SET-BASED DESIGN TECHNIQUES FOR EVOLVABILITY EXPLORATION DURING CONCEPTUAL AIRCRAFT DESIGN

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Abstract

The ability of a design to evolve beyond its initial entry-into-service date is an essential consideration during the development of a new aircraft. Because of the strong influence the conceptual design stage exerts over overall aircraft development programme cost and duration, it is important that the design space is explored thoroughly during this stage to identify evolvable designs. While computational approaches to perform such exploration exist, they 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. These methods were implemented in a computational tool, AirCADia, enabling rapid and interactive evolvability design space exploration. The use of these techniques is demonstrated through their application to the evolvability investigation of design options for a future short-to-medium range environmentally friendly civil transport aircraft.

Keywords: aircraft conceptual design; evolvability; set-based design; multi-attribute tradespace exploration.

1. Introduction

To manage the risk associated with developing a new aircraft, which must be competitive far into the future, airframers usually endeavour to ensure that their design is '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" [1]. Evolvability is often difficult to assess, as it requires careful consideration of a multitude of varying scenarios related to future commercial, economic, political, and societal events, along with 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 factors. Because of the importance of the conceptual design phase in determining the overall lifecycle cost, airframers typically already consider evolvability at this phase. However, evolvability adds 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 aircraft 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).

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 [2,3].

'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 manage such problems [2]. Set-based filtering techniques can be employed to eliminate infeasible or knowingly inferior options systematically, rather than trying to identify an 'optimal' design too early. However, the literature on how these techniques could be applied to 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 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 [1] and much of the text in Section 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 future short-to-medium range (SMR) single-aisle civil transport aircraft incorporating new technologies and powered by alternative fuels.

2. Overview of Previous Related Research

2.1 Evolvability Design Space Exploration

The purpose of evolvability design space exploration is to identify evolvable designs – i.e., designs that will perform well (i.e., provide value to their customers) when entering service in the 'near future' and can then be subsequently changed at low development cost and duration to create derivatives that meet new requirements and provide value when entering service in the 'far future'.

Many techniques exist, but here the focus is on methods where the near future and the far future timeframes are explored simultaneously. Perhaps the most well-known framework for this type of exploration is 'Multi-Attribute Tradespace Exploration' combined with 'Epoch-Era Analysis' such as described in Refs. [1,4,5], but similar techniques have been used in [6] and [7].

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 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 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' 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,' which represents some scenario-dependent aggregated 'measure of goodness,' which 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" [8]. The main expected benefit of SBD is to reduce redesign rework due to early decisions proven defective at later design stages [9].

Many SBD techniques can be employed for design space exploration, but the focus of this study was on the techniques of Malak et al. [8] and Rekuc et al. [10], which were formulated specifically to deal with uncertainty in the design process. They have proposed three SBD filtering criteria that work on imprecise information: ‘interval dominance,’ ‘maximality,’ and ‘E-admissibility.’

Interval dominance [8,10] 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 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.

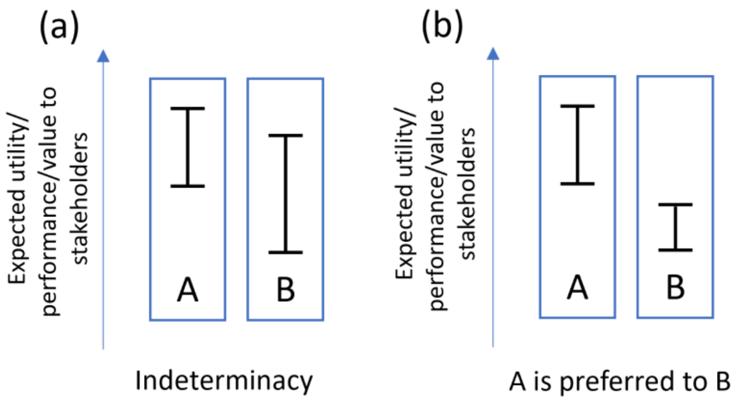


Figure 1 – Interval dominance (adapted from [8]).

The ‘maximality’ criterion, originally introduced by Walley [11], 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. Maximality eliminates at least as many solutions as interval dominance [8]. 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.

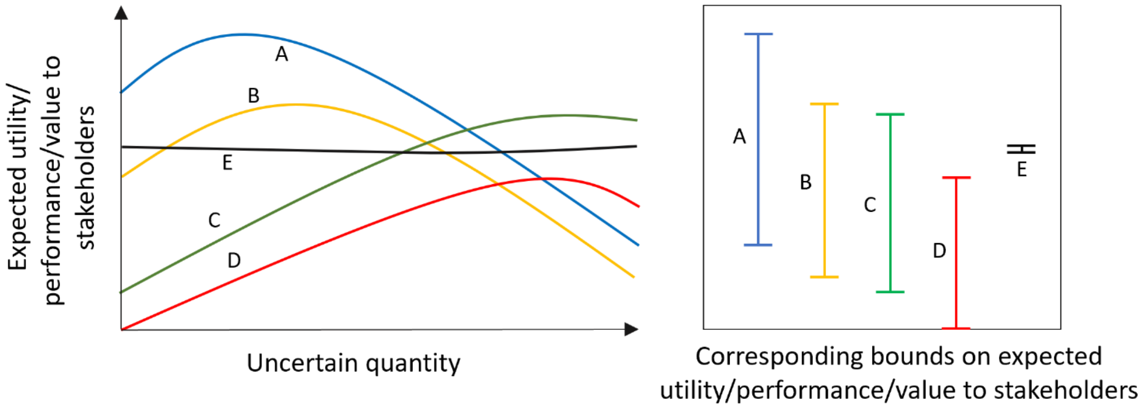


Figure 2 – Variation of expected utility across the range of an uncertain parameter (adapted from [8]).

