

Set-based design techniques for the systematic and interactive exploration of complex product evolvability

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ABSTRACT

While computational approaches to perform design exploration of product evolvability during conceptual design exist, these are often hindered by a lack of interactive methods and down-selection criteria that can reduce the number of design options when evolvability is considered. This paper presents computational techniques that address these limitations, introducing design filtering techniques that apply set-based design criteria for systematic down-selection of potential designs. In particular, the set-based design criteria of interval dominance, maximality, and E-admissibility were adapted for evolvability exploration studies. Additionally, a novel interactive filtering strategy, called ‘constrain and union’, is proposed to further narrow down the number of design options in an interactive manner. These methods were implemented in a computational tool, AirCA-Dia, enabling rapid and interactive evolvability design space exploration. The use of these techniques is then demonstrated through their application to the evolvability investigation of design options for a future short-to-medium range environmentally friendly civil transport aircraft. Maximality and E-admissibility were shown to be particularly effective in reducing the far-future design space, which could guide the focus of designers on particular far-future technologies. On the other hand, the constrain and union strategy showed promise in filtering out both near- and far-future design options.

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1. Introduction

To manage the risk associated with developing complex products with long lifecycles, product designers often endeavour to ensure that their designs are ‘evolvable.’ Evolvability is the ‘extent to which a baseline design could be reused, or “easily” modified to create descendant designs that would meet future requirements’ (van Heerden 2019). Evolvability is often difficult to assess at the early stages of product development, as it requires careful consideration of a multitude of varying scenarios related to future commercial, economic, political, and societal events, uncertainty related to new and upcoming technologies, as well as the potential effort and cost of making changes to the design to respond appropriately to these

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factors. Because of the importance of the conceptual design phase in determining the overall lifecycle cost, designers typically already consider evolvability at this phase. However, in cases where the product development process relies heavily on computational procedures, such as with aerospace vehicles, automotive products, and other complex engineered systems, the consideration of evolvability can add a substantial computational and design space exploration burden to this phase, as explained next.

During evolvability studies in conceptual design, a multitude of design options are usually generated for both baselines and derivatives. Here, ‘design option’ refers to a single design with each of its attributes fixed to a particular value. The vast design spaces that result from an enumeration of design parameters to create these design options need to be explored efficiently to identify the most promising options. This needs to be done for both the ‘near-future’ entry-into-service (EIS) and ‘far-future’ EIS design spaces (the far-future design options are those that are to evolve from the near-future designs, i.e. the second generation of the baseline or ‘derivatives’).

To perform such design space exploration, optimisation techniques are often used. However, because of the added uncertainty associated with considering far-future scenarios, it is often desirable to delay commitment to a single or small set of optimised designs. This is because, when there is substantial uncertainty, a supposedly ‘optimised’ design could quickly prove to be infeasible or less desirable as new knowledge comes forth, which could lead to expensive and time-consuming reiterations (Riaz 2015; Riaz, Guenov, and Molina-Cristobal 2017). Therefore, design space exploration techniques are required that could allow for a systematic reduction in the feasible design space. ‘Systematic’, here, implies that the feasible design space is reduced progressively, based on emerging or changing design criteria, constraints, and/or requirements.

Furthermore, optimisation could limit the ability of a designer to explore the design space in an ‘interactive’ manner. Interactive is defined by the Oxford Dictionary as an adjective meaning ‘... a two-way flow of information between [a computer/or system] and a user ...’ (Oxford English Dictionary 2023). For interactivity to be effective, this exchange of information should be fast (i.e. the response from the system to a user’s input should be perceived by the user as ‘immediate’ Guzman, Dormido, and Berenguel 2013) and information presented to the user should be presented in an accurate but manageable manner. Effective visual representation of underlying data is therefore imperative. Interactive exploration could potentially empower the designer to develop an improved understanding of the nature of the design space and to test ‘what-if’ questions and scenarios. In the current context, interactivity would allow a designer to swiftly test how changing circumstances, design requirements, etc. could affect designs over future scenarios and, subsequently, how evolvability could be employed to counter any negative effects associated with these.

Systematic and interactive techniques together could be employed to complement each other to provide a powerful means to explore the evolvability design for complex products.

‘Set-Based Design’ (SBD), where the design space is kept open for as long as possible to increase knowledge and gradually reduce uncertainty, is one effective approach that is often proposed to enable the type of systematic and interactive design space exploration described above, and therefore to address some of the pitfalls of optimisation (Riaz 2015). Set-based filtering techniques can be employed to eliminate infeasible or knowingly inferior options systematically and/or interactively, rather than trying to identify an ‘optimal’

design too early. However, the literature on how set-based design techniques could be applied to product evolvability studies is scant.

Therefore, the aim of the work presented in this paper was to devise new and/or adapt existing set-based design criteria to enable systematic and interactive filtering of the evolvability design space. To achieve this aim, the set-based design criteria of interval dominance, maximality, and E-admissibility were adapted for evolvability exploration studies. Additionally, a novel interactive filtering strategy, called ‘constrain and union’, is also proposed to further narrow down the number of design options.

This paper is organised as follows. A brief overview of previous related research is presented in Section 2. In Section 3, the techniques for evolvability exploration are introduced, followed in Section 4 by the case study and the evaluation results. Finally, the paper is concluded, and future work is presented in Section 5.

Note that the theoretical development of this work is based, to a large extent, on the PhD research of the lead author (van Heerden 2019) and much of the text in Sections 2 and 3 comes from the thesis resulting from that work. However, the use case in Section 4 is a new application of the techniques, focusing on the evolvability exploration of a future civil transport aircraft incorporating new technologies, and powered by alternative fuels.

Also note that a shorter version of this paper has been published as part of the proceedings of the 34th Congress of the International Council of the Aeronautical Sciences, held in 2024 (van Heerden et al. 2024).

2. Overview of previous related research

2.1. *Evolvability design space exploration*

The purpose of evolvability design space exploration is to identify evolvable designs – designs that will perform well (i.e. be competitive and/or provide value to all the stakeholders of the design) when entering service in the ‘near-future’ and which can then subsequently be changed at low development cost and time to create ‘derivatives’ that meet new requirements and be competitive/provide value when entering service in the ‘far-future’.

Many techniques to perform evolvability exploration exist (please refer to Cardin 2013 for a comprehensive overview of techniques for designing for ‘flexibility – a related concept that includes evolvability). However, here the focus is on methods where the near-future and the far-future timeframes are explored simultaneously in a computational setting. Perhaps the most well-known framework for this type of exploration is ‘Multi-Attribute Tradespace Exploration’ (MATE) combined with ‘Epoch-Era Analysis’ such as described in (Rader, Ross, and Rhodes 2010; Ross 2006; Ross and Rhodes 2008; van Heerden 2019). Similar techniques have been employed in (Lim 2009) and (van Heerden et al. 2022). Additionally, the use of interactive techniques has been proposed as a fundamental tool to enable new capabilities and derive new insights from Epoch Era Analysis, in particular using coordinated plots for the visualisation of results and interactive selection of design points (Curry and Ross 2015).

Normally, in these cases, a pool of design options is modelled for the near-future timeframe, and a separate pool of designs is modelled for the far-future (however, note that

more than two timeframes in sequence can also be considered). The latter pool would usually incorporate several technologies or combinations of technologies that may or may not become available in the far future. A metric is then applied to every near-future/far-future pair of designs that accounts for the 'effort' to change (redesign) the near-future design in the pair to the far-future design. This metric is usually expressed as the level of 'commonality' (Boas 2008) between these two designs or, if available, an indication of the cost to perform the redesign.

Economic, political, and technology availability scenario filters are then applied to the separate design pools to determine the cost and value of each design in multiple possible near- and far-future scenarios. The value of the design in each scenario could be expressed in monetary terms, some performance metric of interest, or as 'multi-attribute utility' (Ross 2006), which represents some scenario-dependent aggregated 'measure of goodness'. This is calculated based on a combination of attributes of interest for a particular design.

With the above scenario and redesign effort metrics at hand, the two EIS timeframes can be explored simultaneously to find pairs of design options that provide high value in the scenarios of both time frames and have high levels of commonality or low redesign cost. High-value near-future designs that pair at high commonality or low redevelopment cost with many high-value future designs would be considered more evolvable than those that do not.

2.2. Set-based design

Set-Based Design (SBD) design space exploration techniques enable the systematic removal of 'inferior' solutions from the design space as opposed to selecting a limited number of 'optimal' design solutions. The aim of this approach is to maintain design freedom and 'delay commitment to a particular design alternative in favour of gathering information about the problem' (Malak, Aughenbaugh, and Paredis 2009). The main expected benefit of SBD is to reduce redesign rework due to early decisions proven defective at later design stages (Kennedy, Sobek, and Kennedy 2014).

As a recent review on quantitative SBD methods points out (Dullen et al. 2021), many SBD techniques can be employed for design space exploration. These methods include constraint satisfaction problems, fuzzy logic, Bayesian networks, Multi-Objective Optimisation and Multi-Attribute Utility-based methods, Markov Decision Processes, as well as hybrid methods. The focus of this study was on Multi-Attribute Utility-based methods, as they are a natural, intuitive and flexible way of selecting design alternatives (Dullen et al. 2021). Particularly, the focus was on the techniques of (Malak, Aughenbaugh, and Paredis 2009) and (Rekuc et al. 2006), which were formulated specifically to manage uncertainty in the design process. These authors have proposed three SBD filtering criteria that work on imprecise information: 'interval dominance,' 'maximality,' and 'E-admissibility.' Each of these techniques is discussed separately in the subsections that follow.

