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Domain-driven multiple-criteria decision-making for flight crew decision support tool

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A B S T R A C T

During the flight, the crew might consider modifying their planned trajectory, taking into account currently available information, such as an updated weather forecast report or the already accrued amount of delay. This modified planned trajectory translates into changes on expected fuel and flying time, which will impact the airline's relevant performance indicators leading to a complex multiple-criteria decision-making problem. Pilot3, a project from the Clean Sky Joint Undertaking 2 under European Union's Horizon 2020 research and innovation programme, aims to develop an objective optimisation engine to assist the crew on this process. This article presents a domain-driven approach for the selection of the most suitable multiple-criteria decision-making methods to be used for this optimisation framework. The most relevant performance indicators, based on airline's objectives and policies, are identified as: meeting on-time performance, leading to a binary value in a deterministic scenario; and total cost, which can be disaggregated into sub-cost components. The optimisation process consists of two phases: first, Pareto optimal solutions are generated with a multi-objective optimisation method (lexicographic ordering); second, alternative trajectories are filtered and ranked using a combination of multi-criteria decision analysis methods (analytic hierarchy process and VIKOR). A realistic example of use shows the applicability of the process and studies the sensibility of the optimisation framework.

1. Introduction

During a flight, when a disruption (or an update on information affecting the trajectory prediction, such as a change of the weather forecast) arises, the crew might consider modifying the planned trajectory to optimise their operations. However, pilots face three main challenges: (i) consider comprehensive optimisation objectives by translating fuel and time values, which are the two main variables adjusted when trajectories are modified, into performance indicators relevant to airlines; (ii) account for the multi-objective nature of the problem, since different high-level goals are defined by airlines operators, such as minimising costs and maximising customer satisfaction; (iii) understand the expected deviations between planned and executed trajectories due to the stochasticity of the operational environment. Pilot3, an innovation action from Clean Sky Joint Undertaking 2 under the European Union's Horizon 2020 research and innovation programme, develops an optimisation engine, within a multiple-criteria decision-making (MCDM) framework, to assist the crew with this process.

Currently, available solutions to assist crew rely on systems embedded in electronic flight bags (EFB) or commercial off-the-shelf tablets. Historically, the first type of pilot support applications in such devices aimed to reduce the amount of printed documents pilots needed to carry-on. For instance, these applications allow digital briefings, performance calculations, digital flight logging and reporting, digital archive of navigation charts and airport diagrams. Examples of such systems include FlySmart[1] by Airbus, Boeing Onboard Performance Tool[2], eWAS Pilot[3] from SITA and Lido/mPilot[4] by Lufthansa Systems. Moreover, increased aircraft connectivity has enabled the use of more complex systems that can rely on cloud computation. For example, Pacelab Flight Profile Optimizer[5] considers the most up-to-date weather forecast to optimise the flight vertical profile.

All these systems, however, rely on pre-computed costs or merit functions that might not reflect the overall airline performance objectives, this would imply a multi-objective optimisation, nor provide a set of alternatives presenting the different trade-offs to be used by the pilot. Therefore, the pilot is faced with the challenge of interpreting the

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1 https://www.navblue.aero/product/flysmart-plus/.
2 https://services.boeing.com/flight-operations/navigation-solutions/onboard-performance-tool.
3 https://www.sita.aero/solutions/sita-for-aircraft/digital-day-of-operations/ewas-pilot/.
4 https://www.lhsystems.com/solutions-services/flight-deck-solutions/lidonavigation/lidompilot.
5 https://www.txtgroup.com/markets/solutions/pacelab-flight-profile-optimizer/.

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results of these systems, as the *costs* they provide might not reflect the overall situation.

Since Vilfredo Pareto first introduced the concept of Pareto optimality more than 120 years ago (Pareto, 1896), hundreds of researchers have addressed the problem of multi-objective (or criteria) optimisation. Dozens of methods, with subsequent refinements and extensions, have been proposed, especially in the last half-century, with thousands of scientific publications in a wide diversity of applications, including air transportation systems (Asadi et al., 2021). Yet, none of these methods or refinements can be said to be generally superior to all the others. In fact, selecting an appropriate MCDM method is by itself a MCDM problem, as seen in Guitouni and Martel (1998), Roy and Słowiński (2013) and Cinelli et al. (2022).