E-admissibility, which was originally discussed by Levi [12], covers an even more strict scenario. For a design option in this scenario, it is checked whether for every point across the input uncertain quantity, there is at least one other option that is better. 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 [10].

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. Their extension to be used for this purpose is discussed next.

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. 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 was considered for EIS1 ($s_{1,1}$), whereas multiple scenarios are considered for EIS2 ($s_{2,1}, s_{2,2}, \dots, s_{2,n_{s2}}$).

Given a design option a and scenario s, a function $u(a, s)$ can be specified that calculates utility 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. The development cost for the design option can be calculated similarly by a function, called $c(a)$, which assumes that cost is independent on the scenario. 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 $r(b_i, f_j)$.

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 of the changing scenarios and not endogenous uncertainty associated with the design itself.

3.1 Elimination Criteria

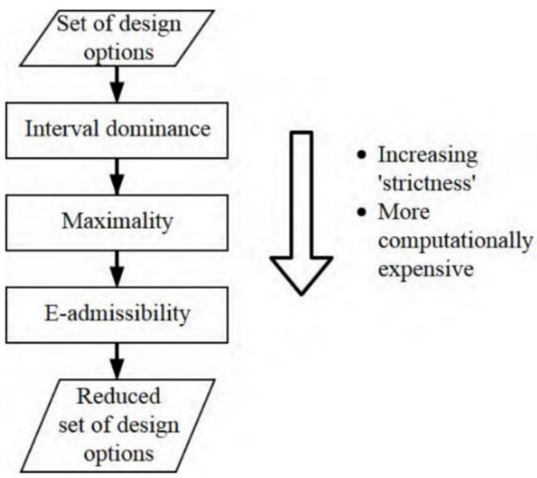
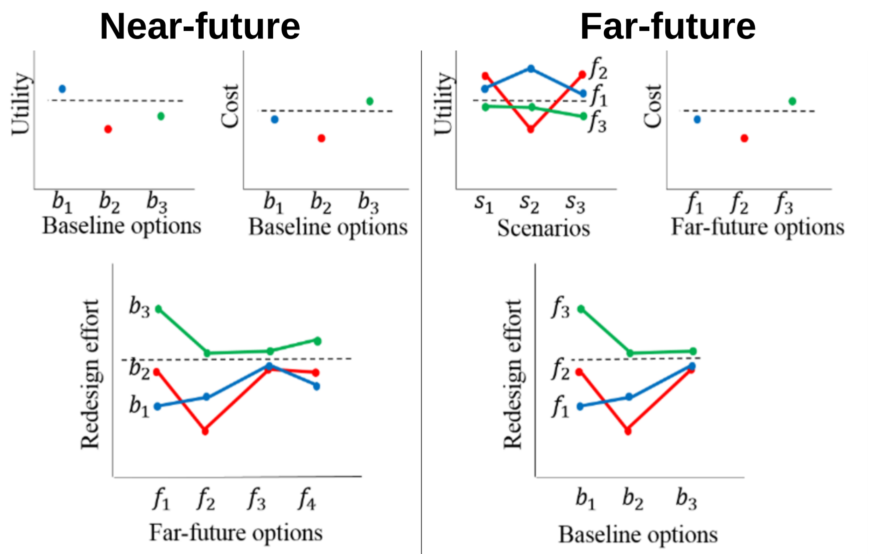


Figure 3 – Evolvability SBD elimination criteria [1].

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.

3.1.1 Interval dominance

The interval dominance criterion determines 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 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.



Formal criterion:

$b_i \in B, \exists b_j \in B$
$[u(b_i, s_{1,1}) < u(b_j, s_{1,1}) \wedge c(b_i) > c(b_j) \wedge$
$\min(r(b_i, F)) > \max(r(b_j, F))] \Rightarrow$ remove b_i from B

Formal criterion:

$f_i \in F, \exists f_j \in F$
$[\max(u(f_i, S_2)) < \min(u(f_j, S_2)) \wedge c(f_i) > c(f_j) \wedge$
$\min(r(B, f_i)) > \max(r(B, f_j))] \Rightarrow$ remove f_i from

Figure 4 – Interval dominance applied to near-future (baseline) design options (left) and far-future options (right) [1].

The technique is demonstrated in Figure 4, which also presents the filtering criterion as formal mathematical expressions for the two consecutive timeframes. 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 with a more stringent condition for 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.

This concept along with the formal filtering criteria 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.

