are not considered in the calculation of the importance of each EC [15]. For better comprehensibility of the mathematics behind the ACRM, the mHoQ is split into the *Requirement Weighting Vector* $W_{r\times1}$ and the *Correlation Matrix* $C_{r\times n}$. The following variables are valid for the ACRM:

- $r \in \mathbb{N}$: Number of requirements with $k = 1,...,r$ as counting variable
- $n \in \mathbb{N}$: Number of ECs with $j = 1,...,n$ as counting variable
- $m \in \mathbb{N}_{>1}$: Number of concepts with $i = 1,...,m$ as counting variable

Similarly to the set of n ECs, the set of r requirements is defined once when first creating the mHoQ for VTOL designs. In case the methodology is applied to other design problems, a new requirement set must be created. The specific design mission and requirements, stemming from customers or other participants of the development process, then have to be translated into weightings of the common VTOL requirements. These weightings are collected in the *Requirement Weighting Vector* $W_{r\times1}$, which consists of r weighting factors w_k, one per requirement k. The higher w_k, the greater the importance of the corresponding requirement k. In case w_k is defined as *0*, requirement k does not factor into the assessment, whereas $w_k := 10$ stands for the highest possible importance that can be assigned to a requirement. The selected requirement set, in combination with their weighting factors w_k, defines the fundamentals of the intended mission [15]. The general *Requirement Weighting Vector* $W_{r\times1}$ is displayed below.

$$W_{r\times1} = \begin{array}{c} \begin{bmatrix} w_1 \\ \vdots \\ w_k \\ \vdots \\ w_r \end{bmatrix} \end{array} \begin{array}{c} \text{Req. } 1 \\ \vdots \\ \text{Req. } k \\ \vdots \\ \text{Req. } r \end{array} \tag{3}$$

$$\text{with } w_k \in \mathbb{R}_{\geq 0} \ \forall \ k$$

The *Correlation Matrix* $C_{r\times n}$ consists of r requirements and n ECs. In contrast to the relationships listed in the original HoQ, the elements c_{kj} are not limited to non-negative values but extended to all possible real numbers. The value c_{kj} hence represents the correlation between requirement k and EC j. Negative values signify that an increase in the amount of EC j leads to a worse result regarding requirement k and vice-versa for positive values. In case there is no correlation between the requirement k and the EC j, the value c_{kj} is defined as *0*. In this paper, $c_{kj} := -b$ represents the strongest possible negative correlation, whereas $c_{kj} := b$ stands for the strongest possible positive correlation. Usually, the correlations c_{kj} are defined by engineers or experts so that their knowledge and experiences are included in the concept selection process. The general *Correlation Matrix* $C_{r \times n}$ is displayed below.

$$C_{r\times n} = \begin{array}{c} \begin{array}{ccccc} \text{EC } 1 & \cdots & \text{EC } j & \cdots & \text{EC } n \end{array} \\ \begin{bmatrix} c_{11} & \cdots & c_{1j} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{k1} & \cdots & c_{kj} & \cdots & c_{kn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{r1} & \cdots & c_{rj} & \cdots & c_{rn} \end{bmatrix} \end{array} \begin{array}{c} \\ \text{Req. } 1 \\ \vdots \\ \text{Req. } k \\ \vdots \\ \text{Req. } r \end{array} \tag{4}$$

with $c_{kj} \in [-b, b] \; \forall \; k, j$ and $b \in \mathbb{R}_{>0}$

Finally, the steps to create the mHoQ are:

1. Determination of a common set of requirements through market research (once)
2. Determination of the weighting factors for each requirement through customer survey (for each new design)
3. Determination of the ECs through literature research (once)
4. Determination of the relationships between requirements and ECs through expert surveys, models, or empirical data (once)

Automated Concept Assessment and Ranking

The subsequent step is to assess the concept's suitability to fulfill the predefined requirements. In the methodology presented by BILTGEN AND MAVRIS [8], this process is performed manually by the design team for each EC of each concept. However, the results are highly affected by subjective assumptions and perceptions. Furthermore, the manual assessment is not efficiently applicable to a large number of concepts, as the execution time would be far too long. For this reason, the ACAA was developed. This algorithm is part of the ACRM (see Fig. 8) and is based solely on mathematical relations, which makes complete automation possible in the first place. The concept assessment is entirely based on the EC-values d_{ij} listed in the *Concept Data Matrix* $D_{m\times n}$ (Eq. 2), as well as on the requirement weighting factors w_k and the correlations c_{kj} from the mHoQ. Consequently, the ACAA enables a well-founded assessment of thousands of concepts within seconds, making it crucial for automating the ACRM. In the following, the mathematics behind the ACAA are explained step by step.

Step 1: Calculation of the relative importance l_j of EC j

$$l_j = \frac{\left|\sum_{k=1}^{r} \left(w_k \cdot c_{kj}\right)\right|}{\sum_{j=1}^{n} \left|\sum_{k=1}^{r} \left(w_k \cdot c_{kj}\right)\right|} \tag{5}$$