A multiplicity of aspects should be considered in this selection process, and, to a certain degree, many of the comparison criteria are difficult to quantify and are based on the expertise and preferences of the decision maker (DM). The features of the problem to be solved and the capabilities of the DM should be charted before a solution method can be chosen: some methods may suit some problems and some DMs better than others. For this reason, the selection of the method(s) must be domain-driven.

From a general point of view, the criteria to consider when evaluating alternative MCDM methods can be defined among others as (Hobbs, 1986):

- appropriateness: the method should be appropriate to the problem to be solved;
- ease of use: the effort and knowledge required from the analyst and the DM should be considered;
- validity: the method should measure what it is supposed to and the assumptions should be consistent with reality; and,

Nevertheless, some researchers have expanded the number of criteria to consider, such as Gershon and Durckstein (1983) who present 28 different criteria. According to Stewart (1992), three criteria can summarise the main aspects that need to be assessed: (i) the input required from the DM must be meaningful and unequivocal; (ii) the transparency of the method should be assessed; and (iii) the final aspect to consider is the method simplicity and efficiency.

During a flight, trajectory modifications are usually translated into changes on expected fuel and flying time, which will impact the airline's relevant performance indicators, leading to a complex MCDM problem. This paper provides a specific domain-driven approach to identify the criteria to be used, and to select the most suitable MCDM method(s). Based on consultation with Pilot3 project's Advisory Board, composed in part by airline representatives, dispatchers and pilots, the airline's most relevant objectives are first identified. A two-phase MCDM process is then started: first, Pareto optimal solutions are generated. Second, the obtained set of optimal alternative trajectories is filtered and ranked. The most suitable MCDM methods are chosen for both phases. The resulting optimisation framework is able to consider the multi-objective nature of the flight operations.

The paper is structured as follows: Section 2 introduces the current flight management practices with their limitations, as well as Pilot3 architecture configuration and its execution logic. Section 3 presents a literature review on potentially relevant MCDM methods. In Section 4, a domain-driven selection of the most suitable methods is conducted, considering a set of criteria for the different phases of the Pilot3 optimisation and decision-making processes. The paper then applies the selected methods and the global optimisation process to a realistic example in Section 5 and closes with conclusions and further work in Section 6.

2. Context of the study

When assessing different alternatives to adjust the trajectory during a flight, the pilot should consider the airline's targets and policies. These trajectory alternatives will result in the modification of two flight's parameters: its expected duration (time) and/or the amount of fuel to be used. However, airlines do not necessarily focus on these two indicators (fuel and time) but on other high-level objectives (see Section 4.1.1). This raises the need of multi-objective optimisation.

2.1. *Current tactical flight management*

Current Flight Management Systems (FMS) (re)compute flight trajectories by minimising a compound objective function that considers both fuel and time costs. In this two-objective optimisation problem, a weighting scalar – named cost index (CI) – is used to translate the variation in time and fuel into equivalent fuel usage. More specifically, the CI represents the ratio between time and fuel costs (Airbus, 1998). The CI could be considered as a proxy to the real indicators that are relevant to the airline. An update of the CI in order to consider the evolution of the operational environment is a complex task, and optimisation tools usually rely on prior-departure defined values (Cook et al., 2009; Gurtner et al., 2021). This means that the pilot (or ground dispatcher) must manually assess the trade-offs between alternatives.

Usually, the crew considers the outcome of these optimisations along other available data (such as the list of on-board connecting passengers, or previous experience on expected delay at arrival for that particular route), and estimate existing trade-offs, to decide if it is worth recovering a given amount of time using a certain amount of extra fuel. During this analysis and selection exercise, the crew might discard options, which they do not accept as valid (*e.g.* avoiding changing cruise altitude to a level where the pilot knows turbulence is experienced), and mentally rank the different possibilities to select the one that is considered best. Thus, the pilot is performing a manual iterative analysis of alternatives within a multi-criteria optimisation. On top of this, uncertainties on the realisation of the trajectories, due to the operational environment (*e.g.* actual weather encountered, holding at arrival, taxi-in time), might lead to sub-optimal decisions.