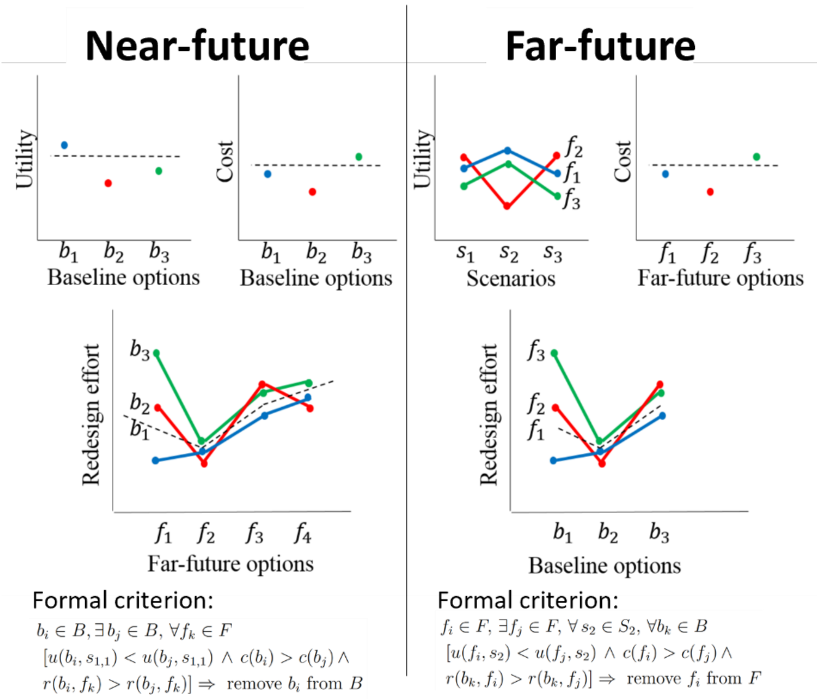


Figure 5 – Maximality applied to near-future (baseline) options (left) and far-future options (right) [1].

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.

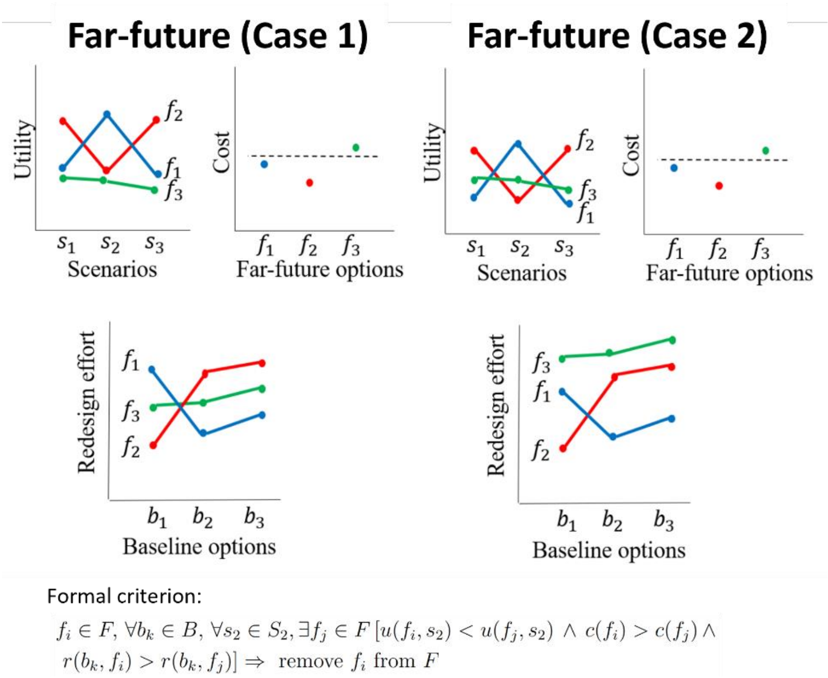


Figure 6 – E-admissibility applied to the far-future [1].

3.1.3 E-admissibility

E-admissibility assesses if, 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 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.

A graphical illustration of E-admissibility for evolvability, along with its formal mathematical formulation, is illustrated 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