with $l_j \in [0,1] \; \forall \; j$ and $\sum_{j=1}^{n} l_j = 1$

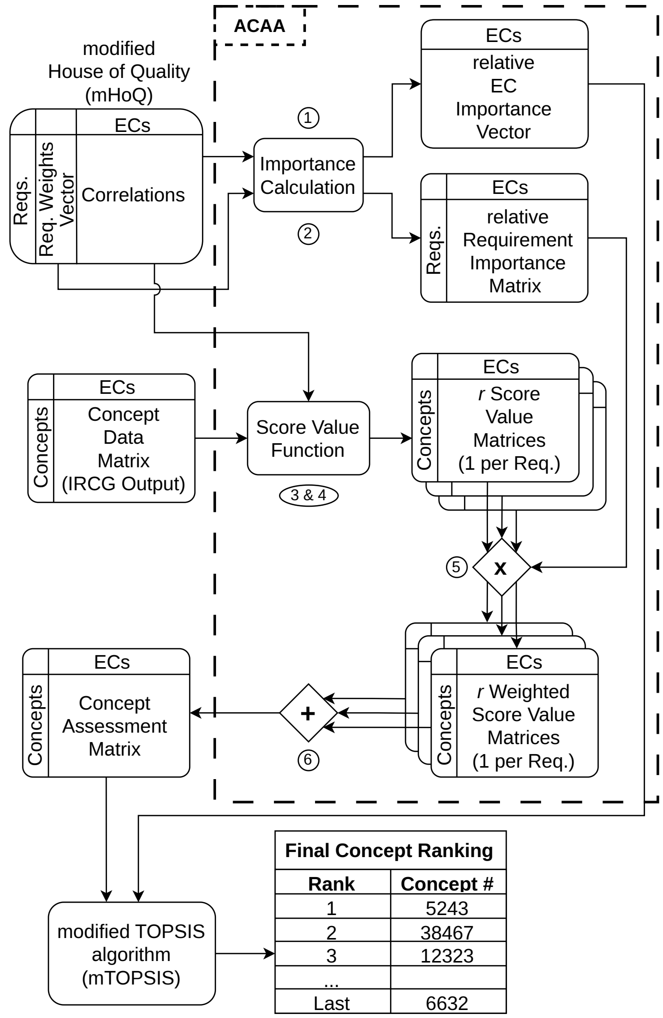


Figure 8: Flow diagram of the Automated Concept Ranking Methodology (ACRM) (Steps of the ACAA denoted as circled numbers)

This value indicates how strongly EC j affects the final ranking. It is, therefore, used in the mTOPSIS as a weighting factor for the respective EC. The results are allocated in a row vector, called in this paper *Relative EC Importance Vector* $L_{1\times n}$ (see Fig. 8). Due to the mathematics of the TOPSIS, described by HWANG AND YOON [16], which also applies to the mTOPSIS, the co-domain of this calculation must be limited to real numbers between zero and one, while the sum of all values for l_j is equal to one. Since the correlations c_{kj} can also be negative, absolute values must be used in this calculation.

Step 2: Calculation of the relative requirement importance v_{kj} of requirement k related to EC j

$$v_{kj} = \frac{w_k \cdot \left|c_{kj}\right|}{\sum_{k=1}^{r} \left(w_k \cdot \left|c_{kj}\right|\right)} \tag{6}$$

with $v_{kj} \in [0,1] \; \forall \; k, j$ and $\sum_{k=1}^{r} v_{kj} = 1 \; \forall \; j$

The relative requirement importance v_{kj} determines the overall contribution of a requirement k to the concept ranking process with respect to a specific EC j by combining its weighting factor w_k with the absolute value of the corresponding correlation c_{kj}. Comparable to the relative EC importance l_j (Eq. 5), v_{kj} is used as a weighting factor. But unlike l_j, it is already applied in the concept assessment in Step 5. Since v_{kj} is an importance, it does not represent whether an influence is positive or negative. Therefore, it is calculated using the absolute value of c_{kj}. The results for v_{kj} are compiled in a matrix called *Relative Requirement Importance Matrix* $V_{r\times n}$ (see Fig. 8).

Step 3: Calculation of the ideal value d^*_{kj} for EC j to fulfill requirement k

$$d^*_{kj} = \min_{i=1}^{m}(d_{ij}) + \left(\frac{c_{kj}}{2b} + \frac{1}{2}\right) \cdot \left(\max_{i=1}^{m}(d_{ij}) - \min_{i=1}^{m}(d_{ij})\right) \quad (7)$$

$$\text{with } d^*_{kj} \in \left[\min_{i=1}^{m}(d_{ij}), \max_{i=1}^{m}(d_{ij})\right] \ \forall\, k, j$$

The ideal value d^*_{kj} for EC j to fulfill requirement k is mainly dependent on the respective predefined correlation c_{kj}. For strong correlations c_{kj} close to the maximum values $-b$ or b, concepts with d_{ij} close to one of the extreme values, $\min_{i=1}^{m}(d_{ij})$ or $\max_{i=1}^{m}(d_{ij})$ are assumed to be more suitable to fulfill the requirement k. The sign of the correlation c_{kj} determines whether more $(+)$ or less $(-)$ of the EC is deemed beneficial by the algorithm. For a correlation c_{kj} close to zero, however, the concepts with d_{ij} close to the center of the range of values d_{ij} for EC j are considered to be superior to the other concepts for this requirement k. This represents an assumption that, in general, medium values of any EC should be less complicated to implement in an aircraft compared to extreme values. This is done to mitigate that the algorithm would otherwise always only choose extreme values of the ECs. The ideal value d^*_{kj} must be calculated for each correlation c_{kj}.

Step 4: Calculation of the assessment score value $f_{k,ij}$ for concept i related to EC j and requirement k

$$f_{k,ij} = \begin{cases} f_{max} - \left| \frac{f_{min}-f_{max}}{\max_{i=1}^{m}(d_{ij}) - d^*_{kj}} \cdot \left(d_{ij} - d^*_{kj}\right) \right| & ; c_{kj} \le 0 \\ \\ f_{max} - \left| \frac{f_{max}-f_{min}}{d^*_{kj} - \min_{i=1}^{m}(d_{ij})} \cdot \left(d_{ij} - d^*_{kj}\right) \right| & ; c_{kj} \ge 0 \end{cases} \quad (8)$$

$$\text{with } f_{k,ij} \in [f_{min}, f_{max}] \ \forall\, k, i, j \text{ and } f_{min} \in \mathbb{R}_{\ge 0},\ f_{max} \in \mathbb{R}_{>0}$$

The assessment score $f_{k,ij}$ for concept i related to EC j and requirement k is now calculated with two equations, depending on the sign of correlation c_{kj}. For $c_{kj} := 0$, either equation is valid. With the previously calculated ideal value d^*_{kj} (Eq. 7), the expert knowledge included in the *Correlation Matrix* $C_{r\times n}$ (Eq. 4) is directly used to assess the concepts according to their suitability to fulfill the specific requirement k.