Finally, different airlines might have different policies in place. Yet, one common approach to manage larger disruptions is to estimate alternatives from the ground (*e.g.* monitoring flight operations by dispatchers) and to indicate to the pilot how they should operate (*e.g.* which CI to select). But even if the decision is performed on-ground, the same principles of multi-criteria considerations (and uncertainty) apply. In some instances, for example, when encountering small variations (*e.g.* weather update), or when considering tactical operational issues (*e.g.* where to perform the top of descent), pilots still maintain some autonomy. Moreover, pilots might still make decisions based on their own interpretation of priorities, which might vary from flight to flight. As previously indicated, current support systems are thus not able to consider the multi-objective dimension of the problem.

2.2. *Pilot3 – flight decision support tool*

Pilot3 aims to develop a prototype decision-support tool able to automatically generate alternative trajectories for the pilot, considering both airlines objectives and operational uncertainty. The system must present these alternatives in a simple and effective manner with the adequate level of information to understand the impact of the solutions on the objectives (and sub-objectives: criteria) and the involved trade-offs. Finally, the tool must be able to accept and consider inputs for the pilot, such as constraints. Pilot3 system is composed of five sub-systems:

- *Alternatives generator*, which computes different alternatives to be considered by the system. This is a multi-objective optimisation aiming at exploring Pareto solutions. The alternatives generator considers inputs from two independent sub-systems:

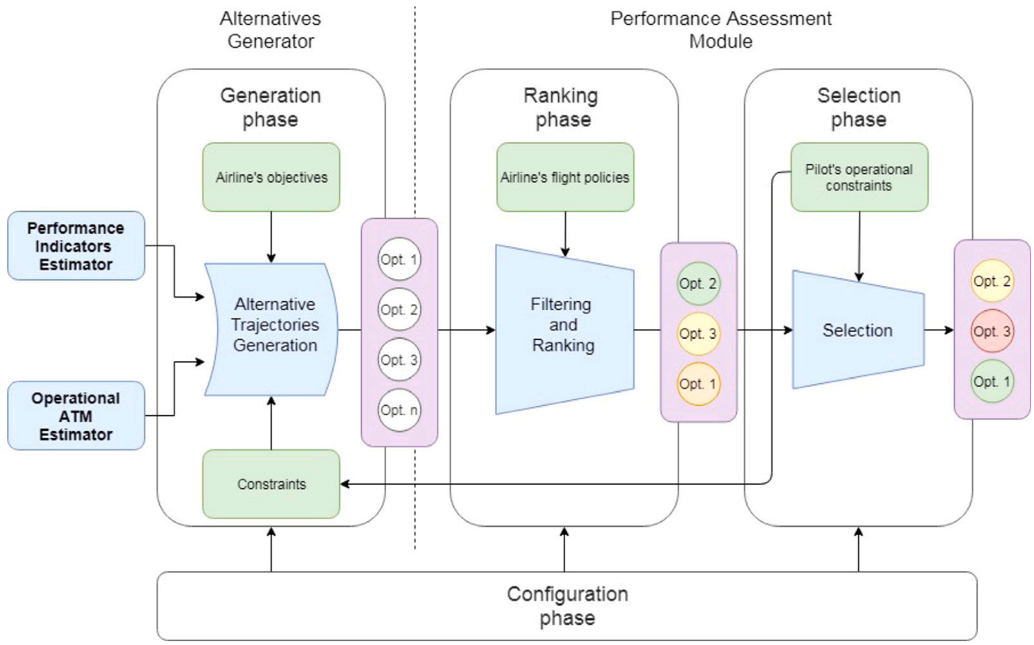

Fig. 1. Pilot3 execution diagram with example.