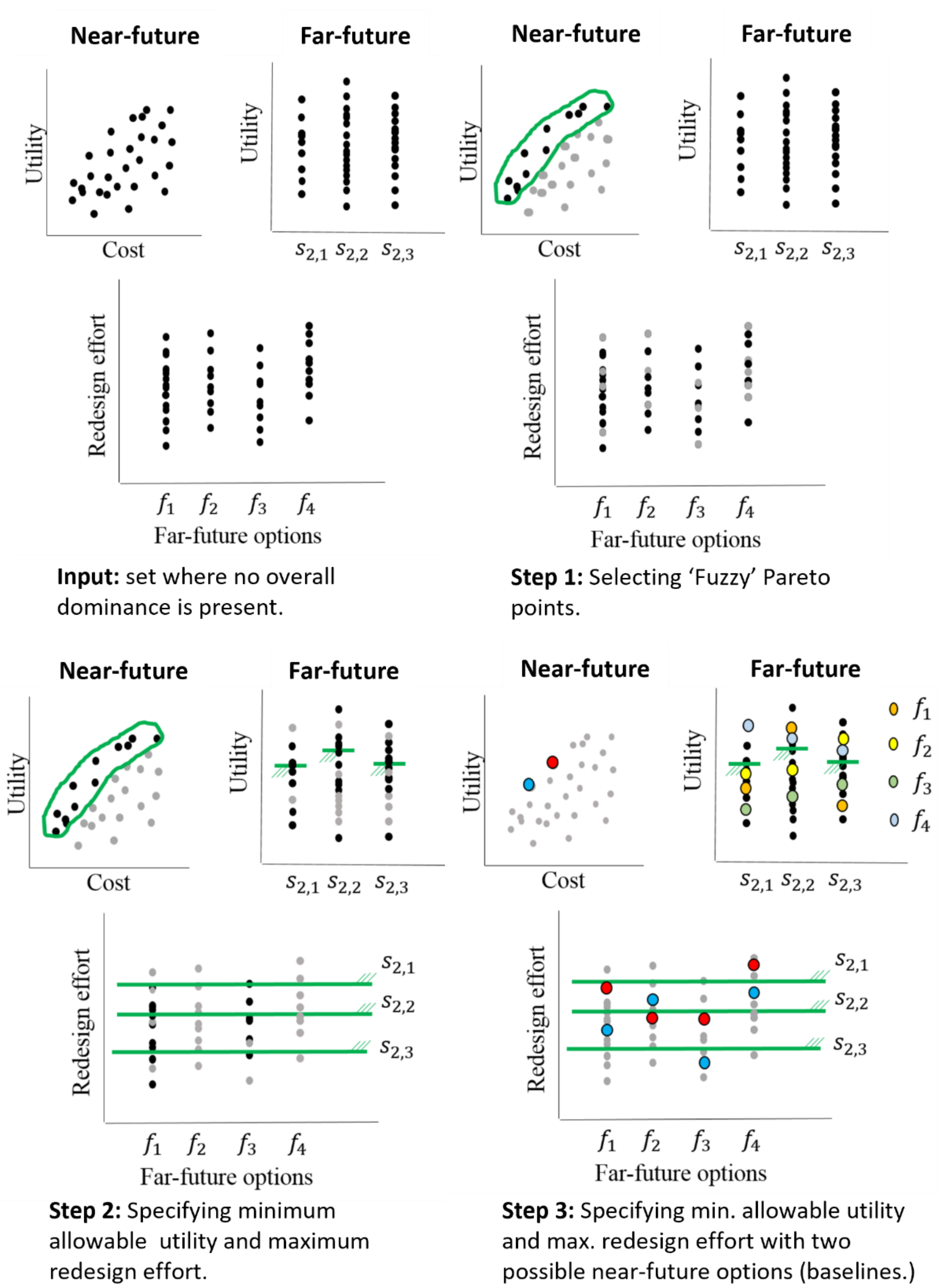


Figure 7 – The constrain and union procedure [1].

The constrain and union is a two-step procedure that could be employed to (further) filter out less desirable design options, based on the designer's preferences. It is expected to be particularly useful for interactive evolvability exploration. 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 [13]. 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 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 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 far-future designs that did not meet these requirements are now also filtered out and shown in grey.

The design space on 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.

4. 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 a new single-aisle, environmentally friendly passenger airliner was created. The near-future entry-into-service (EIS) is assumed to be 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 tanks, as the wing carry-through structure would interfere with the tank. The coloured shapes in Figure 2 identify the corresponding CTCs in the MATE 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.

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

Table 2 – Full factorial factor values.

Factor	Values
Number of passengers [-]	150, 170, 190
Design range [nm]	1500, 200, 2500

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.