Concepts with d_{ij} equal to the ideal value d^*_{kj} obtain the highest possible assessment score f_{max}. For positive correlation values $(c_{kj} > 0)$ concepts with $d_{ij} := \min_{i=1}^{m}(d_{ij})$ receive the lowest possible score f_{min}. For negative correlations $(c_{kj} < 0)$, however, $f_{k,ij}$ is equal to f_{min} for concepts with $d_{ij} := \max_{i=1}^{m}(d_{ij})$. The score values for all other concepts for the respective EC j and requirement k are calculated using a linear interpolation. Both values, f_{min} and f_{max} must be defined beforehand.

It is also possible that d^*_{kj} is not present in the *Concept Data Matrix* $D_{m\times n}$ (Eq. 2). In this case, no concept receives f_{max}. However, the minimum possible score value f_{min} is always assigned to at least one concept during the assessment for each EC and requirement. All score values $f_{k,ij}$ are then consolidated into r *Score Value Matrices* $F_{k,m\times n}$, each valid for the specific requirement k (see Fig. 8).

Step 5: Calculation of the weighted assessment score value $g_{k,ij}$ for concept i related to EC j and requirement k

$$g_{k,ij} = v_{kj} \cdot f_{k,ij} \quad (9)$$

$$\text{with } g_{k,ij} \in [0, f_{max}] \text{ and } g_{k,ij} \le f_{k,ij} \ \forall\, k, i, j$$

To consider the requirement weightings w_k formulated by customers or the designer, the respective score value $f_{k,ij}$ (Eq. 8) is weighted according to the relative importance v_{kj} (Eq. 6) of requirement k related to EC j. This results in the weighted score value $g_{k,ij}$ for concept i, valid for EC j and requirement k. By execution of the weighting for each EC, the *Weighted Score Value Matrix* $G_{k,m\times n}$ for requirement k is created (see Fig. 8).

Step 6: Calculation of the overall assessment score value a_{ij} for concept i related to EC j

$$a_{ij} = \sum_{k=1}^{r} g_{k,ij} \quad (10)$$

$$\text{with } a_{ij} \in [f_{min}, f_{max}] \ \forall\, i, j$$

Since the assessment score values $f_{k,ij}$ (Eq. 8) and the weighted assessment score values $g_{k,ij}$ (Eq. 9) are only valid for the specific requirement k, Step 4 and Step 5 must be repeated for all requirements listed in the mHoQ. Hence, r *Score Value Matrices* $F_{k,m\times n}$ and r *Weighted Score Value Matrices* $G_{k,m\times n}$ are generated, respectively one for each requirement. In order to calculate the overall assessment score a_{ij} for concept i and EC j, all weighted score values $g_{k,ij}$ for the same concept i and the same EC j are added together. Therefore, the overall assessment score a_{ij} considers all correlations of this EC j together with all requirements and their respective weighting. Consequently, this value combines expert knowledge and customers' or regulatory bodies' expectations into one assessment score. The overall assessment scores a_{ij} form the *Concept Assessment Matrix* $A_{m\times n}$ (see Fig. 8). It is the final result of the ACAA and contains the overall assessment scores of all concepts. These values are thus the equivalent to the subjective assessment scores essential for the manual assessment. But due to the separate consideration of each requirement and the automation, the accuracy and the efficiency of the assessment performed with the ACAA is significantly enhanced compared to the manual assessment required in the methodology presented by BILTGEN AND MAVRIS [8]. In the manual assessment, the score values are determined independently from the values listed in the HoQ. This process is not only highly time-consuming for a large number of concepts, but can also be influenced by subjectivity. The ACAA minimizes the time required and significantly reduces the influence of subjective assumptions on the assessment. However, the requirement weighting factors w and correlations c are still highly affected by subjectivity and uncertainty. This issue is addressed in the *Subjectivity & Uncertainty* section.

Step 7: Final concept evaluation using a slightly modified version of the TOPSIS algorithm (not part of ACAA)

The *Relative EC Importance Vector* $L_{1\times n}$ (Step 2) and the *Concept Assessment Matrix* $A_{m\times n}$ (Step 6) are used as input for the concept evaluation using the mTOPSIS algorithm. This slightly adapted version of the original TOPSIS algorithm creates the final concept ranking. With the ACAA, only values between the minimum score value f_{min} and the maximum score value f_{max} are assigned. However, due to the weighting process (Step 5) and eventually the summation of all *Weighted Score Value Matrices* $G_{m\times n}$ (Step 6), the range ultimately available in the *Concept Assessment Matrix* $A_{m\times n}$ can vary from EC to EC. Comparable to the original TOPSIS, the input matrix must, therefore, be normalized to avoid falsified results caused by different ranges of the ECs. In this case, the vector normalization proposed by HWANG AND YOON [16] is utilized. However, due to the enormous number of concepts, the normalization employed in the original TOPSIS algorithm may cause critical rounding errors during the calculation, as the normalized values for each concept can become very small. To prevent this, a scaled vector normalization is introduced. The normalized assessment score z_{ij} for concept i and EC j is calculated according to the following equation with the overall assessment score value a_{ij} (Eq. 10) and the total number of concepts m.

$$z_{ij} = \frac{a_{ij}}{\sqrt{\frac{\sum_{i=1}^{m} a_{ij}^2}{m}}} \tag{11}$$

with $z_{ij} \in \mathbb{R}_{\geq 0} \; \forall \; i, j$

Comparable to the original TOPSIS presented by HWANG AND YOON [16], the final ranking generated with the mTOPSIS is based on the n-dimensional Euclidean distance of the concepts to the *ideal* and *anti-ideal* solution for the specific design challenge defined by the requirements and their weightings. In the TOPSIS, this step requires a differentiation concerning the ECs between the *cost* criterion and the *benefit* criterion to define the *ideal* and *anti-ideal* concept. However, due to the automated calculation of assessment score values with the ACAA, such a differentiation is not necessary anymore. For all ECs, the same principle applies: The higher a_{ij} (Eq. 10), the *better* concept i regarding EC j compared to other concepts with lower overall assessment score values. Consequently, all ECs can be allocated to the *benefit* criterion in the mTOPSIS.