- *performance indicators estimator*, which provides information on how to estimate the impact of each solution for the different performance indicators (PIs) required to estimate the optimisation objectives relevant to the airline.
- *operational Air Traffic Management (ATM) estimator*, which estimates uncertainties linked to operational aspects. For example, estimation of expected arrival procedure, holding time, distance flown in terminal airspace due to arrival sequencing and merging operations, or taxi-in time.

• *Performance assessment module*, which filters and ranks the alternatives considering airlines and pilots' preferences. This is a multi-criteria decision analysis process and it is crucial to produce a support tool suitable for the tactical analysis and exploration of alternatives.
• *Human machine interface (HMI)*, which presents information to the crew in a simple but complete form to facilitate the understanding of the trade-offs, and where inputs are required by the DM to select and filter alternatives.

For more information on Pilot3 architecture the reader is referred to Pilot3 Consortium (2020a, 2022). The full optimisation process can be seen as an exploration of alternatives consisting in an optimisation framework including the following phases (as presented in Fig. 1):

1. Configuration phase, performed prior the flight to indicate airline's preferences and settings.
2. Generation phase, which aims at generating Pareto optimal solutions.
3. Ranking phase, required to filter and rank the set of generated optimal alternatives to facilitate its analysis by the crew.
4. Selection phase, where the pilot analyses the output of the system and considers if further operational constraints should be introduced in the optimisation.

2.2.1. Configuration phase

This phase will be performed by the airline prior to the flight. This could be done strategically, or some parameters could be selected at dispatching level on a flight-by-flight basis. The objectives of this phase are to select how the indicators and the operational ATM parameters should be estimated, and to configure Pilot3 to reflect the airline flight policy. For example, in case of alternative trajectories with equivalent impact on different criteria, which ones should be prioritised, etc.

2.2.2. Generation phase

This phase consists in solving a multi-objective optimisation (MOO) problem, in which the alternatives generator generates feasible trajectory alternatives based on airlines objectives and constraints. In a MOO problem, one might have a set of Pareto optimal solutions (*i.e.*, solutions equally acceptable from a mathematical point of view), and manually assessing all trade-offs arising from various objectives might be a complex and time consuming task. Moreover, different trajectories might lead to equivalent values on the objectives (*e.g.* two different profiles might produce statistically equivalent expected cost and on-time performance). Note that buffers could be considered when assessing if different values of the objective function are deemed as *equivalent*.

A first automatic generation and selection of candidate solutions will be produced by the alternatives generator. The alternatives generator uses a trajectory generation engine that considers (Prats et al., 2022; Delgado et al., 2022):

• objective functions as set by the airline key performance indicators;
• constraints: operational (*e.g.* airways) and ad-hoc defined by the pilot (*e.g.* 'do not provide solutions which imply an altitude change');
• environment data (*e.g.* weather, aircraft performance); and
• information from the *performance indicators estimator* and the *operational ATM estimator* on how to estimate these indicators and operational parameters. Note that uncertainty might exist on the PI to be estimated, *e.g.* for a given arrival time passengers might or not miss a connection depending not only on the current flight but on the status of the other flight in the network or airport processes.

Trajectory optimisers tend to generate one set of commands to produce a single alternative for a given trade-off between time and fuel (Dalmau et al., 2018; Prats et al., 2022). This reduces the number of alternatives generated in this generation phase. Rounding (*e.g.* considering the fuel consumption at a resolution of ten kilograms, or the arrival delay at a resolution of one minute), using buffers (*e.g.*

considering equivalent two trajectories whose expected costs lie within a given range, due to uncertainty or in order to provide some flexibility to the crew), and considering the addition of constraints may be used to increase the number of potential trajectories considered equivalent.

2.2.3. Ranking phase

Once a finite set of feasible and optimal alternatives is known, a multi-criteria decision analysis (MCDA) process takes place. The alternatives' ranking phase is the first part of the performance assessment module, and it consists in ranking the alternatives provided by the alternatives generator. This post-processing of the trajectories generated by the alternatives generator is performed to filter and pre-compute how and which alternatives will be presented to the pilot.