2.2.1. Interval dominance

Interval dominance (Malak, Aughenbaugh, and Paredis 2009) is the simplest criterion of the three. It applies when imprecision in design inputs is modelled as an interval, which in return results in an interval for the output measure of goodness (i.e. utility, performance, or value to stakeholders). For two design options, if their measure of goodness intervals do

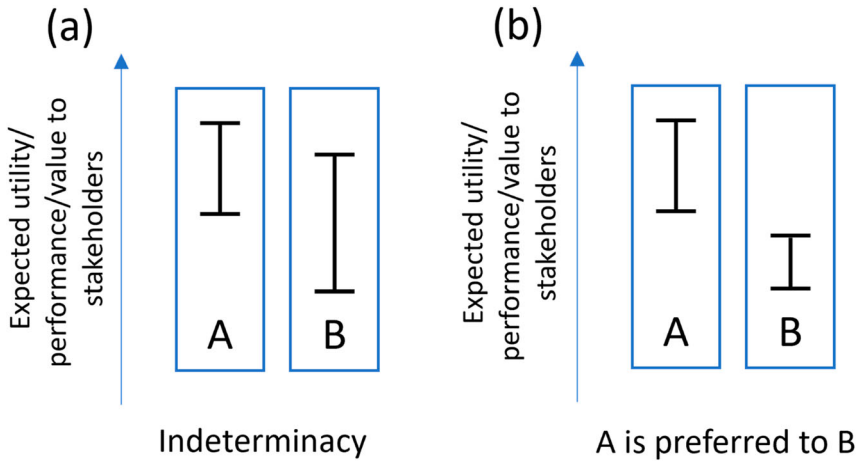


Figure 1. Interval dominance – adapted from (Malak, Aughenbaugh, and Paredis 2009).

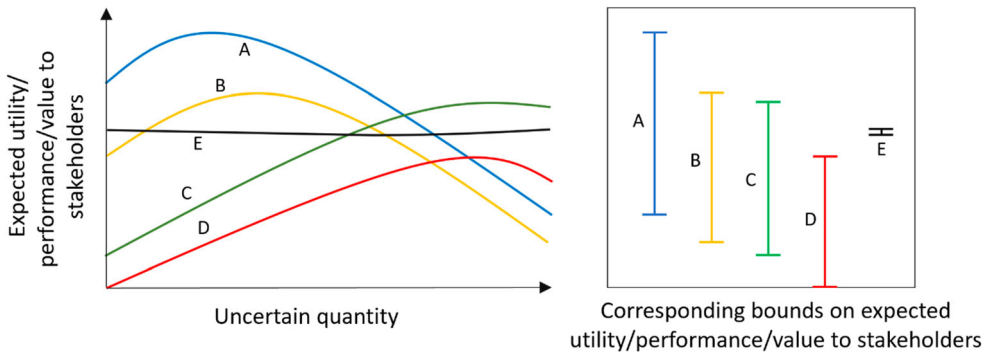


Figure 2. Variation of expected utility across the range of an uncertain parameter – adapted from (Malak, Aughenbaugh, and Paredis 2009).

not overlap, it means that the design with the lower (inferior) measure interval is always dominated and can therefore be discarded. This is illustrated graphically in Figure 1.

2.2.2. Maximality

The 'maximality' criterion, originally introduced by (Walley 1990), states that if an option is worse than another for all the possible values for the uncertain inputs, then such an option is dominated and can be eliminated. This principle is illustrated in Figure 2, which shows that, over the range of the uncertain input quantity, design option A dominates option B, and C dominates D. B and D can therefore be eliminated.

Formally, this criterion can be expressed as (Malak, Aughenbaugh, and Paredis 2009):

$$\min_{\mathbf{y} \in \mathbf{Y}} E[U(A, \mathbf{y}) - U(B, \mathbf{y})] > 0 \Rightarrow A \succ B$$

In the above equation, $\mathbf{y}$ is a k -dimensional vector that contains the values of k uncertainties; $\mathbf{Y}$ represents a set that contains all k -dimensional vectors that are within the domain of imprecision (Malak, Aughenbaugh, and Paredis 2009). The relationship is therefore that if

the minimum difference between the utility of A and B over the entire imprecise region is positive, then A would be preferred to B (Malak, Aughenbaugh, and Paredis 2009).

Maximality is 'stricter' than interval dominance, which means that it could eliminate at least as many alternatives as (and typically more than) interval dominance (Malak, Aughenbaugh, and Paredis 2009). A 'stricter' measure might be preferred in contexts where less 'strict' measures fail to sufficiently reduce the design space. How much it is desirable to reduce a design space is specific to a particular design project and is influenced by factors such as the designers' intent and the available resources for later design phases. For instance, if resources are scarce and only a few designs can be analysed in later phases, stricter measures can help reduce the design space. Conversely, if resources are more abundant, less strict measures – which do not excessively reduce the design space – may be preferable.

2.2.3. *E-admissibility*

E-admissibility, which was originally discussed by (Levi 1974), covers an even stricter scenario. For a design option in this scenario, it is ascertained whether for every point across the input uncertain quantity, there is at least one better option. This is demonstrated in Figure 2. Although Design Option E is not dominated by any other single design over the range of the uncertain input quantity, there is always a design that performs better than it. Therefore, option E can be eliminated from the set. Caution should, however, be applied in this case. This is because, as is evident from Figure 2, design E could be seen as a robust solution as it will perform reasonably well over the entire range of the uncertain input. This would not be a problem if the designer could still choose between options A and C after the uncertainty is resolved (Rekuc et al. 2006).

2.2.4. *Application to evolvability*

The above techniques cannot be used as-is for evolvability design space exploration. This is because they do not account for the multiple periods, predicted development cost, and redesign effort typically considered in evolvability studies. This lack of SBD techniques for evolvability is consistent with the result presented in the review paper by (Shallcross et al. 2020), who identified a lack of comprehensive SBD methodologies as they tend to focus narrowly on a particular SBD aspect. The extension of these SBD techniques to be used for studying evolvability is discussed in the next section.

3. Proposed set-based design techniques for evolvability exploration

In this section, it is shown how the SBD design techniques described in Section 2.2 can be applied to evolvability design space exploration. The format of the input sets is described first, after which the discussion will turn to the SBD decision-making criteria. The input is described in terms of timeframes, as well as scenarios and design options in each timeframe. A scenario corresponds to 'a period of time for which the system has fixed context and fixed value expectations' and is characterised by 'static constraints, available design concepts, available technology, and articulated attributes' (Ross and Rhodes 2008, 5). Note that this concept is equivalent to the epoch concept in 'Epoch-Era Analysis' (Rader, Ross, and Rhodes 2010; Ross 2006; Ross and Rhodes 2008). Utility and cost metrics are calculated for each design-scenario pair, and redesign costs relate designs across timeframes.

Only two (consecutive) ‘entry-into-service’ (EIS) timeframes are considered – the ‘near-future’ (EIS1) and ‘far-future’ (EIS2) timeframes. Only one scenario is considered for EIS1 ($s_{1,1}$), whereas multiple scenarios are considered for EIS2 ($s_{2,1}, s_{2,2}, \dots, s_{2,n_{s2}}$), which can be collectively referred to as the set $S_2 = \{s_{2,1}, s_{2,2}, \dots, s_{2,n_{s2}}\}$. The near-future scenario usually considers technology that is already available or that is expected to become available soon, and an economic and political situation similar to the one at the time of the study. Far future scenarios can be used to explore the impact of novel technologies and changing economic and political situations that affect which design attributes are desirable. E.g. a far future scenario might consider that liquid hydrogen aircraft are available, and another one might consider that it is not available, or only partially available, for example, considering limited hydrogen production. Additionally, some scenarios might give more importance to reducing emissions, while others might also consider other attributes such as noise and comfort.

Given a design option a and scenario s , a function $u(a, s)$ can be specified that calculates utility (or other measure of goodness) with measures for the stakeholder preferences, social, political, and economic circumstances in s , as well as the attributes of the design option, a , as inputs. If a set of scenarios S is given as an input, an array of utilities (one for each scenario $s \in S$) is returned instead of a single value. The development cost for the design option can be calculated similarly by a function called $c(a)$, which assumes that cost is independent of the scenario (an assumption that will need to be relaxed in future work). Given a baseline b_i (design option for the near-future EIS1) and a descendant f_j (design option for the far-future EIS2), the ‘redesign effort’ of changing the baseline into the specific descendant is computed from some function $r(b_i, f_j)$. Similarly to the function u , if a set of baselines B_i or a set of derivatives F_i is given as input to r , an array of redesign values is returned instead. The array contains one value for each of the baselines $b_i \in B_i$ or derivatives $f_j \in F_j$.

Note that for this first attempt at devising these techniques, it was assumed that the attributes of a specific design option that map to its utility, as well as its development cost and redesign effort values with respect to other designs, are deterministic (i.e. not uncertain). Therefore, the uncertainty accounted for here is only that arising from the changing scenarios and not endogenous uncertainty associated with the design itself.

3.1. Elimination criteria

In this section, it is shown how the three SBD elimination criteria of interval dominance, maximality, and E-admissibility were adapted for evolvability design space exploration. These could be applied sequentially, as shown in Figure 3, to eliminate infeasible or inferior design options systematically. However, the order shown is not prescriptive, but when following it, the criteria will be increasingly ‘strict’ and use progressively more computational resources. It would therefore enable a systematic exploration of the evolvability design space.

3.1.1. Interval dominance

With the interval dominance criterion, it is determined whether a near-future (baseline) design option, b_i , is dominated by at least one other near-future design, b_j , in terms of utility (i.e. design option j has higher utility than i), development cost (design option j has a lower cost than i), and redesign effort (i.e. the minimum value of redesign effort between i and

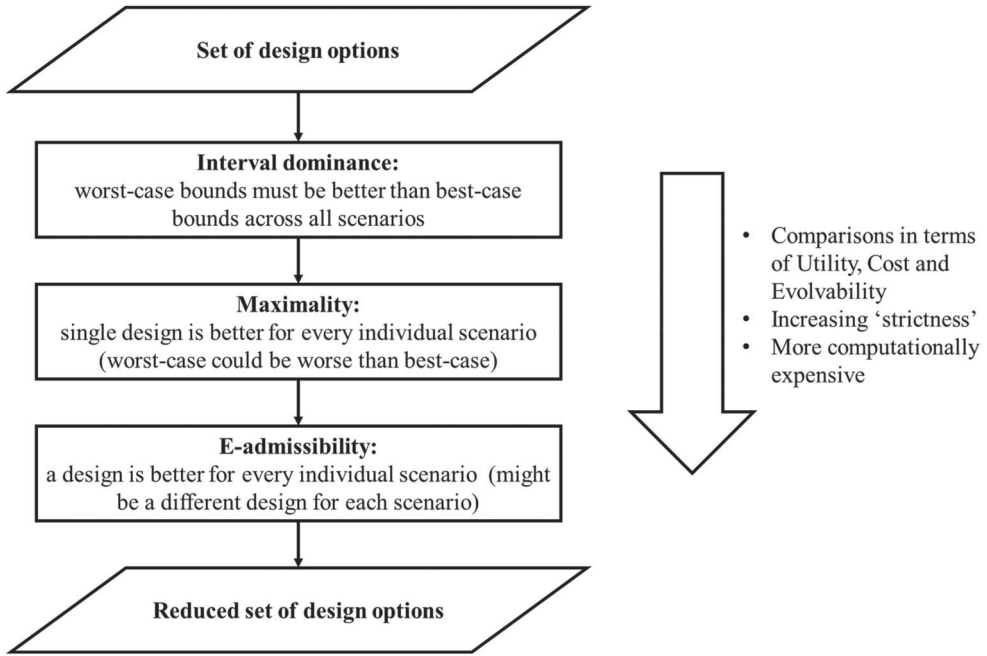


Figure 3. Evolvability SBD elimination criteria (van Heerden 2019).

all the descendant options is higher than the maximum value of redesign effort between j and all the descendant options). The same is done for the far future.