All subsequent calculations in the mTOPSIS are equal to the TOPSIS, resulting in a single value for each concept. This value is called performance p_i in this paper. The final concept ranking is created by sorting the performance values p_i in descending order. Consequently, the most suitable concept for the intended mission according to the ACRM has the maximum performance $\max_{i=1}^{m}(p_i)$. In contrast, the least suitable one has the minimum performance $\min_{i=1}^{m}(p_i)$ of all concepts. With the creation of this concept ranking, a single execution of the ACRM is completed.

Subjectivity & Uncertainty

Comparable to the methodology presented by BILTGEN AND MAVRIS [8], the results of the ACRM are still primarily based on subjective assumptions. In this case, however, the primary source of subjectivity lies in the mHoQ, more precisely in gathering the values of requirement weightings w_k and correlations c_{kj}. The requirement weighting factors w_k are determined by customers or design engineers, whereas the correlations c_{kj} are defined by engineers or experts of the corresponding field of research. As explained above, these values are essential for the ACAA and the mTOPSIS and, therefore, also the final ranking of concepts. Similarly to BILTGEN AND MAVRIS [8], a *Monte Carlo Simulation* with multiple executions of the ACRM is employed to address this challenge.

To consider uncertainties concerning the importance of each requirement, a random number generator using a normal distribution with a predefined standard deviation σ_k is applied for each requirement weighting factor w_k. The user defines σ_k for each requirement. The value should correspond to the level of certainty that the customer or designer has regarding the given requirement weighting. Very high confidence corresponds to $\sigma_k \approx 0$. High uncertainty regarding a given requirement or above can be expressed by $\sigma_k > 5$, which results in a distribution almost akin to a uniform distribution (for a value range of zero to ten). The normal distribution generated for each requirement weighting is clipped to only have values inside the possible value range. This offsets the mean value of weightings with a high w_k and σ_k. However, this is not seen as undesirable since it means that these values are pushed to the middle of the range, which is deemed appropriate for cases with high uncertainty.

Since each correlation c_{kj} between requirement k and EC j is also affected by uncertainty and subjectivity, a random number generation is applied for these values as well. In this case, however, the approach differs from that for the requirement weighting factors w_k. Possible correlation values c_{kj} are identified through a survey. A Probability Density Function (PDF) is approximated using all stated values for each correlation and used for the random number generation. The generated values are again kept within the predefined value range of the correlations c_{kj}. This ensures that each randomly generated correlation is a value that the participants of the survey could have also selected. In Fig. 9, an exemplary histogram of the survey results for one correlation is displayed. The corresponding approximated PDF and the calculated mean value are also included.

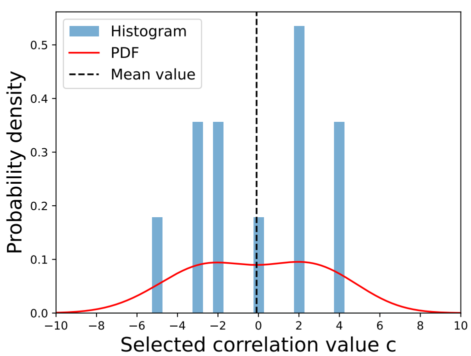


Figure 9: Exemplary histogram of survey results for one correlation, including the approximated PDF and the mean value

The randomly generated values for the requirement weighting factors w_k and the correlations c_{kj} are then used for the ACRM. The entire process is run through once for each set of random numbers, resulting in a different ranking for each execution. To display the result of the simulation, a new ranking according to the ascending order of the mean rank of each concept is created. The concepts, that are constantly ranked in the upper area of the ranking for each set of random requirement weighting factors and correlations, obtain a relatively low mean rank. Consequently, the mean rank indicates the robustness of a concept against changes in the requirement weighting factors w_k or correlations c_{kj}.

An alternative approach to display the result of the *Monte Carlo Simulation* is a ranking according to the mean performance score of each concept. However, it was decided to focus on the mean rank as primary ranking parameter, as it better illustrates the variability of concepts during the simulation and is, therefore, more suitable to determine the robustness of the concepts.

EXAMPLE IMPLEMENTATION

Implementing the ISAR-CSM methodology to its full potential requires multiple labor intensive steps. The taxonomy has to be defined in its final form. Since the mHoQ is based on the taxonomy, changing it retroactively would partially invalidate the mHoQ. Therefore, the taxonomy needs to be thoroughly researched using input from literature and experts before it can be declared final. The same is true for the requirements set. It has to be ensured that the requirements chosen can sufficiently represent customer requirements and mission at this early design stage.

Even more time-consuming is the collection of correlation data. The aim is to create a database containing mHoQs filled out by as many experts as possible. New answers from more experts can also be added to this database over time but a solid number of expert answers is required even as a base to reach an acceptably high amount of certainty and low amount of subjectivity in the results. Even though the methodology overall represents a decrease in work for design engineers through the automation, filling out all correlation values of the mHoQ still represents a considerable time investment by the experts. This in terms means that it can not be repeated frequently when updates to the taxonomy or the methodology are made. Therefore, the survey with which the data is gathered requires careful design of the questions and explanations.

Since more future work is planned on the methodology and the taxonomy (see *Future Work* section), it is not sensible at this time to commit to a full implementation of the methodology with survey requests to industry and academic experts. Therefore, a limited implementation of the ISAR-CSM using a reduced set of requirements and ECs was created for the purpose of this paper. The correlation data was gathered from employees of the Institute for Rotorcraft and Vertical Flight at Technical University of Munich (TUM).

Example Taxonomy

The reduced set of ECs used in the proof-of-concept is shown in Fig. 4 as the ECs above the dotted lines (where one is present). All ECs used are listed in Tab. 3 with the corresponding value range.