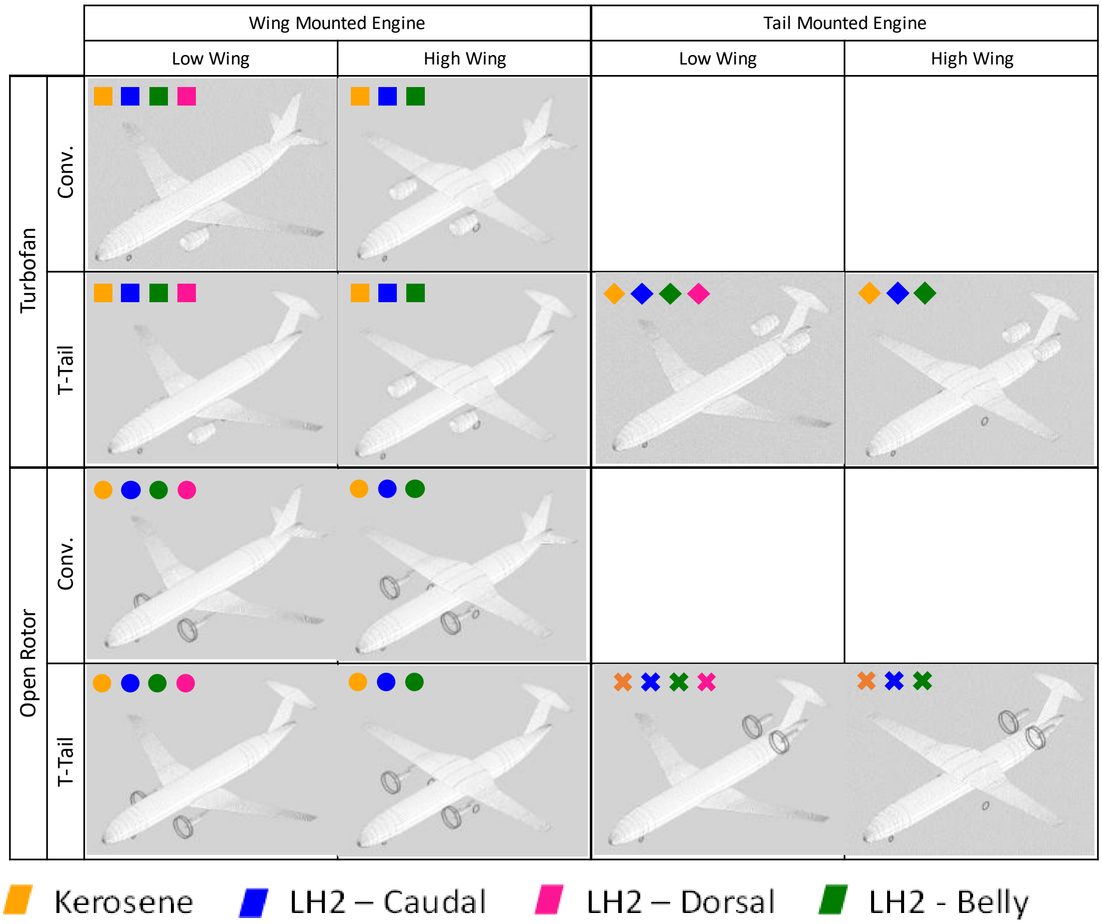


Figure 8 – Configuration-technology combinations (CTCs) for the case study

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 [14] and [15] respectively. The first scenario ECC 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.

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

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 [16] combined with the cost model by Markish [17] and the corrections used in [7]. 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 [1] 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, the potential cost savings are estimated also using the same cost model as used for individual designs. Each of the techniques presented in this paper was implemented in AirCADia Vision [18] (an in-house software tool for data visualization) and applied sequentially to the resulting design space.

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

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

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 $\eta_{vol} = \mathrm{V}_{\mathrm{LH}_2}/V$. Finally, the maximum mass of hydrogen that the tank can contain is obtained from $W_{LH_2} = \rho_{LH_2} V_{LH_2}$, where $\rho_{LH_2}$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 [1]. The geometries and mass distributions from [1] 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 to, 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 (10^6 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. 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.

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.

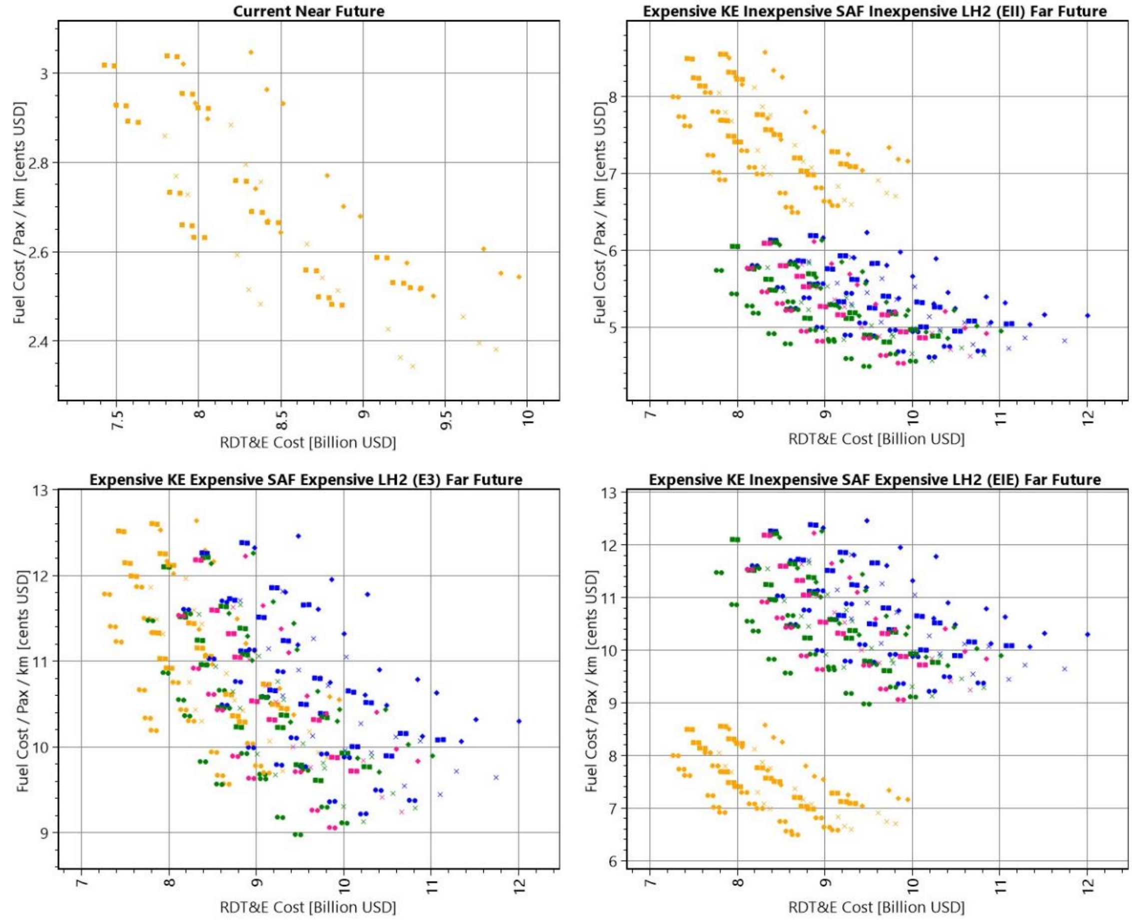


Figure 9 – Evolvability design space resulting from the use case.