Formally, interval dominance applied to near-future design options can be stated as follows:

$$b_i \in B, \exists b_j \in B [c_{utility_{ij}} \wedge c_{cost_{ij}} \wedge c_{redesign_{ij}}] \Rightarrow \text{remove } b_i \text{ from } B \quad (1)$$

where

$$c_{utility_{ij}} \stackrel{\text{def}}{=} u(b_i, s_{1,1}) < u(b_j, s_{1,1})$$

$$c_{cost_{ij}} \stackrel{\text{def}}{=} c(b_i) > c(b_j)$$

$$c_{redesign_{ij}} \stackrel{\text{def}}{=} r(b_i, F) > r(b_j, F)$$

For the far-future options, where there are multiple scenarios, interval dominance can be expressed as:

$$f_i \in F, \exists f_j \in F [c_{utility_{ij}} \wedge c_{cost_{ij}} \wedge c_{redesign_{ij}}] \Rightarrow \text{remove } f_i \text{ from } F \quad (2)$$

where

$$c_{utility_{ij}} \stackrel{\text{def}}{=} \max(u(f_i, S_2)) < \min(u(f_j, S_2))$$

$$c_{cost_{ij}} \stackrel{\text{def}}{=} c(f_i) > c(f_j)$$

$$c_{redesign_{ij}} \stackrel{\text{def}}{=} \min(r(B, f_i)) > \max(r(B, f_j))$$

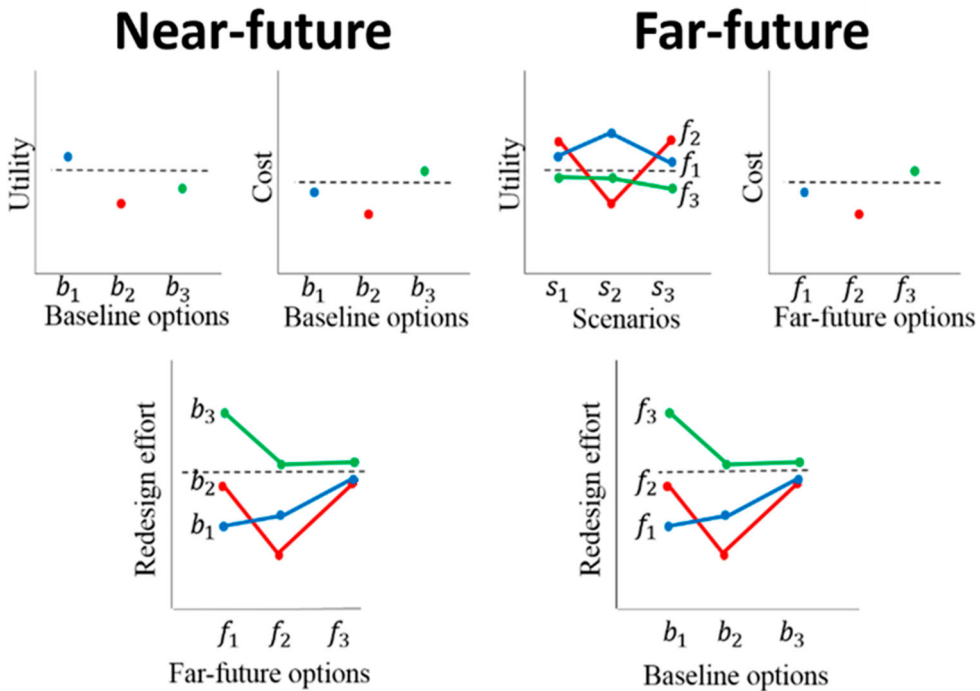


Figure 4. Interval dominance applied to near-future (baseline) design options (left) and far-future options (right) (van Heerden 2019).

When considering development cost in the far-future form of interval dominance (for all the criteria presented in this chapter), care must be taken. The reason for this is that the redesign effort could already include the full development cost, which might not be desirable if the option of creating the far-future designs as clean-sheet designs is not considered.

A stricter form of the interval dominance criterion (i.e. likely to eliminate more designs) would be to ascertain whether any one or two of the three inequalities in Equations 1 and 2 are equalities instead. This is equivalent to using non-strict inequality, where the sign $>$ becomes $\geq$, and the sign $<$ becomes $\leq$. This would mean that, for example, a design might have the same utility and cost as another but is still dominated by the redesign interval and could therefore be eliminated. Both forms are considered for all the criteria in this research. The number of additional designs eliminated by using non-strict inequality depends on the shape of the input data, and therefore, the choice of which inequality to employ is at the designer's discretion.

The application of interval dominance to evolvability is graphically demonstrated in Figure 4. When interval dominance is applied to the near-future timeframe, design option b_3 will be eliminated, as it is dominated by b_1 with respect to both utility and cost, as well as the whole interval of redesign effort (which in this case represents the uncertain output). In the far-future timeframe, f_3 can be eliminated because f_1 has superior utility in all future scenarios, lower cost, and a lower redesign effort over the whole interval from all baselines.

3.1.2. Maximality

The maximality criterion is similar to interval dominance regarding utility and cost, but more stringent regarding redesign effort (and utility for the far-future). In this case, it suffices that

the redesign effort with b_i as baseline is lower than the effort with b_j for each separate descendant, instead of considering the minimum/maximum values between all the descendants. The same holds for the far future in terms of utility and redesign effort. Maximality can formally be expressed for near-future design options as:

$$b_i \in B, \exists b_j \in B [c_{utility_{ij}} \wedge c_{cost_{ij}} \wedge c_{redesign_{ij}}] \Rightarrow \text{remove } b_i \text{ from } B \quad (3)$$

where

$$\begin{aligned} c_{utility_{ij}} &\stackrel{\text{def}}{=} u(b_i, s_{1,1}) < u(b_j, s_{1,1}) \\ c_{cost_{ij}} &\stackrel{\text{def}}{=} c(b_i) > c(b_j) \\ c_{redesign_{ij}} &\stackrel{\text{def}}{=} \forall f_k \in F [r(b_i, f_k) > r(b_j, f_k)] \end{aligned}$$

For the far-future options, the following form should be employed:

$$f_i \in F, \exists f_j \in F [c_{utility_{ij}} \wedge c_{cost_{ij}} \wedge c_{redesign_{ij}}] \Rightarrow \text{remove } f_i \text{ from } F \quad (4)$$

where

$$\begin{aligned} c_{utility_{ij}} &\stackrel{\text{def}}{=} \forall s_2 \in S_2 [u(f_i, s_2) < u(f_j, s_2)] \\ c_{cost_{ij}} &\stackrel{\text{def}}{=} c(f_i) > c(f_j) \\ c_{redesign_{ij}} &\stackrel{\text{def}}{=} \forall b_k \in B [r(b_k, f_i) > r(b_k, f_j)] \end{aligned}$$

Similar to interval dominance, allowing two of the three inequalities in the above statements to be equalities will lead to stricter forms of the criteria.

The concept of maximality applied to evolvability is illustrated using Figure 5. In this figure in the near-future timeframe, b_1 dominates b_3 in terms of utility and cost, but the maximum value for redesign effort to all possible descendants is not lower than the minimum redesign effort for b_3 . Interval dominance will therefore not work here. However, when considering each far-future option separately, the redesign effort from b_1 would still be less for each far-future option than from b_3 . Based on this, the maximality criterion will remove b_3 . In the case of the far-future timeframe, it can be seen from Figure 5 that, although there is no interval dominance, f_1 has a better utility than f_3 for each individual far-future scenario, lower cost (always), and lower redesign effort from each separate baseline option. It can therefore be eliminated based on maximality.