Requirement Sets

For this paper, two example UAM use-cases, also called missions, are investigated. The same set of require-

Index	Name	Type	Min	Max	Step
Propulsion					
1	Jet Propulsion	1	-	-	-
2	El. Propulsion	1	-	-	-
3	Total # of TGs	2	1	30	1
4	# of Tiltable TGs	2	0	30	1
5	# of Vertical TGs	2	0	18	1
6	# of Horizontal TGs	2	0	10	1
7	Torque Countermeasures	1	-	-	-
Powertrain					
8	El. Powertrain	1	-	-	-
9	Conv. Powertrain	1	-	-	-
10	Hybrid Powertrain	1	-	-	-
Landing Gear					
11	Retractable Wheeled	1	-	-	-
12	Skids	1	-	-	-
Aerodynamics					
13	# of Wings	2	0	4	1
14	% Weight Supported by Wings	2	0	100	20

Table 3: Implemented EC table showing the range of values deemed suitable for the proof-of-concept

Requirement	**Air-Metro**		**Intercity**	
	w_k	σ_k	w_k	σ_k
Low Noise	9	0.0	1	0.0
High Ride Comfort	3	0.5	7	0.5
High Safety Level	7	1.0	7	1.0
High Reliability	5	1.0	5	1.0
Good Maintainability	4	1.0	4	1.0
Red. Infrastr. Reqs.	5	5.0	3	5.0
Increased Range	1	0.0	9	0.0
Reduced Turnaround	6	2.0	4	2.0

Table 4: Requirements with their weighting factors and standard deviations for the *air-metro* mission (1) and the *intercity* mission (2)

ments is applied for both missions, while each use-case is represented by a different distribution of requirement weighting factors w_k with a range of zero to ten. However, the sum of all weighting factors (40) remains the same. The requirements selected for this proof-of-concept, as well as their weighting factors w_k and standard deviations σ_k, required for the *Monte Carlo Simulation*, are listed in Tab. 4.

In the first mission, the VTOL aircraft shall act as an *air-metro* for public transportation between fixed points within a densely populated city. The idea is to offer a fast and reliable but also affordable means of transport for daily commuters. For this use-case, the requirement *Low Noise* obtained the highest weighting factor of all requirements, as the VTOL aircraft shall use an airspace solely above inhabited areas. Additionally, the distances to be covered shall be comparably short, so the range requirement is weighted with the lowest factor. At the same time, a fast dispatch shall be prioritized over ride comfort, on the one hand, to reduce the overall costs and, on the other hand, to transport as many passengers as possible. Consequently, the requirement *High Ride Comfort* received a rather low weighting factor, whereas *Reduced Turnaround Time* obtained the third highest importance of all requirements. As for all aircraft, a high safety level is mandatory to receive the required certifications, resulting in the second-highest weighting factor assigned. *High Reliability*, *Good Maintainability* and *Reduced Infrastructure Requirements* are placed in the middle in terms of importance.

For the second use case, the ISAR-CSM is supposed to find VTOL aircraft concepts suitable for a long-range *intercity* mission. In this case, the target group is limited to wealthier individuals who are willing to pay a higher price for an exclusive, comfortable, and fast way to travel from one city to another. The VTOL aircraft shall be capable of covering large distances. Therefore, *Increased Range* is weighted most. The requirement *Low Noise* obtained the lowest weighting factors, as the aircraft shall fly less over densely populated areas at low altitudes. Due to longer flight times and to justify high ticket prices, a high ride comfort is considered to be particularly important. As the VTOL aircraft shall connect two or more cities, it is also possible to use already existing infrastructure, such as airports or heliports. In contrast to the *air-metro* use case, it is not mandatory to have vertiports in urban centers. Consequently, the aircraft for the *intercity* mission does not necessarily have to meet reduced infrastructure requirements, which results in a lower weighting factor for this requirement compared to the other use case. Furthermore, a fast dispatch is regarded as less important for the *intercity* mission, than for the *air-metro* mission. Therefore, longer turnaround times are acceptable and the respective requirement was assigned a lower weighting factor. The requirements *High Reliability* and *Good Maintainability* remain unchanged concerning their weighting factors.

However, it must be stated that the requirement weighting factors w_k were selected based on the assumptions of the authors of this paper and not according to expert knowledge. Nevertheless, that is regarded as sufficient for this basic proof-of-concept. The same applies to the standard deviations σ_k required for the *Monte Carlo Simulation*. The weighting factor of the requirements *Low Noise* and *Increased Range* shall not be randomly generated but fixed on the predefined value ($\sigma_1 = \sigma_7 := 0.0$). This is due to the exceptionally high, respectively low importance of these requirements that shall be maintained during the entire simulation. This is comparable to the requirement *High Ride Comfort*, which is either rather less, or rather more important, depending on the mission. However, slight changes concerning the corresponding weighting factor w_2 shall be considered in the *Monte Carlo Simulation*. Consequently, the standard deviation was defined to *0.5* for both missions. For the requirement *Reduced Infrastructure Requirements*, the highest standard deviation of all requirements ($\sigma_6 := 5.0$) was assigned as there was disagreement regarding the correct weighting factor w_6 within the project team. A similar issue occurred with the requirement *Reduced Turnaround Time*, resulting in a standard deviation $\sigma_8 := 2.0$. For all other requirements, the standard deviation was set to *1.0* for this proof-of-concept in order to simulate a moderate variability of the respective requirement weighting factors.

Correlation Data Survey

Engineering Characteristics (ECs) → / Requirements ↓	Jet Propulsion (1)	Rotor Propulsion (1)	No. of Total Thrust Generators (2)	No. of Tiltable Thrust Generators (2)	No. of Vertical Thrust Generators (2)	No. of Horizontal Thrust Generators (2)	Torque Countermeasure (1)	Electric Powertrain (1)	Conventional Powertrain (1)	Hybrid Powertrain (1)	Retractable Landing Gear (1)	Landing Skids (1)	Number of Wings (2)	Total Weight Supported by Wings (2)
Low Noise	-8	3	0	0	0	3	-3	8	-5	-2	1	-1	0	6
High Ride Comfort	0	-2	2	0	0	2	0	5	-3	0	1	-1	4	6
High Safety Level	0	0	5	-5	5	3	-2	4	-2	0	2	0	6	8
High Reliability	0	-3	0	0	0	0	-2	4	-2	-5	-5	4	0	0
Good Maintainability	0	-3	-3	-7	-2	-3	0	2	-2	-4	-5	4	-3	0
Reduced Infrastructure Requirement	3	-2	0	2	0	0	0	-2	4	4	5	-4	-5	-5
Increased Range	-4	4	-1	3	-3	-1	-4	-8	8	6	2	-2	9	9
Reduced Turnaround Time	0	0	0	0	0	0	0	-5	5	5	3	-3	0	0

Figure 10: Example of filled out *Correlation Matrix* survey

The proof-of-concept survey consists of an Excel table that represents the *Correlation Matrix* and an explanatory document. Each requirement and EC is defined briefly and the possible value range for each EC is given. The experts fill out one Excel sheet each, and all filled-out sheets are saved as a database. For this proof-of-concept, correlation values between -10 and 10 are possible. At the beginning of every new execution of the ISAR-CSM, all available filled out *Correlation Matrices* are processed to calculate the mean value and to approximate the PDF for each correlation. This way, expert surveys taken at a later point can be integrated seamlessly into the methodology. Fig. 10 shows one of the *Correlation Matrices* filled out by a member of the institute.