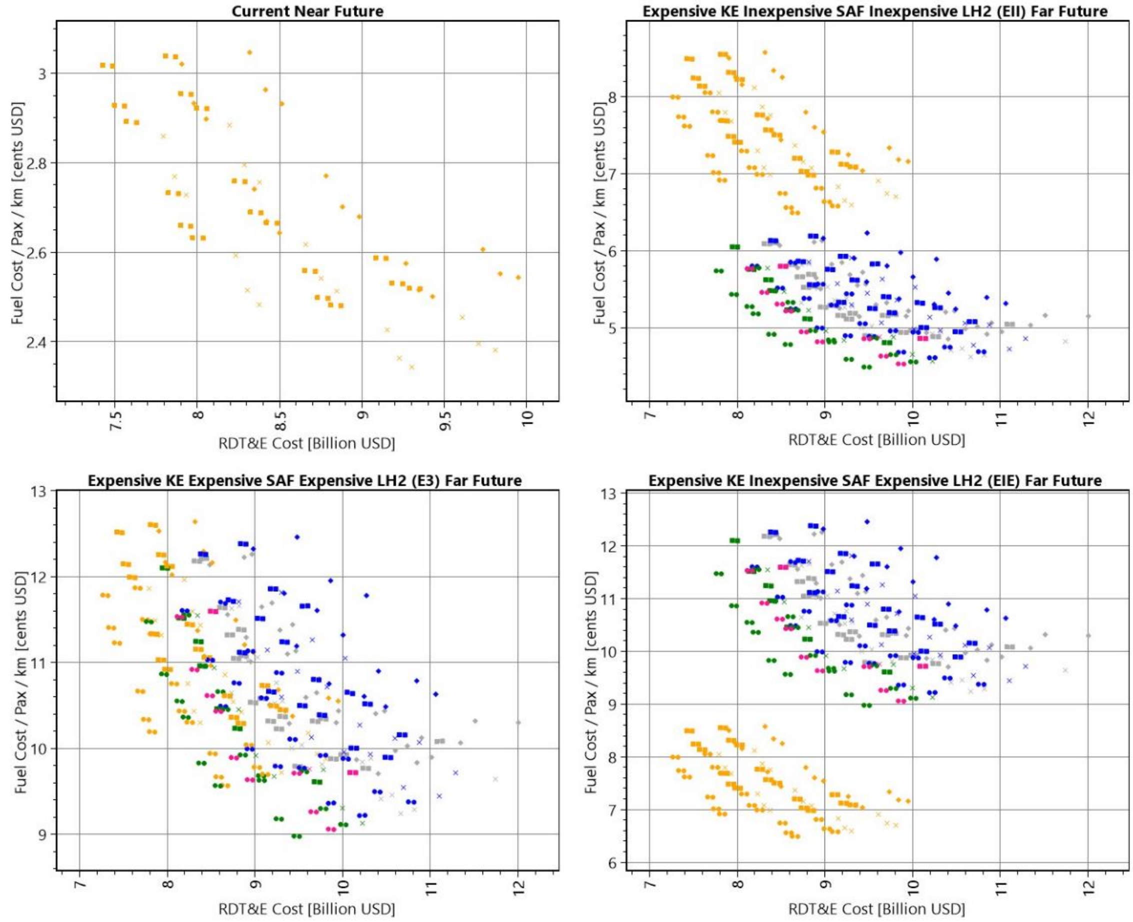


Figure 10 – Result from the application of interval dominance and maximality.

4.2.4 Design space after E-admissibility

E-admissibility, the last SBD technique results in the further elimination of 132 far-future designs as illustrated in Figure 11, which filters out around 60% of the 2045 designs. The less stringent fuel cost requirement from E-admissibility makes it easier to find aircraft that dominate in terms of fuel cost. Therefore, only the aircraft with the lowest redesign and RDT&E cost are kept. Since LH2 aircraft are more dissimilar with respect to the kerosine baselines, only caudal tank configurations survive (higher commonality as stretching the fuselage is easier than changing its height). There is one exception with the LH2 aircraft with belly fairing tank which has the lowest fuel cost in scenarios EII and E3, which is not filtered out either.

It must be noted that 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). However, a more detailed analysis could discard baselines that are less evolvable to the surviving LH2 options.