3.1.3. E-admissibility

E-admissibility assesses whether, for each possible option, there is at least one other option in each scenario that has higher utility, lower cost, and lower redesign effort. This criterion would not always be appropriate for baseline designs due to the uncertainty regarding which designs will subsequently be preferred in the far future. However, E-admissibility would be useful for filtering out far-future concepts. It is important to note that a future design option, f_i , is dominated as long as there is another future design that meets the

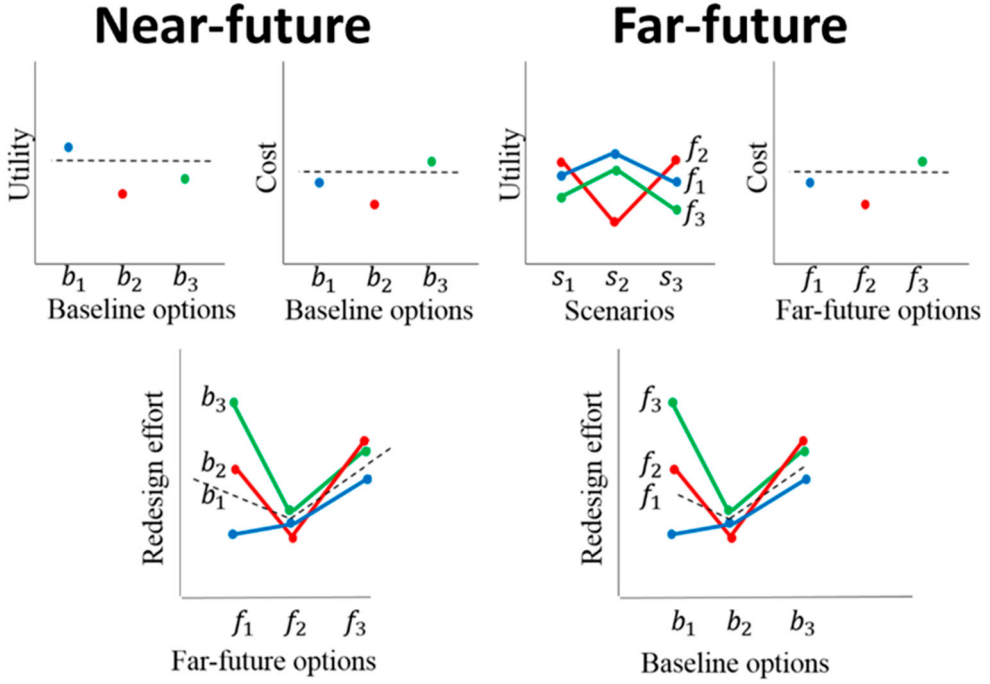


Figure 5. Maximality applied to near-future (baseline) options (left) and far-future options (right) – from (van Heerden 2019).

stated condition, $f_{j,s}$, for each scenario s . This is unlike interval dominance and maximality, which require that a single future design, f_j , meets the condition for all scenarios simultaneously. E-admissibility can be expressed mathematically as follows:

$$f_i \in F, \forall s_2 \in S_2 \left(\exists f_j \in F [c_{utility_{ij,s}} \wedge c_{cost_{ij,s}} \wedge c_{redesign_{ij,s}}] \right) \Rightarrow \text{remove } f_i \text{ from } F \quad (5)$$

where

$$\begin{aligned} c_{utility_{ij,s}} &\stackrel{\text{def}}{=} u(f_i, s_2) < u(f_j, s_2) \\ c_{cost_{ij,s}} &\stackrel{\text{def}}{=} c(f_i) > c(f_j) \\ c_{redesign_{ij,s}} &\stackrel{\text{def}}{=} \forall b_k \in B [r(b_k, f_i) > r(b_k, f_j)] \end{aligned}$$

A graphical illustration of E-admissibility for evolvability is shown in Figure 6. As can be seen for both the far-future cases, far-future option f_3 can be eliminated because, for every far-future scenario and baseline combination, there would be at least one alternative design that has higher utility, lower cost, and lower redesign effort than it.

3.2. Constrain and union strategy

The constrain and union is not a filtering criterion, but rather a systematic two-step procedure that could be employed to (further) filter out less desirable design options, based

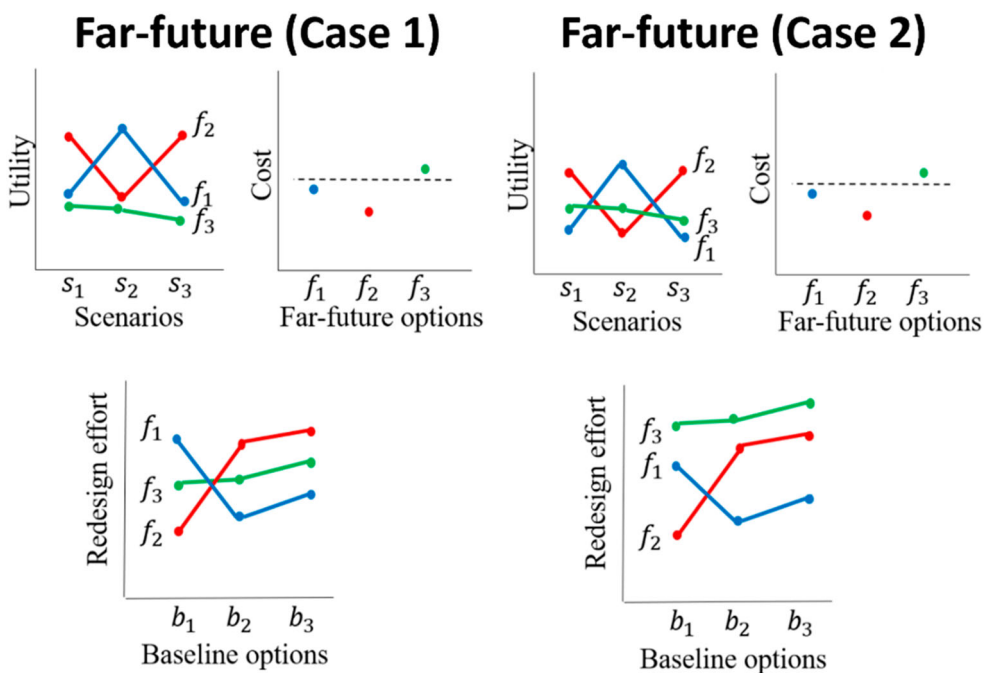


Figure 6. E-admissibility applied to the far-future (van Heerden 2019).

on the designer's preferences. It is expected to be particularly useful for interactive evolvability exploration, as it would, if implemented into a suitable software application, enable real-time evolvability-related inputs from the user, with a correspondingly swift response.

Intuitively, the 'constraint' phase reduces a scenario tradespace by only considering options within a user-specified 'distance' from the Pareto front. One technique for doing this is to calculate the 'Fuzzy-Pareto' set as described in (Fitzgerald and Ross 2012). A minimum utility and maximum allowable redesign effort to the far-future options could also be specified for each future scenario. The union phase consists of the set union of the feasible designs in each scenario. In other words, as long as a design is a feasible option for one of the future scenarios, it should not be discarded.

This procedure is illustrated in Figure 7, which shows the unfiltered evolvability design space on the top left, the design space during the two steps of the procedure in the top right and bottom left of the figure, and the same design space after further filtering in the bottom right. The latter is included to better illustrate the type of result that can be obtained. Note that in this design space, the top-left plot represents the utility and cost for the near-future options, the top-right plot shows the utility of far-future design options for different far-future scenarios (each dot is a far-future option), and the bottom-centre plot maps redesign effort from near-future options to far-future options (i.e. each dot represents a near-future option).

In Step 1, a fuzzy-pareto front is specified for the near future, which eliminates several near-future design options from consideration (the filtered-out designs are depicted in grey in Figure 7). In Step 2, the user selects a minimum utility and maximum redesign effort threshold for each far-future scenario, as depicted by the green constraint lines. The

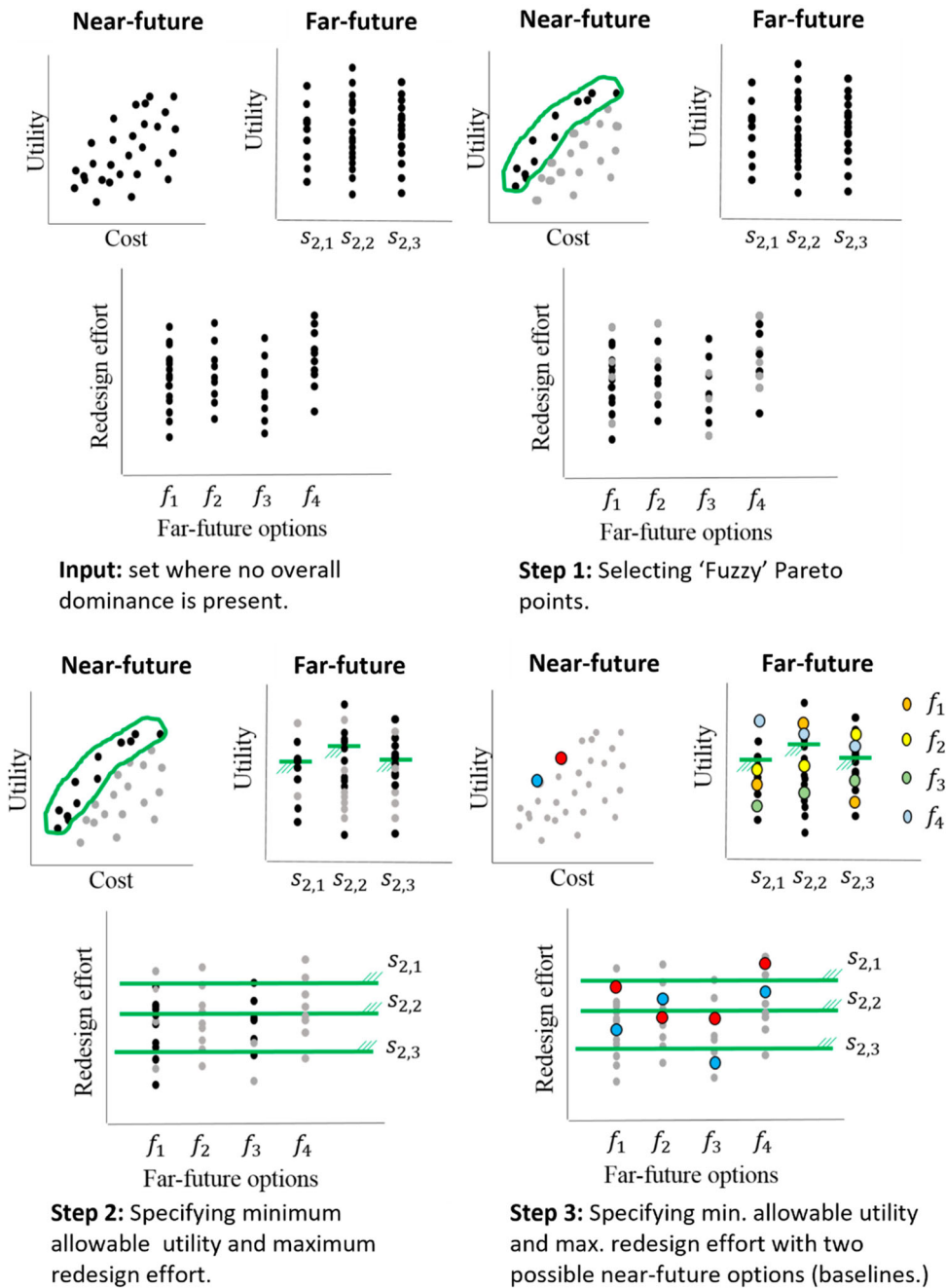


Figure 7. The constrain and union procedure (van Heerden 2019).

far-future designs that did not meet these requirements are now also filtered out and shown in grey.