RESULTS & DISCUSSION

Based on the reduced implementation shown in the section before, the correlation data survey was conducted with eleven employees of the Institute for Rotorcraft and Vertical Flight at TUM. Using the gathered data the ISAR-CSM was then executed for the two shown requirement sets. Results of the survey and final concept rankings are presented and discussed in the following.

Survey Results

While the number of survey responses is relatively low, it still allows to showcase of the functionality of the ISAR-CSMs features regarding expert knowledge gathering and uncertainty handling. Fig. 11 shows the mean value of each correlation, calculated from all responses, and whether the responses agreed on this value (green) or if there was a high standard deviation in the sampled responses (red). It shows correlations with different strengths, and indicates where definitions may be incomplete, no consensus on a perceived correlation could be reached, or there is possibly no definite correlation. Correlations, like for example between *Low Noise* and *Jet Propulsion* show a high correlation value and a moderate to good agreement of responses, whereas no agreement could be reached for the correlation between *High Reliability* and *Number of Vertical TGs*. The best agreement in responses can be found for correlations where the consensus was that requirement and EC do not correlate at all, as can be seen in Fig. 12 for example. This results in a narrow probability distribution used for the *Monte Carlo Simulation*. For the correlation between *Increased Range* and *Total Weight Supported by Wings* a high positive value was expected, as wings are significantly more efficient at producing lift in cruise compared to TGs. This is indeed the case. However, two deviating answers skew the results lower, as can be seen in Fig. 13. The fact that one surveyed person answered 0 and one gave a high negative score could mean that the question was not posed well enough. Alternatively, the negative value might also be a simple error, in which case a higher number of responses would mitigate the effect this has on the final result. These are just two examples out of 112 correlations. Overall, many of the correlations show subpar agreement between results. While the ACAA accounts for these uncertainties within the responses, it still remains very important to critically evaluate the results of the survey when looking to improve the information and data provided to the ISAR-CSM.

ISAR-CSM execution

After all requirements, engineering characteristics, requirement weighting factors, and correlations were defined, the ISAR-CSM was applied to identify the most suitable VTOL concept for the intended missions. The IRCG generated over 800 million concepts for this trial. This number was reduced to 655872 by filtering out unfeasible concepts. With this set of concepts, a *Monte Carlo Simulation* with 10000 executions of the ACRM was performed for each mission.

Tabs. 5 and 6 show excerpts of the final rankings. Due to the high number of concepts evaluated by the ACRM (655872), the mean rank must always be seen relative to this number. The shown configurations are represented

	Jet Propulsion (1)	Rotor Propulsion (1)	No. of Total TGs (2)	No. of Tiltable TGs (2)	No. of Vertical TGs (2)	No. of Horizontal TGs (2)	Torque Countermeasure (1)	Electric Powertrain (1)	Conventional Powertrain (1)	Hybrid Powertrain (1)	Retractable Landing Gear (1)	Landing Skids (1)	Number of Wings (2)	% Weight on Wings (2)
Low Noise	-6.27	1.09	-1.36	-0.27	0.09	0.45	-2.27	6.09	-4.82	0.91	1.73	-1.27	-1.27	2.55
High Ride Comfort	1.00	-2.00	1.91	-0.73	0.55	0.82	-0.55	4.09	-2.09	0.91	1.18	-0.91	1.18	3.73
High Safety Level	0.82	-0.73	5.73	-2.82	4.73	3.64	-0.55	0.36	1.45	0.91	-1.27	2.00	2.82	4.27
High Reliability	-0.82	-0.45	-2.27	-4.09	0.27	0.00	-1.18	1.73	0.55	-1.64	-3.45	3.73	0.18	2.09
Good Maintainability	-2.09	-0.36	-3.27	-5.18	-2.91	-2.91	-2.36	2.27	-1.09	-3.64	-3.64	4.00	-3.27	1.09
Red. Infrastructure Req.	-0.64	-0.09	-0.45	-0.45	-0.27	-0.27	-1.73	-1.27	1.36	-2.18	1.73	-1.64	-2.64	-2.82
Increased Range	2.45	-0.09	-1.55	0.64	-4.18	-0.73	-3.27	-5.45	5.91	2.91	4.64	-3.91	0.82	5.00
Red. Turnaround Time	0.55	-0.09	-0.73	-0.45	-0.55	-0.55	-0.55	-5.45	4.64	1.27	1.36	-1.45	-1.64	-0.73

Figure 11: Results of the proof-of-concept correlation data survey.
Values are the mean value calculated from all responses for that correlation. Color corresponds to standard deviation of responses for each correlation (dark green $\hat{=} < 1$; dark red $\hat{=} > 4.5$)

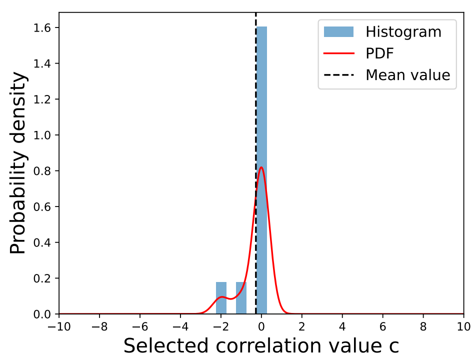


Figure 12: Correlation between *Reduced Infrastructure Requirements* and *No. of Horizontal Thrust Generators*