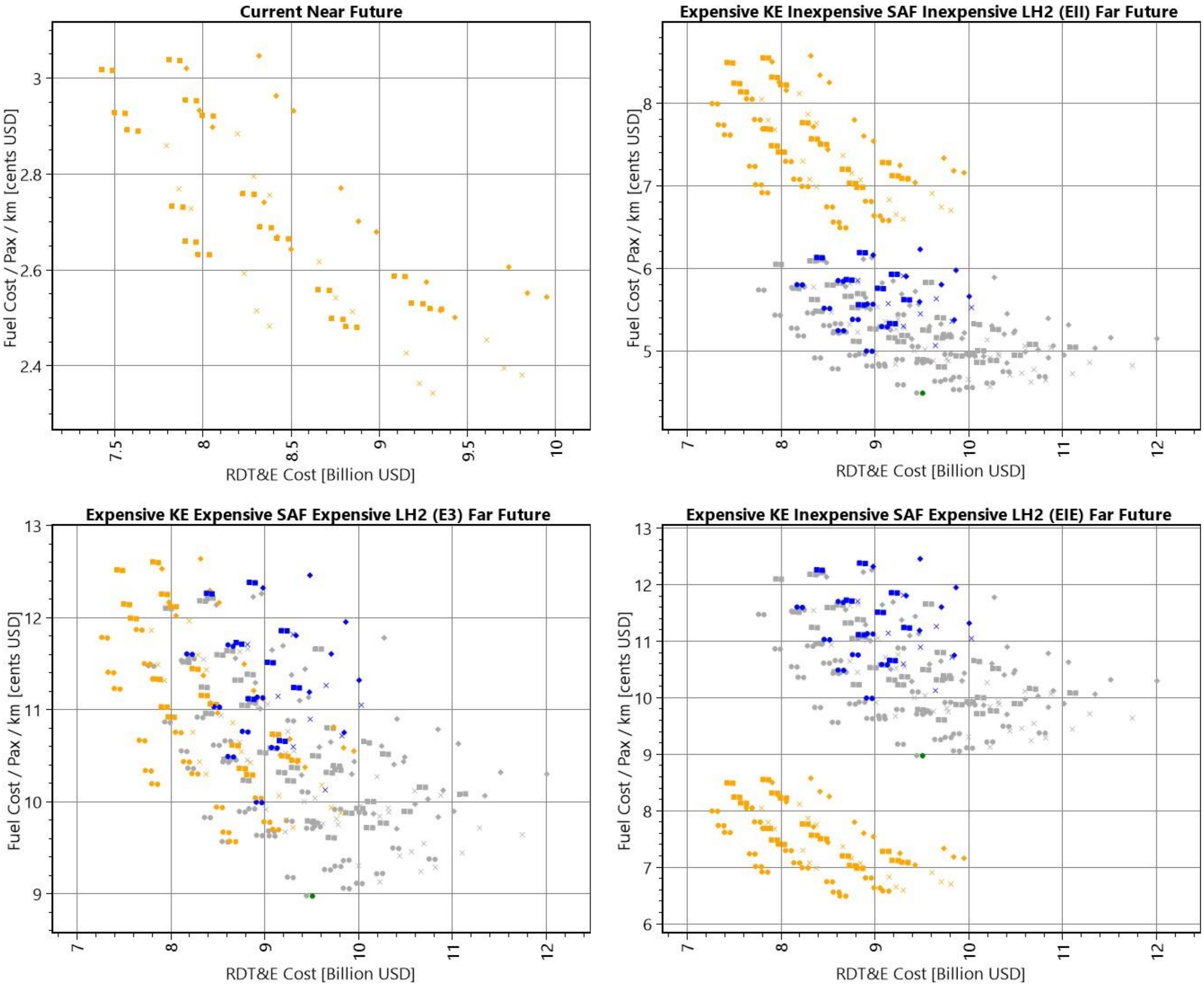


Figure 11 – Result from the application of E-admissibility.

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 12. These values have been chosen to try to remove designs with high fuel costs and that are difficult to evolve to. 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.

Table 4 – Constraint values.

Scenario	Maximum Fuel Cost [10^{-2} USD]	Maximum Redesign Effort [10^{9} USD]
EII	5.5	8.2
EIE	8.0	8.2
E3	10.0	7.6