This phase will consider the airlines' policies with respect to the different key performance indicators (KPIs). For example, two solutions might provide the same cost but trading fuel cost and passenger cost. One solution might produce lower fuel usage with higher expected cost from compensation due to European air passenger rights regulation Regulation 261 (European Commission, 2004), while another alternative might use more fuel but reduce the expected cost due to passengers compensation, leading to equivalent total operating costs. In this case, even if the total expected cost for both alternatives is equivalent, the airline might define that passengers should be prioritised. Note that this ranking considers information defined in the configuration phase of Pilot3.

2.2.4. Selection phase

The final step of the performance assessment module considers pilot operational related aspects via interaction with the HMI. Information on the trajectories and their impact on the different indicators will be presented to the pilot, who will be able to explore the alternatives, rejecting solutions or, based on the information provided, adding new constraints and requesting a re-evaluation of the alternatives. Note that, this process implies at least the reevaluation of the ranking phase, as the finite set of alternatives used in the MCDA is modified, *e.g.* if alternatives are rejected. In some cases, it might also require the regeneration of alternatives, *e.g.* if constraints are added. This will trigger the generation phase, producing new alternatives, which will be added to the set available for the ranking phase.

3. Literature review of relevant MCDM methods

We present here a list of MOO methods that could be used in the generation phase where alternatives are generated based on airline's objectives, and of MCDA methods suitable for the ranking phase of the set of optimal alternatives, based on the airline's flight policies. More details on this literature review can be found in Pilot3 Consortium (2020b).

3.1. Generation phase: multi-objective optimisation methods families

In an MOO problem, a set of optimal solutions that are equally acceptable from a mathematical point of view (the Pareto optimal solutions) can be reached. Mathematically speaking, the problem is solved when the Pareto optimal set is found. In order to finally select one solution (or a subset of solutions), this set must then be ranked according to some preferences set by the decision maker(s).

A typical technique to select the preferred Pareto solution, consists in assigning to each individual objective a given weight, which reflects their priority or relative importance. Then, a linearly weighted sum of the individual optimisation objectives is typically done, yielding to a single compound optimisation objective, which can be solved with standard (single-objective) optimisation techniques. As mentioned before, the optimisation done in current FMS (and in general by most flight planning or dispatching tools) uses, as objective function, a linear weighted sum expressing the relative importance of fuel and time costs, given by a weighting parameter: the cost index. As presented below, this corresponds to an *a priori* MOO method.

Although the weighting technique is widely used in many applications (for its apparent simplicity), it presents several important drawbacks. The first one is that choosing the exact values for the different weights (if done beforehand) is not a straightforward task, since it is based either on an intuition of the user about the relative importance of different objectives, or on trial-and-error experimentation with different weighting values. Another problem is that once they have been established, the optimisation algorithm will find the best solution for that particular setting of weights, missing the opportunity to find other solutions that may represent a considered better trade-off between different objectives.

In this context, it is usual to perform *a posteriori* sensitivity studies, but altering the weighting vectors linearly does not ensure that the values of the objective functions also change linearly, making these sensitivity studies not obvious to conduct. Furthermore, this method has the limitation that it cannot find solutions in a non-convex region of the Pareto front, which can happen when involving non-linear constraints or objective functions (Miettinen, 1999). More difficulties appear when the objective functions involve summations/subtractions of terms representing different magnitudes (such as noise annoyance, emissions, fuel consumption, flight time, reactionary delay, or missed passenger connections), often with very different scales in their units of measurement (non-commensurable functions). It is true that this can be partially dealt with by normalising the different objectives, but this approach suffers from a subtle problem rarely discussed: in general there are several different ways of normalising, see for instance (Marler and Arora, 2005); the decision about which normalisation procedure should be applied tends to be ad-hoc, and different normalisation techniques may lead to significantly different results.