The design space at the bottom right of Figure 7 is an example, included to further clarify the process. Here, instead of a fuzzy-pareto front, only two near-future options (represented

by the red and blue dots) are selected. All the other near-future options are eliminated. This can be seen in both the utility-cost and redesign plots by the greyed-out options. Far-future scenario-dependent utility and redesign effort constraints are also applied, as shown by the green constraint lines. This has the following effects: f_1 exceeds the utility requirement for scenario $s_{2,2}$ and there is one available baseline option from which it could be developed for less than the specified maximum redesign effort. It should therefore be retained as a feasible design for scenario $s_{2,2}$. Option f_2 only meets the utility constraint for one scenario ($s_{2,3}$) but not the corresponding redesign effort. There are also no other scenarios in where it meets the constraints, so it can be filtered out. Option f_3 can also be eliminated, as it does not meet the utility constraint for any scenario. Finally, f_4 meets the utility constraints for all the far-future scenarios and meets the redesign effort constraint for one remaining feasible baseline in scenario $s_{2,1}$, so it should be retained for this scenario.

Note that this procedure may lead to no feasible designs remaining for a particular scenario(s), in which case some of the constraints could be relaxed or the design space further populated.

3.3. Using results from previous stages

The presented techniques are applied in sequence, but using the same input data, which contains all the baselines and derivatives used to populate the unfiltered design space. However, the filtered sets of baselines and derivatives from an earlier stage can be used as input for the later stages. E.g. after the application of constrain and union, only a reduced set of baselines B' and a reduced set of derivatives F' remain. If this data is used as input to the SBD elimination algorithms, a different, more detailed result can be obtained. The reduced set could also consider other constraints or elimination criteria before applying the design techniques presented in this manuscript.

Considering the result from previous stages can result in more or fewer designs being eliminated depending on the characteristics of the design space. For instance, in the case of a baseline b_1 being eliminated due to a baseline b_2 having more utility, lower cost and being more evolvable, if b_2 is eliminated in a previous stage, then b_1 will cease to be eliminated. On the contrary, other cases result in more designs being discarded. For example, if derivative f_1 is surviving only because it can be easily evolved to from baseline b_3 and such a baseline is filtered out at a previous stage, then there would be no reason to keep f_1 and it could be eliminated. It must be noted that the first case, which results in less design being discarded, is less likely to happen as all the techniques presented here favour points closer to the pareto front. Therefore, the points that might benefit from considering previously discarded points are also more likely to have been discarded themselves. However, if the discarded design were determined by constraints that are not so correlated with the distance to the pareto front, the situation where points cease to be discarded would be more likely to occur.

4. Application case study

A demonstration case study was developed to test the techniques and demonstrate how they could be used in evolvability exploration during conceptual design. A design study for

Table 1. Technology options.

	Near & Far Future	Far Future Only
Energy Source	Kerosene, SAF	LH2
Empennage	Conventional, T-Tail	–
Wing	Low Wing, High Wing	–
Fuel Tank	Wing Tank	Caudal Tank, Belly Fairing Tank, Dorsal Tank
Engine	Tail-Mounted Turbofan, Wing-Mounted Turbofan, Tail-Mounted Open Rotor	Wing-Mounted Open Rotor

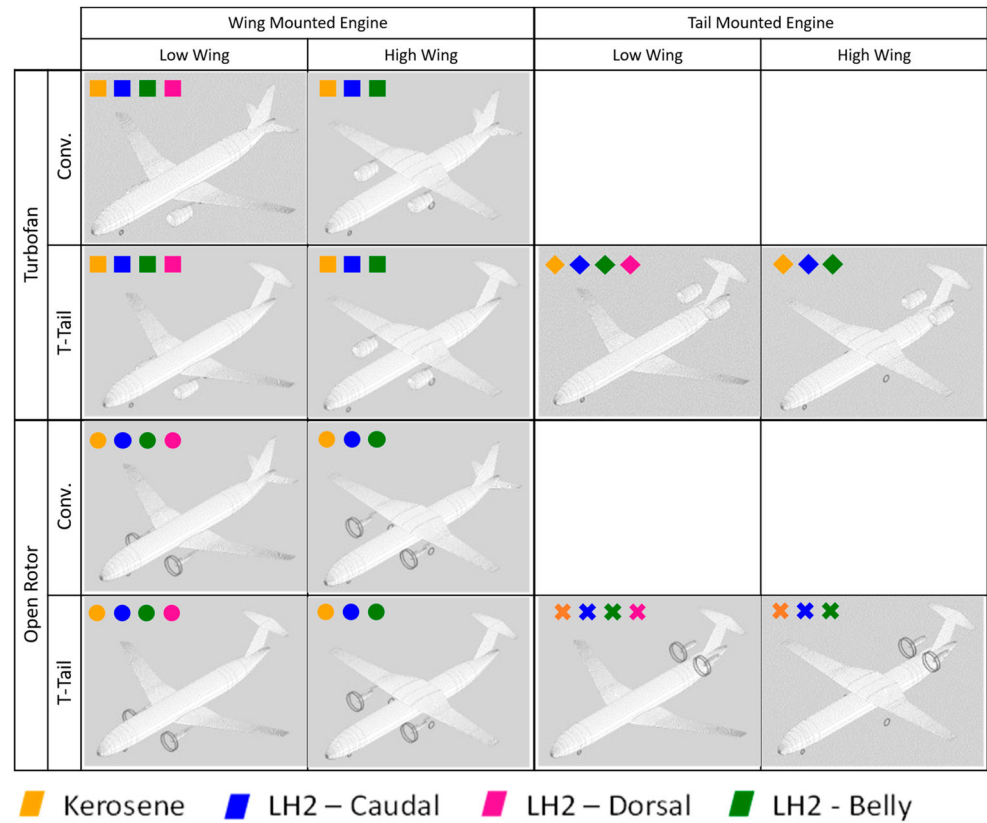


Figure 8. Configuration-technology combinations (CTCs) for the case study.

a new single-aisle, environmentally friendly passenger airliner was created. The near-future entry-into-service (EIS) is assumed to occur in 2035, and the far-future EIS is scheduled for 2045. Both EIS design spaces were populated with potential design options upon which the set-based design techniques were applied.

The technology options displayed in Table 1 were used to generate the configuration-technology combinations (CTCs) depicted in Figure 8, by selecting all possible combinations (one element from each row). The following three constraints were applied to limit the number of combinations: 1) conventional empennage cannot be selected together with tail-mounted engines, as the geometries of both components would clash; 2) hydrogen is not stored in wing tanks, since it would not be possible to store enough LH2 in the wings; and 3) wing geometry and high wings are not compatible with dorsal LH2

Table 2. Full factorial factor values.

Factor	Values
Number of passengers [-]	150, 170, 190
Design range [nm]	1500, 2000, 2500

tanks, as the wing carry-through structure would interfere with the tank. The coloured shapes in Figure 8 identify the corresponding CTCs in the utility-cost MATE (Multi-Attribute Tradespace Exploration) plots presented in this section. The resulting CTCs were used in combination with full-factorial sampling, where both the number of passengers and the design range were varied according to the values described in Table 2. There is a total of nine distinct combinations for range and number of passengers, so there are nine aircraft per configuration.

For the 2035 EIS, a total of eight kerosene configurations are considered: four with wing-mounted turbofan, two with tail-mounted turbofan and two with tail-mounted open rotor. For the 2045 EIS, tail-mounted open rotors are assumed to be available, as well as liquid hydrogen – which can be stored in caudal, belly fairing and dorsal tanks. All available technologies at the far-future EIS timeframe yield a total of 42 CTCs: 14 with wing-mounted turbofan, 14 with wing-mounted open rotor, seven with tail-mounted turbofan and seven with tail-mounted open rotor.

A single scenario is considered for 2035, where a percentage of 25% SAF is considered, and fuel prices are similar to the current ones. To account for the uncertainty in the far-future EIS, three main possible scenarios are considered for 2045. These scenarios differ in how expensive kerosene, SAF and LH2 are relative to each other. A mixture of 50% SAF is considered in all three future scenarios. The values for the fuel prices are presented in Table 3. The near future fuel prices and the SAF percentages draw inspiration from (IATA 2024) and (EASA 2024) respectively. The first scenario (EII) features relatively inexpensive SAF and LH2. The second scenario (EIE) is more pessimistic regarding the availability of hydrogen, which as a result becomes more expensive. The third scenario (E3) is the most pessimistic as SAF prices are also considered to be high.

4.1. Modelling and software implementation

To use MATE plots in conjunction with the presented SBD filtering techniques, it is necessary to calculate the cost and utility values for each design in the 2035 and 2045 timeframes and for each scenario, as well as the redesign effort for each pair of near and far-future EIS aircraft. Cost is calculated as the RDT&E cost by using the weight outputs from FLOPS (Langley

Table 3. Scenario-dependent values.

Scenario	EIS	SAF %	Kerosene Price [USD/kg]	SAF Price [USD/kg]	LH2 Price [USD/kg]
Current Near Future	2035	25	1.00	2.40	–
Expensive Kerosene Inexpensive SAF Inexpensive LH2 (EII)	2045	50	4.00	3.60	8.00
Expensive Kerosene Inexpensive SAF Expensive LH2 (EIE)	2045	50	4.00	3.60	16.00
Expensive Kerosene Expensive SAF Expensive LH2 (E3)	2045	50	4.00	7.20	16.00

Research Center 2019) combined with the cost model by (Markish 2002) and the corrections used in (van Heerden et al. 2022). Fuel cost per passenger per kilometre is used as a substitute for utility (note that this implies that the inequality signs in the SBD filtering techniques formulation need to be reversed). The required fuel amount is obtained from FLOPS, and the fuel cost is determined by fuel prices under each scenario. The similarity techniques from (van Heerden 2019) were applied to obtain the potential cost reduction and redesign effort due to commonality. These techniques provide values for mass commonality for major aircraft components, and the potential cost savings are also estimated using the same cost model as used for individual designs. Each of the techniques presented in this paper was implemented in AirCADia Vision (Guenov et al. 2014) – an in-house software tool for data visualisation – and applied sequentially to the resulting design space. One of the main reasons for the selection of AirCADia Vision for this purpose was because of its interactive design space exploration features, such as efficient interactive visualisation algorithms and the provision of several powerful means to present data (Guenov et al. 2014). AirCADia Vision provides a graphical user interface that allows designers to choose which filtering techniques to apply and set values for the constraints in the constrain and union stage. This is achieved by checking or unchecking checkboxes and by filling constraint values in a table. Additionally, when the plot points representing the designs are hovered over by the mouse pointer, the software displays their id – so the user can obtain more information about the design, such as the corresponding configuration or parameter values – and the results from any of the applied filtering techniques – indicating the reason the design was filtered out.