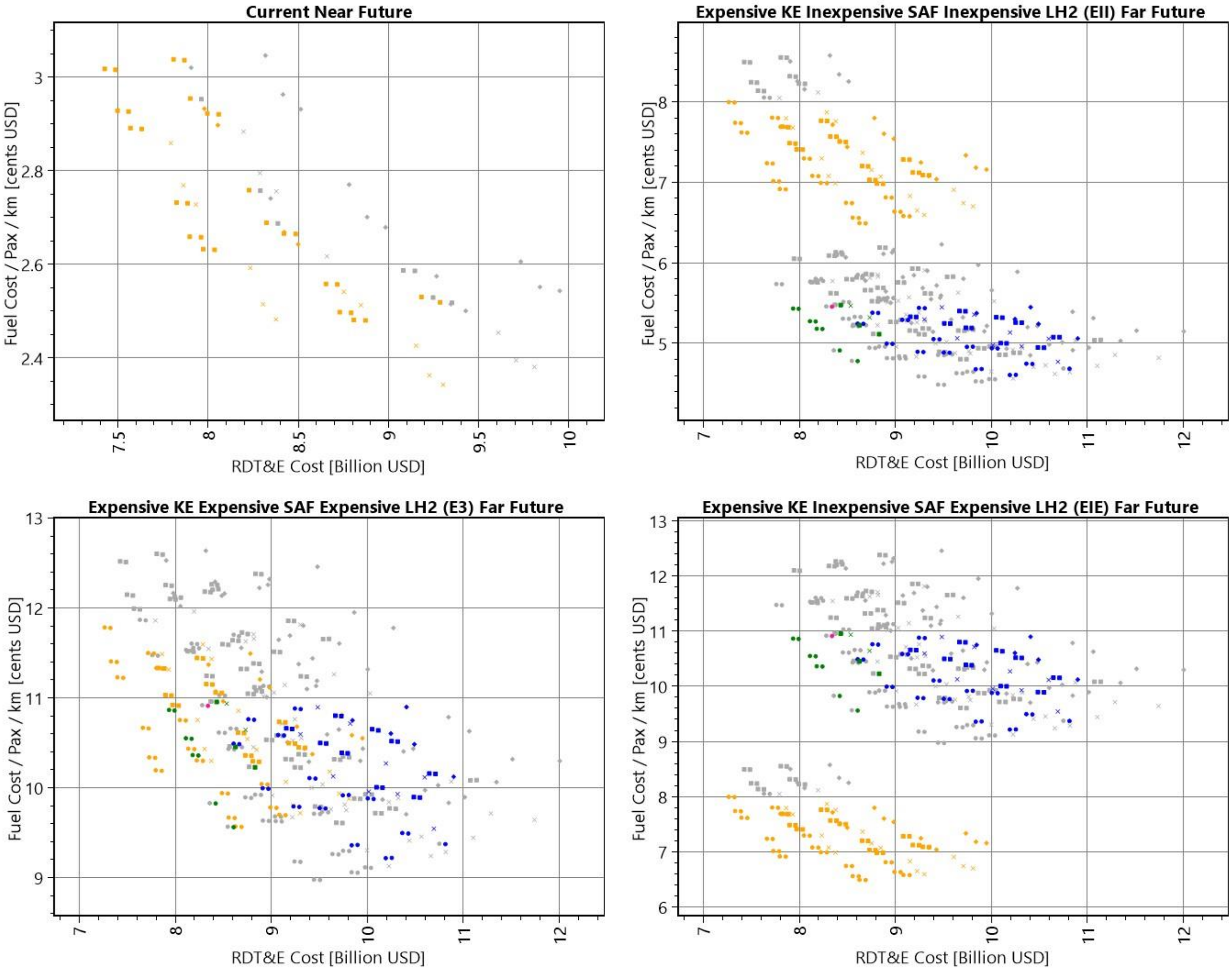


Figure 12 – Result from the application of constrain and union.

5. Conclusions and Future Work

In this paper, set-based design computational techniques to enable rapid and systematic 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 systematic 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 airframers 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.

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

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7. Data Availability Statement

Data supporting this study are openly available from the Cranfield research data repository under the name 'Data supporting "Set Based Design Techniques for Evolvability Exploration During Conceptual Aircraft Design"'.

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9. Copyright Statement

10. References

[1] Van Heerden, A. S. J. "Computational Techniques for Aircraft Evolvability Exploration during Conceptual Design," PhD Thesis. Cranfield University, 2019.
[2] Riaz, A. "A Set-Based Approach to Passenger Aircraft Family Design," PhD. Cranfield University, 2015.
[3] Riaz, A., Guenov, M. D., and Molina-Cristobal, A. "Set-Based Approach to Passenger Aircraft Family Design," *Journal of Aircraft*, Vol. 54, No. 1, 2016, pp. 310–326. https://doi.org/10.2514/1.C033747
[4] Rader, A. A., Ross, A. M., and Rhodes, D. H. "A Methodological Comparison of Monte Carlo Simulation and Epoch-Era Analysis for Tradespace Exploration in an Uncertain Environment," 2010.
[5] Ross, A. M. "Managing Unarticulated Value: Changeability in Multi-Attribute Tradespace Exploration," Massachusetts Institute of Technology, 2006.
[6] Lim, D. "A Systematic Approach to Design for Lifelong Aircraft Evolution," Georgia Institute of Technology, 2009.
[7] van Heerden, A. S. J. Sasi, S., Ghelani, R., Sanders, D. S., and Roumeliotis, I. "A Scalable Hydrogen Propulsion System for Civil Transport Aircraft," 2022.
[8] Malak, R. J., Aughenbaugh, J. M., and Paredis, C. J. J. "Multi-Attribute Utility Analysis in Set-Based Conceptual Design," *Computer-Aided Design*, Vol. 41, No. 3, 2009, pp. 214–227. https://doi.org/https://doi.org/10.1016/j.cad.2008.06.004
[9] Kennedy, B. M., Sobek, D. K., and Kennedy, M. N. "Reducing Rework by Applying Set-Based Practices Early in the Systems Engineering Process," *Systems Engineering*, Vol. 17, No. 3, 2014, pp. 278–296. http://www.scopus.com/inward/record.url?eid=2-s2.0-84904053125&partnerID=40&md5=103f18d40beeca4a634a5dc8b580e92d
[10] Rekuc, S. J., Aughenbaugh, J. M., Bruns, M., and Paredis, C. J. J. "Eliminating Design Alternatives Based on Imprecise Information," 2006.
[11] Walley, P. "Statistical Reasoning with Imprecise Probabilities," Chapman and Hall, New York, 1991.
[12] Levi, I. "On Indeterminate Probabilities," *The journal of philosophy*, Vol. 71, No. 13, 1975, pp. 391–418.
[13] Fitzgerald, M. E., and Ross, A. M. "Mitigating Contextual Uncertainties with Valuable Changeability Analysis in the Multi-Epoch Domain.," 2012.
[14] IATA. "Sustainable Aviation Fuel Output Increases, but Volumes Still Low," IATA Sustainability and Economics, Sep 01 2023. Retrieved 24 May 2024. https://www.iata.org/en/iata-repository/publications/economic-reports/sustainable-aviation-fuel-output-increases-but-volumes-still-low/
[15] European Aviation Safety Agency. "Current Landscape and Future of SAF Industry," EASA Eco, 2024. Retrieved 24 May 2024. https://www.easa.europa.eu/eco/eaer/topics/sustainable-aviation-fuels/current-landscape-future-saf-industry
[16] NASA Langley Research Center. "Flight Optimization System (FLOPS) Software v.9 (LAR-18934-1)."
[17] Markish, J. "Valuation Techniques for Commercial Aircraft Program Design," Master's thesis. Massachusetts Institute of Technology, 2002.
[18] Advanced Engineering Design Group, "AirCADia Vision," Cranfield University, 2024.