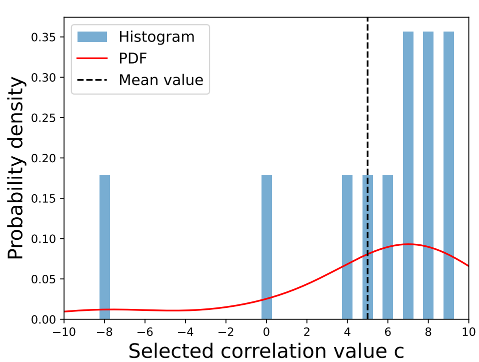


Figure 13: Correlation between *Increased Range* and *Total Weight Supported by Wings*

by value combinations of the ECs as shown in Tab. 3. They show that the top ranked configurations for both missions have similar traits. They feature rotor propulsion with a high number of TGs and a mix of fixed horizontal and vertical TGs as well as tiltable TGs. They use one or more wings to produce most of the lift during cruise flight. The main differences come in the powertrain and landing gear configuration. For the *air-metro* mission, the best-rated configurations use electric power and skid landing gear. Whereas the *intercity* case produces configurations using conventional powertrains (in this case meaning turbo-electric).

The differences in powertrain and landing gear configuration appear logical. The *intercity* mission requires long range flight which means that battery electric powertrains might struggle to provide sufficient energy. Furthermore, fixed landing skids would produce significant drag in cruise flight and, therefore, again reduce range. This is also represented in the survey results through high correlations between range and the ECs. Additionally, range was the requirement with the highest difference in weightings between the missions, so it makes sense that these ECs are changed.

However, apart from these two ECs the results for both missions resemble one another closely. One would expect differences in the lift configuration due to the different mission profiles. This is not represented in the results. Neither the wing-related ECs nor the number of different TGs shows a clear tendency. This is in part due to mainly low correlation values for these ECs. Looking at current developments for urban and regional VTOL designs, it could be expected to especially see a difference regarding the wing configuration. Yet, even the values of *Total Weight Supported by Wings* are the same for the best-ranked concepts. A reason for this is the correlation between this EC and the requirement *Increased Range*. A high positive value is expected for this correlation. However, as can be seen in Fig. 13, some survey participants selected values, which are contrary to this expectation. Especially the results for the *intercity* mission are influenced by that. Another cause is that the EC *Total Weight Supported by Wings* has only one significantly negative correlation identified by the corre-

Rank	Mean Rank	EC Configuration
1	77868	0;1;21;6;9;6;0;1;0;0;0;1;2;80
2	78116	0;1;21;6;9;6;0;1;0;0;0;1;1;80
75	82896	0;1;21;6;9;6;0;1;0;0;0;1;2;60
642	96938	0;1;21;6;9;6;0;1;0;0;0;1;3;80
744	98538	0;1;21;6;9;6;0;1;0;0;1;0;2;80
1076	102354	0;1;16;0;10;6;0;1;0;0;0;1;2;80
1193	103502	0;1;21;6;9;6;0;1;0;0;0;1;2;100
3045	116419	0;1;21;6;9;6;0;1;0;0;0;1;1;40
5541	127811	0;1;17;7;10;0;0;1;0;0;0;1;1;80
5617	128107	0;1;21;6;9;6;0;0;1;0;0;1;1;80

Table 5: Comparison of different design approaches for the *air-metro* mission

Rank	Mean Rank	EC Configuration
1	49863	0;1;19;7;6;6;0;0;1;0;1;0;2;80
107	57953	0;1;19;7;6;6;0;0;1;0;1;0;3;80
230	61696	0;1;19;7;6;6;0;0;1;0;1;0;1;80
584	68174	0;1;19;7;6;6;0;0;1;0;1;0;2;60
695	69765	0;1;19;7;6;6;0;0;1;0;0;1;2;80
850	71566	1;0;10;10;0;0;0;0;1;0;1;0;2;80
930	72330	0;1;13;0;7;6;0;0;1;0;1;0;2;80
1338	76267	0;1;19;7;6;6;0;0;1;0;1;0;2;100
2774	85006	0;1;19;7;6;6;0;0;1;0;1;0;4;80
2855	85346	0;1;15;8;7;0;0;0;1;0;1;0;2;80

Table 6: Comparison of different design approaches for the *intercity* mission

lation survey, being the correlation with *Reduced Infrastructure Requirement*. On the one hand, the requirement weightings for this requirement differ only slightly for both missions. On the other hand, it might be that a requirement that would show a negative correlation is missing from the list in the proof-of-concept implementation. This highlights that in addition to the taxonomy, the set of generalized requirements also needs to be carefully assessed and potentially appended.

The stated goal for the ISAR-CSM is not to give one ideal concept design that the design should be restricted on from this point going forward. It is rather a tool that should narrow down the pool of potential designs so that further high-fidelity investigations can be focused on promising configurations. Therefore, the designer needs to be able to select multiple concepts from the top of the final ranking that are sufficiently different. Tabs. 5 and 6 show an attempt at doing this for the final rankings of the proof-of-concept study. One aspect that stands out is, how far apart in rank the selected concepts are. This was necessary because the concepts in between were mostly very similar concepts with slightly varying numbers of TGs or wings. This gives reason to believe that the current form of the taxonomy produces an overabundance of possible but similar configurations. Especially the large range of TGs leads to many nearly identical concepts filling the top ranking spots. Therefore, choosing the most promising concepts for further investigations is made unnecessarily difficult for the DM. Reducing the number of options to distinct ranges, for example, restricting values for *Vertical TGs* to 0|1|2-4|5-8|8+, could make the methodology more efficient and the results less cluttered. The risk here is, that through this pre-categorization, a new kind of bias by the creators of the methodology is introduced.

CONCLUSIONS

Selecting the best-fitting VTOL aircraft concepts at the beginning of a new development is simultaneously an extremely impactful choice with a very large pool of possible options and one with a minimal amount of objective data available. This combination leads to significant challenges facing a new VTOL development, as can be seen from the number of new concepts entering the stage every week and the number of concepts being abandoned at the same time. By automating and objectifying the process, the methodology addresses the inherent biases and inefficiencies associated with traditional, expert-based evaluations. The Interactive Semi-Automated Reconfigurable Concept Selection Methodology (ISAR-CSM) combines elements from existing methodologies, notably Biltgen and Mavris' IPMADM and the IRMA method, to create a robust framework capable of evaluating a vast number of potential VTOL aircraft concepts.