FLOPS does not feature LH2 aircraft modelling capabilities, therefore, it had to be extended to be able to study the LH2 aircraft in this study. The engine deck fuel flow values were reduced proportionally to the energy per mass ratio between LH2 and kerosene. This results in a lower fuel flow, which is consistent with the higher amount of energy per mass of LH2. Additionally, the fuselage geometry was enlarged to contain the hydrogen tanks, and the additional tank weight was also considered. Tanks are assumed to be elliptical cylinders, with a maximum available volume of

$$V = \pi \frac{w_t}{2} \frac{h_t}{2} l_t$$

where w_t , h_t and l_t are the width, height, and length of the tank, respectively. Only a fraction of the volume can be used to contain LH2, which is modelled via a volumetric efficiency $\eta_{vol} = V_{LH_2}/V$. Finally, the maximum mass of hydrogen that the tank can contain is obtained from $W_{LH_2} = \rho_{LH_2} V_{LH_2}$, where ρ_{LH_2} is the density of liquid hydrogen. A Newton solver is used to obtain the tank geometry that can hold as much fuel as required by FLOPS. One of the tank dimensions (l_t in the case of caudal tanks and w_t otherwise) is varied while the others are kept fixed until the results converge. It must be noted that FLOPS needs to be run for each dimension guess, as changing the tank dimension changes the fuselage dimensions and fuel system weights, which impact the amount of fuel needed.

The mass distributions for wings and fuselages and the geometries of major aircraft components are required to run the similarity techniques from (van Heerden 2019). The geometries and mass distributions from (van Heerden 2019) were reused, scaling them to match the desired dimensions and weights determined by FLOPS.

4.2. Discussion of results

4.2.1. Unfiltered design space

Figure 9 shows the resulting design space before applying any filtering technique. The shape and colour of the points provide information about the CTC to which the point belongs, as displayed in Figure 8. In all MATE plots in this section, the RDT&E cost (x-axis) is expressed in billions of US dollars (10^9 USD) and the fuel cost per passenger per kilometre is expressed in dollar cents (10^{-2} USD). Scenario 'Current Near Future' features a total of 72 aircraft (8 CTCs with 9 aircraft per CTC); far future scenarios have 378 aircraft (42 CTCs with 9 aircraft per CTC). The results show that the cost of hydrogen-powered aircraft is around 5% to 20% higher than the cost of kerosene aircraft under the assumptions used for these specific configurations and models employed in this research. The fuel cost varies depending on the scenario, being more expensive in the future as fuel prices are assumed to increase. When LH2 is assumed to be inexpensive (EII), LH2 aircraft show the lowest fuel cost as opposed to when SAF is inexpensive but LH2 is not (EIE), which results in kerosene aircraft performing better in terms of cost. In the most pessimistic scenario (E3), the fuel costs are of similar magnitude.

The next few subsections cover how the evolvability design space was systematically reduced using the developed set-based criteria. Unless explicitly stated, the strict inequality versions of the filtering techniques are employed.

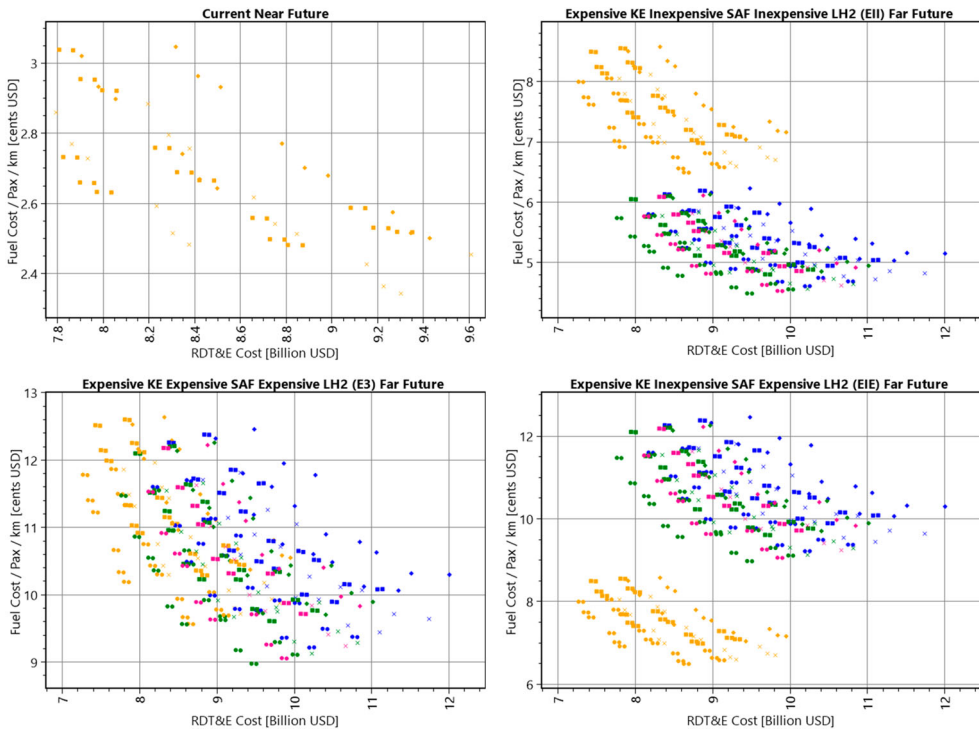


Figure 9. Evolvability design space resulting from the use case. Data point marker colours and shapes follow the conventions in Figure 8.

4.2.2. Design space after interval dominance

The application of interval dominance does not result in the elimination of any future designs. This is because this dominance criterion is the most difficult to meet, as it requires the lowest fuel cost of an aircraft in any scenario to be higher than the highest fuel cost of another in any scenario to be dominated. As Figure 10 shows, this condition cannot be met as the aircraft with the maximum fuel cost (kerosene diamond in scenario E3) is still better in scenario EIE than the aircraft with the lowest fuel cost in E3 (LH2 belly fairing circle).

4.2.3. Design space after maximality

As depicted in Figure 10, the application of the stricter criterion of maximality allowed the removal of 88 (roughly a quarter) of the far-future designs. The removed aircraft are depicted in grey. Since the aircraft relative positions within kerosene and LH2 aircraft groups are similar across future scenarios, a great proportion of the aircraft with higher cost and fuel cost is dominated by others with respect to these magnitudes. However, the designs that are easier to evolve to (lower redesign effort) cannot be discarded according to the maximality criterion. This fact explains why a larger portion of LH2 aircraft has been discarded, as these aircraft are usually larger than the kerosene-based near future designs, and even when similar in size, fuselages with fuel tanks are considered to be less common than a fuselage with the same geometry and no tanks.

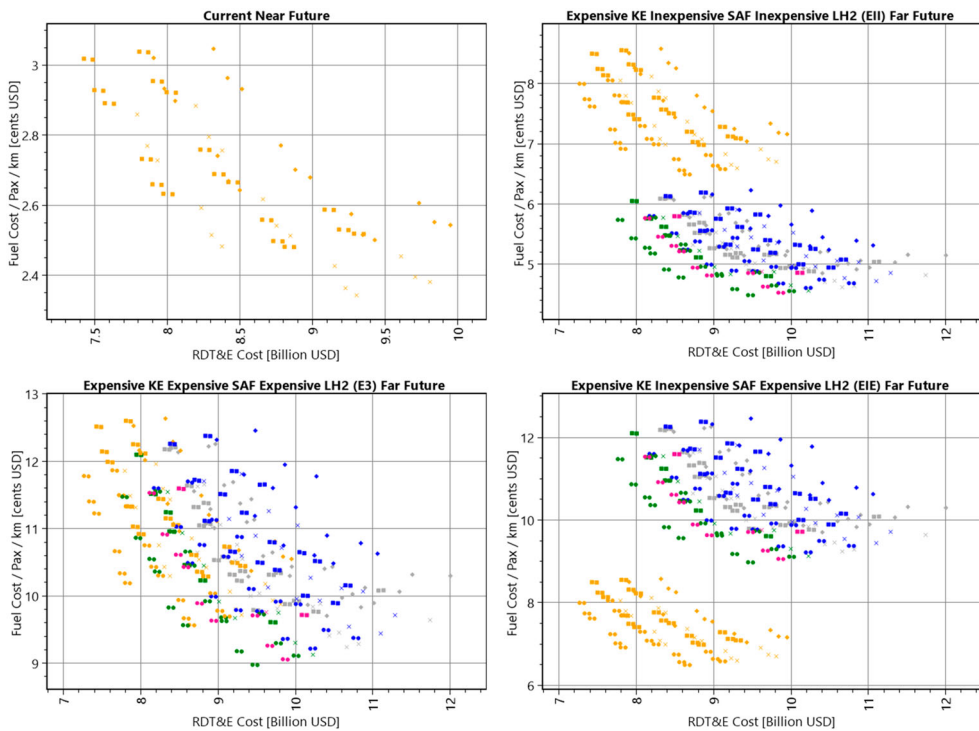


Figure 10. Result from the application of interval dominance and maximality.

Table 4. Constraint values.

Scenario	Maximum Fuel Cost [10–2 USD]	Maximum Redesign Effort [109 USD]
EII	5.5	8.2
EIE	8.0	8.2
E3	10.0	7.6

4.2.4. Design space after E-admissibility

Although the fuel requirements imposed by the E-admissibility criterion are less stringent than the previous criteria, the application of E-admissibility did not result in the elimination of any additional design. Regarding far-future designs, as in the case of maximality, it was easy to find aircraft dominated in terms of fuel cost, but it was difficult to find designs that were dominated in terms of redesign cost. Similarly, no near-future options have been discarded as there is always a kerosene option which is easy to evolve to (the same design is used for near and far-future EIS). Consequently, the results from E-admissibility are identical to those from maximality. However, a more detailed analysis could discard baselines that are less evolvable to the surviving LH2 options.

4.2.5. Constrain and union

The results from the application of the constrain and union procedure, which uses the values presented in Table 4, are shown in Figure 11. These values have been chosen to try to remove designs with high fuel costs and that are difficult to evolve to. The algorithms supporting the constrain and union procedure (and all the previous filtering techniques) run fast enough (under a second) to be perceived by the user as ‘immediate’ and therefore enable interactivity. These results were achieved with an Intel® Core™ i5-2700U processor, which is not particularly high-performing. The computational effort required to generate the initial unfiltered design space (Figure 9) is also a significant factor regarding the applicability of the presented set-based techniques. The reader is referred to (van Heerden 2019), pp. 4–7 for a detailed comparison of the computational efficiency between SBD and alternative approaches such as applying pre-specified modifications to a baseline.

The maximum redesign constraint for scenario E3 is even more stringent, as the aim is to obtain more affordable aircraft since fuel prices are higher under this scenario. As can be observed, the kerosene-based aircraft with higher fuel costs and LH2-based aircraft with higher fuel costs have been removed. Additionally, aircraft with high costs have also been discarded since they cannot meet the redesign effort constraint. However, it must be noted that constraints do not result in a clear horizontal or vertical line in any of the subplots. This is because of the union step, where meeting the constraint for one scenario is sufficient to retain a particular aircraft. The effects of the maximum redesign effort constraint are even more blurred, as the plots do not display this value directly, but rather the cost of the aircraft without any reduction due to evolvability.

4.2.6. Using results from previous stages

A great number of kerosene-based derivatives do not perform well in terms of cost and fuel cost. These designs have not been discarded yet as they are very easy to evolve to from at least one kerosene-based baseline. However, the application of the fuzzy pareto technique discarded the majority of baselines. If this fact is considered and the reduced

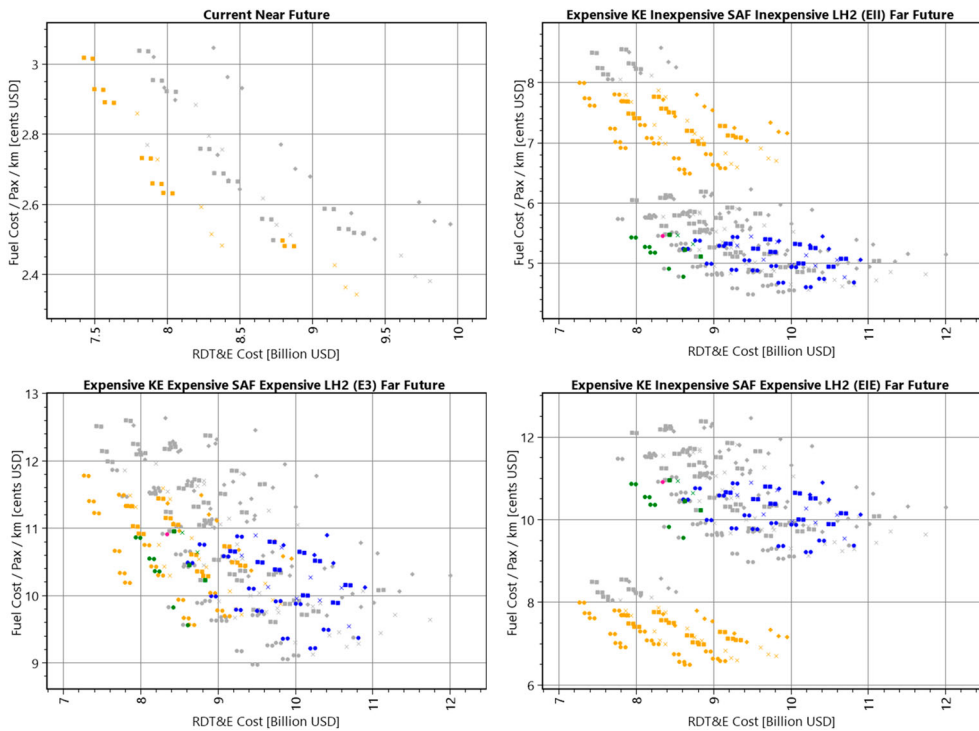


Figure 11. Result from the application of constrain and union.

set of surviving baselines is used as input into the SBD filtering algorithms, a better result is obtained, where more derivatives are discarded. The results are presented in Figure 12, where it can be observed that roughly half of the remaining kerosene-based derivatives have been filtered out as they are dominated both in terms of cost, fuel cost and evolvability with respect to the fuzzy pareto baselines.

4.2.7. Applying non-strict inequality

As shown in Figure 13, the application of maximality using non-strict inequality allowed the removal of 257 results (roughly three quarters) of the far-future designs. This is approximately three times more than the 88 designs removed by the strict inequality version of maximality. When using strict inequality, many designs could not be discarded because, whereas cost and utility criteria were met, the redesign effort criterion was not. By contrast, using non-strict inequality makes it easier to meet the criterion and leads to the elimination of 169 additional designs in this case. It should be pointed out that the redesign effort results obtained from applying the similarity techniques from (van Heerden 2019) contain many repeated values. For other cases, depending on the system being designed, the scenarios considered, and the techniques employed to obtain utility, cost, and redesign cost values, applying non-strict inequality might not eliminate as many points.

4.2.8. Summary and comparison of filtering strategies

Table 5 compares the impact of all filtering approaches applied to the evolvability design space. It shows the six different strategies that were employed in this section, and the

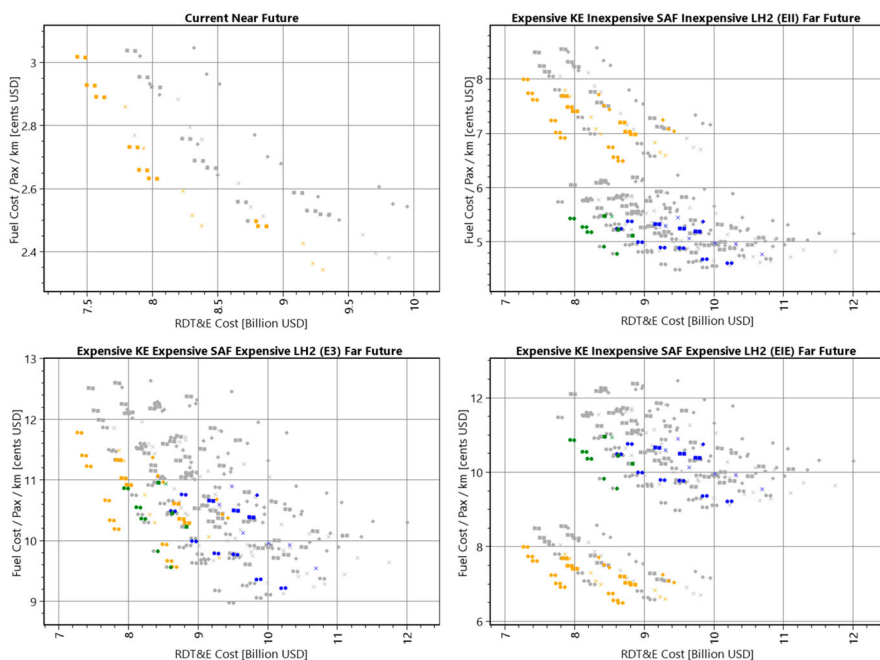


Figure 12. Result from considering constraint and union during SBD filtering.

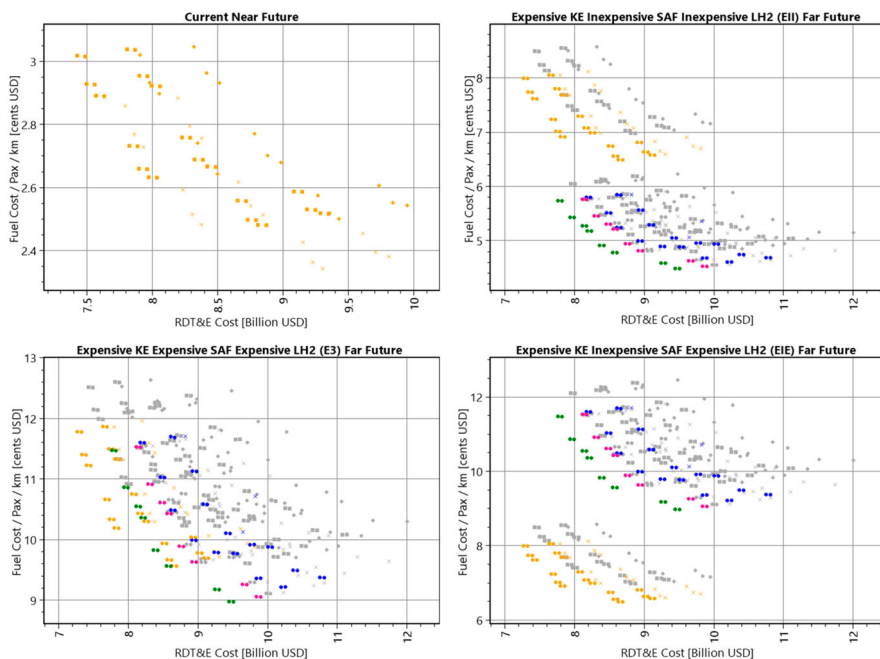


Figure 13. Result from the application of interval dominance and maximality using non-strict inequality.

Table 5. Summary and comparison of filtering strategies.