One of the key strengths of ISAR-CSM is its ability to handle the immense variety and complexity of VTOL designs. It automatically generates and filters a comprehensive concept space, significantly reducing the initial workload and allowing for the evaluation of a broader spectrum of design possibilities. This is enabled by the creation of a generalized taxonomy of VTOL aircraft characteristics.

The use of a correlation matrix between Engineering Characteristics (ECs) and requirements, similar to the classical House of Quality (HoQ), which is created once for the VTOL design problem and continuously fed with expert knowledge, ensures that this expertise is systematically incorporated into the evaluation process. The developed assessment algorithm uses this correlation data, together with requirement weightings defined by designers or customers, for a fully automated assessment of each concept. This not only speeds up the process but also minimizes subjective influences, providing a more objective basis for decision-making. The subsequent ranking of concepts using a modified TOPSIS (mTOPSIS) algorithm allows for a clear, quantitative comparison of design alternatives, aiding in the identification of the most promising candidates for further development.

The execution of two proof-of-concept design studies showcases the functionality of the ISAR-CSM and the implemented uncertainty handling methods. The concepts ranked highest by ISAR-CSM for the two missions are, however, very similar. Differences are found for the optimal powertrain and landing gear configuration. Other ECs show very similar optimal values. Especially the configuration of thrust and lift-producing components is almost the same for both sets of requirements despite the difference in range requirement. This shows some limitations of the methodology in its current state. The quality of the final concept ranking heavily depends on the accuracy and comprehensiveness of the input data, particularly the correlations and requirement weightings. Certain correlations, where clear correlations were expected, for example between *% of Weight Supported by Wings* and *Increased Range*, showed that the question was not posed clear enough in the study so that answers were all over the possible value range. While the *Monte Carlo Simulation* employed in the study helps mitigate some of the uncertainties inherent in these inputs, further refinement of the underlying taxonomy and the survey design is necessary.

Finally, we can conclude that the presented ISAR-CSM is a promising new way of finding viable VTOL concept designs in the early design phase. Employing a generalized approach to requirements and ECs of VTOL aircraft enables a structured, consistent, and continuous gathering of expert knowledge. This knowledge is leveraged through newly developed automated algorithms to efficiently identify optimal VTOL designs in the early design phase. While the proof-of-concept implementation showed potential for improvement, we believe that through continuing development the ISAR-CSM can become a powerful tool for VTOL concept design.

FUTURE WORK

This paper showed a proof-of-concept implementation of the ISAR-CSM, which served mainly to prove the functionality and usefulness of the developed algorithms. Before the methodology can be finalized and knowledge from a large number of industry experts can be gathered, more work has to be conducted on improving key aspects of the methodology.

Taxonomy: The current taxonomy is a known weakness due to its development consisting mainly of a review of existing literature within the field. While this is a good starting point for any taxonomy, further development will require engagement from multiple sources of information. Therefore, the next steps in developing a more robust taxonomy will be to validate what is already implemented, and using new tools to augment the development process. One such tool is the use of current generation Artificial Intelligence (AI) to filter through existing databases of VTOLs, like that of the VFS, giving an insight into overarching themes or important traits that may otherwise have been overlooked.

Requirements: If the taxonomy of a VTOL is to be evaluated and improved, it is important to also consider the requirements that have been set. These requirements should reflect specific goals, or should at the least be understood by those using the program. Therefore, further study into requirement definitions should be carried out. A mixture of methods including gathering data directly from the industry as well as reflecting current mission-spaces of some already existing VTOLs will be used.

Survey: At the core of the ISAR-CSM is the expert knowledge gathered in the form of filled out correlation data surveys. A well-designed survey is key to first of all getting the best, most representative results from experts. Secondly, it is prudent to thoroughly design the survey before asking perhaps hundreds of industry experts to spend time answering the questions. Furthermore, querying the field of expertise of these specialists (e.g. aerodynamics or structural design) could make it possible to either weigh answers according to the correlation between EC and the expertise or to only query them regarding their field of expertise and thereby reducing workload per specialist.

Concept Feasibility: One aspect that the current methodology cannot model is how the combination of two ECs affects the overall feasibility of the concept. BILTGEN AND MAVRIS [8] use the "roof" of their implementation of the HoQ for correlations between ECs which denote favorable or unfavorable relations between the characteristics. In their methodologies, these values are only used to inform the designer but do not influence further calculations. Implementing these values and adding them to the expert survey could enable the calculation of an additional feasibility or technology-readiness score for each concept.

Higher Fidelity Data: One of the main goals for the ISAR-CSM is a reduced influence of subjectivity on the concept evaluation. Ideally, all concepts would be evaluated using higher fidelity physics-derived or data-based models. However, in the early design phase that this methodology targets this is simply not possible. Nevertheless, basing the values of selected correlations on physical modeling could be one more way to reduce subjectivity in the concept selection process. This could be feasible for correlations such as the one between *Increased Range* and *No. of Horizontal Thrust Generators*. However, great care has to be applied how physical relations are scaled to the set range of correlation values.

Filtering of Results: The final rankings resulting from the ISAR-CSM compare many thousands of concepts. Due to the amount of ECs, many of these concepts are slight variations of each other. If the Decision Maker (DM) were to only consider the, for example, five top-rated concepts, this would likely lead to the selection of five very similar concepts. Instead, the DM has to scan the final ranking and manually look for a selection of ideally distinctive concepts that will then be further investigated with higher fidelity methods. This represents an undesirable hurdle in the concept selection process. Therefore, a method to automatically group and filter the concepts present in the final ranking regarding commonality of ECs would greatly enhance the usability of the method.

User Interface: Finally, after all steps mentioned before are implemented, a more polished interface for the ISAR-CSM is planned, so to ease engagement, understanding and therefore usage for designers.

Author contact: victor.zappek@tum.de

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