Strategy	Applied Techniques	Designs Removed		Remarks	Average RDT&E Cost [10–2 USD]		Average Fuel Cost / Pax / km [109 USD]	
		Near Future	Far Future		NF	FF	NF	FF
1	Interval Dominance (strict inequality)	0	0	No designs eliminated due to scenario variability	8.52	9.09	2.69	8.74
2	Maximality (strict inequality)	0	88 (~ 23%)	Removed designs with higher costs and higher redesign costs (LH2)	8.52	8.94	2.69	8.71
3	E-admissibility (strict inequality)	0	88 (~ 23%)	No additional designs eliminated due to ease of finding evolvable baselines	8.52	8.94	2.69	8.71
4	Constrain and Union	49 (~ 68%)	219 (~ 58%)	Removed near future designs far from pareto front. Removed low utility and high cost far future designs	8.15	8.98	2.67	8.45
5	Constrain and Union E-admissibility (strict inequality) considering Constrain and Union	49 (~ 68%)	295 (~ 78%)	Eliminated near future designs result in more far future designs removed compared to 3 and 4	8.15	8.69	2.67	8.43
6	Maximality using (non-strict inequality)	0	257 (~ 68%)	Many more designs with equal redesign cost are eliminated compared to 2	8.52	8.71	2.69	8.43

techniques which were used for each strategy. The table also summarises how many designs were eliminated for the near and far future timeframes. The remarks column displays the most important ideas applicable to each strategy. The last two columns give an idea of how the average values for RDT&E and fuel costs are affected by the filtering. It can be observed that the techniques tend to remove higher-cost and lower-utility (higher fuel cost) designs. Consequently, the more designs are removed, the lower the average cost values and the more 'pareto optimal' are the remaining sets.

5. Conclusions and future work

In this paper, set-based design computational techniques to enable systematic and interactive filtering of the evolvability design space were proposed. Their application was demonstrated by means of a use case involving exploring the evolvability of design options for a future short-to-medium range environmentally friendly civil transport aircraft.

Specifically, it was demonstrated how the existing set-based design criteria of 'interval dominance,' 'maximality,' and 'E-admissibility' could be extended to enable progressive filtering of the evolvability design space. A novel set-based design strategy, 'constrain and union,' was also introduced and shown to be effective in filtering out inferior design options.

Maximality and E-admissibility were shown to be particularly effective in reducing the far-future design space, which could guide the focus of designers on particular far-future technologies. On the other hand, the constrain and union strategy showed promise in filtering out both near- and far-future design options. Using the results from earlier filtering stages as the input to later stages was demonstrated to be successful at refining the results. In addition, the constrain and union strategy, as implemented in the AirCADia Vision design space exploration tool, enables an immediate indication of how the design space would change across different potential future scenarios, based on different evolvability-related inputs from the user. It therefore empowers the user to explore the evolvability of their designs interactively.

Future work will involve extending the accounting of uncertainty to the development cost, redesign effort, and design attributes.

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Data availability statement

Data supporting this study are openly available from the Cranfield research data repository CORD at <https://doi.org/10.57996/cran.ceres-2686>.

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References

- Boas, R. C. 2008. "Commonality in Complex Product Families: Implications of Divergence and Lifecycle Offsets." Thesis, Massachusetts Institute of Technology. Accessed: Dec. 06, 2024. [Online]. Available: <https://dspace.mit.edu/handle/1721.1/53209>.
- Cardin, M.-A. 2013. "Enabling Flexibility in Engineering Systems: A Taxonomy of Procedures and a Design Framework." *Journal of Mechanical Design* 136 (011005), <https://doi.org/10.1115/1.4025704>.
- Curry, M. D., and A. M. Ross. 2015. "Considerations for an Extended Framework for Interactive Epoch-Era Analysis." *Procedia Computer Science* 44:454–465. <https://doi.org/10.1016/j.procs.2015.03.029>.
- Dullen, S., D. Verma, M. Blackburn, and C. Whitcomb. 2021. "Survey on set-Based Design (SBD) Quantitative Methods." *Systems Engineering* 24 (5): 269–292. <https://doi.org/10.1002/sys.21580>.
- EASA. 2024. 'Current Landscape and Future of SAF Industry'. Accessed: May 23, 2024. [Online]. Available: <https://www.easa.europa.eu/eco/eaer/topics/sustainable-aviation-fuels/current-landscape-future-saf-industry>.
- Fitzgerald, M. E., and A. M. Ross. 2012. "Mitigating Contextual Uncertainties with Valuable Changeability Analysis in the Multi-epoch Domain." In *2012 IEEE International Systems Conference SysCon 2012*, 1–8. Vancouver, BC, Canada: IEEE.
- Guenov, M. D., M. Nunez, A. Molina-Cristóbal, V. C. Datta, and A. Riaz. 2014. "AirCADia – An Interactive Tool for the Composition and Exploration of Aircraft Computational Studies at Early Design Stage." 29th Congress of the International Council of the Aeronautical Sciences, St. Petersburg, Russia.
- Guzman, J. L., S. Dormido, and M. Berenguel. 2013. "Interactivity in Education: An Experience in the Automatic Control Field." *Computer Applications in Engineering Education* 21 (2): 360–371. <https://doi.org/10.1002/cae.20480>.
- IATA. 2024. 'Sustainable Aviation Fuel Output Increases, but Volumes Still Low'. Accessed: May 23, 2024. [Online]. Available: <https://www.iata.org/en/iata-repository/publications/economic-reports/sustainable-aviation-fuel-output-increases-but-volumes-still-low/>.
- Kennedy, B. M., D. K. Sobek, and M. N. Kennedy. 2014. "Reducing Rework by Applying Set-Based Practices Early in the Systems Engineering Process." *Systems Engineering* 17 (3): 278–296. <https://doi.org/10.1002/sys.21269>.
- Langley Research Center. 2019. *FLOPS*. Langley Research Center. Accessed: Jan. 09, 2019. [Online]. Available: <https://software.nasa.gov/software/LAR-18934-1>.
- Levi, I. 1974. "On Indeterminate Probabilities." *The Journal of Philosophy* 71 (13): 391. <https://doi.org/10.2307/2025161>.
- Lim, D. April 2009. *A Systematic Approach to Design for Lifelong Aircraft Evolution* [PhD thesis]. Georgia Institute of Technology. Accessed: Jun. 18, 2024. [Online]. Available: <http://hdl.handle.net/1853/28280>.
- Malak, R. J., J. M. Aughenbaugh, and C. J. J. Paredis. 2009. "Multi-Attribute Utility Analysis in Set-Based Conceptual Design." *Computer-Aided Design* 41 (3): 214–227. <https://doi.org/10.1016/j.cad.2008.06.004>.

- Markish, J. 2002. "Valuation Techniques for Commercial Aircraft Program Design." Thesis, Massachusetts Institute of Technology. Accessed: May 22, 2024. [Online]. Available: <https://dspace.mit.edu/handle/1721.1/16871>.
- Oxford English Dictionary. 2023, July. *Interactive, Adj.* Oxford University Press. <https://doi.org/10.1093/OED/1040925831>.
- Rader, A. A., A. M. Ross, and D. H. Rhodes. 2010. "A Methodological Comparison of Monte Carlo Simulation and Epoch-Era Analysis for Tradespace Exploration in an Uncertain Environment." 2010 IEEE International Systems Conference, 409–414.
- Rekuc, S. J., J. M. Aughenbaugh, M. Bruns, and C. J. J. Paredis. 2006. "Eliminating Design Alternatives Based on Imprecise Information." Presented at the SAE 2006 World Congress & Exhibition, 2006-01-0272.
- Riaz, A. 2015. "A Set-Based Approach to Passenger Aircraft Family Design." PhD thesis, Cranfield University. Accessed: Dec. 19, 2023. [Online]. Available: <https://dspace.lib.cranfield.ac.uk/handle/1826/9723>.
- Riaz, A., M. D. Guenov, and A. Molina-Cristobal. 2017. "Set-Based Approach to Passenger Aircraft Family Design." *Journal of Aircraft* 54 (1): 310–326. <https://doi.org/10.2514/1.C033747>.
- Ross, A. M. 2006. "Managing Unarticulated Value: Changeability in Multi-attribute Tradespace Exploration." PhD thesis, Massachusetts Institute of Technology. Accessed: Dec. 20, 2023. [Online]. Available: <https://dspace.mit.edu/handle/1721.1/35089>.
- Ross, A. M., and D. H. Rhodes. 2008. "Using Natural Value-Centric Time Scales for Conceptualizing System Timelines through Epoch-Era Analysis." *INCOSE International Symposium* 18 (1): 1186–1201. <https://doi.org/10.1002/j.2334-5837.2008.tb00871.x>.
- Shallcross, N., G. S. Parnell, E. Pohl, and E. Specking. 2020. "Set-Based Design: The State-of-Practice and Research Opportunities." *Systems Engineering* 23 (5): 557–578. <https://doi.org/10.1002/sys.21549>.
- van Heerden, A. S. J. 2019. "Computational Techniques for Aircraft Evolvability Exploration during Conceptual Design." PhD thesis, Cranfield University. Accessed: Dec. 19, 2023. [Online]. Available: <https://dspace.lib.cranfield.ac.uk/handle/1826/18615>.
- van Heerden, A. S. J., S. Jimeno Altelarrea, A. Riaz, X. Chen, M. D. Guenov, and A. Molina-Cristóbal. 2024. "Set-Based Design Techniques for Evolvability Exploration during Conceptual Aircraft Design." In *34th Congress of the International Council of the Aeronautical Sciences*. Florence, Italy: International Council of the Aeronautical Sciences. Accessed: Dec. 06, 2024. [Online]. Available: https://www.icas.org/icas_archive/icas2024/data/papers/icas2024_0233_paper.pdf.
- van Heerden, A. S. J., S. Sasi, R. Ghelani, D. S. Sanders, and I. Roumeliotis. 2022. *A Scalable Hydrogen Propulsion System for Civil Transport Aircraft*. ICAS. Accessed: Jun. 18, 2024. [Online]. Available: <https://dspace.lib.cranfield.ac.uk/handle/1826/19158>.
- Walley, P. 1990. *Statistical Reasoning with Imprecise Probabilities*. New York: Chapman and Hall. [Online]. Available: <https://api.semanticscholar.org/CorpusID:119675760>.



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Set-based design techniques for the systematic and interactive exploration of complex product evolvability

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van Heerden ASJ, Jimeno Altelarrea S, Riaz A, et al., (2026) Set-based design techniques for the systematic and interactive exploration of complex product evolvability. Journal of Engineering Design, Volume 37, Issue 4, April 2026, pp. 1326-1351