Trying to overcome (some of) these issues, a plethora of MOO methods have been proposed in the last half-century. There are different ways to classify MOO methods, according to different considerations. Here, we adopt the classification presented by Miettinen (1999), which is largely accepted in the literature. The classes are:

- Methods where *a posteriori* articulation of preference information is used (*a posteriori* methods).
- Methods where *a priori* articulation of preference information is used (*a priori* methods).
- Methods where no articulation of preference information is used (*no-preference* methods): these methods could be used when no opinions of the DM are sought, or when she cannot concretely define what she prefers: these are not applicable to the current problem since airlines show some preferences.
- Methods where progressive articulation of preference information is used (*interactive methods*): these can be used when the DM has enough time and capabilities to interact with the system, which is not applicable to the generation phase of the considered optimisation process.

3.1.1. Methods where a posteriori articulation of preference information is used

The underlying philosophy of *a posteriori* methods is that the Pareto front is generated first and presented to the DM, who will select the most preferred solution among a palette of alternatives. This approach could be useful when it is difficult for the DM to express an explicit approximation of her preferences (see *a priori* methods below). Several *a posteriori* methods are proposed in the literature, as outlined in Miettinen (1999) and Marler and Arora (2004). The two principal methods are the *weighting method*, which is a particular case of the scalarisation approach presented above, with example of refinement such as the exponential weighted criterion (Athan and Papalambros, 1996), and the *epsilon-constraint (or bounded objective function) method*, where one of the objective functions is selected to be optimised and all the others are converted into constraints by setting upper bounds to each of them (Haimes et al., 1971).

Hybrid methods are also possible, either combining the previous two, or introducing weighting functions in compromise programming, such as the weighted Tchebycheff approach, which is a popular method for generating Pareto optimal solutions (Bowman, 1976).

These *a posteriori* methods present the advantage that the DM does not need to provide any explicit input. Nevertheless, many shortcomings arise with this approach, one of the main ones being the difficulty of generating the Pareto front, which could be computationally too expensive. In this context, if only a limited number of Pareto solutions are presented, these methods can be ineffective, failing to provide evenly spread points accurately representing the complete Pareto optimal set. Finally, it is likely for the DM to have some difficulties in selecting from a large set of alternatives, and in many cases, presenting these alternatives in an effective way might also be an issue (especially when a large number of objectives are considered).

3.1.2. Methods where a priori articulation of preference information is used

In this case, the DM must specify her preferences, hopes or opinions before starting the process of generating the solutions. This can be articulated in many ways: in terms of goals, relative importance of different objectives, etc. It is worth noting that the weighting methods presented above (including the hybrid methods using weights, such as the weighted Tchebycheff approach) could be considered as *a priori* methods, if the DM specifies beforehand weights for each objective function representing her preferences. Similarly, the epsilon-constraint method can also be considered in this class if the bounds for each objective are also set *a priori*.

Although several authors have proposed methods or guidelines to help the DM to set weights (or bounding values) in an effective manner, understanding and correctly interpreting the conceptual significance of the weights is not always obvious for average DM. This is indeed the main difficulty of *a priori* methods, since the DM might not necessarily know beforehand what it is possible to attain in the problem, nor how realistic her expectations are.

A representative example of *a priori* methods would be the *value function method*, where the DM must be able to give an accurate and explicit mathematical form of the value function that globally represents her preferences (Keeney and Raiffa, 1976). Another classic one is the *lexicographic ordering*, where the DM arranges the objective functions according to their absolute importance. Then the most important objective function is optimised. If the problem has a unique solution, this is the solution of the whole MOO problem. Otherwise, the second most important objective function is optimised, but adding a new constraint in the problem to guarantee that the most important objective function preserves its optimal value found in the previous step. If this new problem has a unique solution, this becomes the solution of the whole MOO problem, otherwise the process continues as described above with the remaining objectives (Fishburn, 1974). The *hierarchical approach* is a modification of lexicographic ordering, where the upper bounds obtained when optimising more important objective functions are relaxed by so-called worsening factors (Bestie and Eberhard, 1997). In *goal programming*, the DM specifies (optimistic) aspiration levels for some of the objective functions (or all of them) forming goals, which are added in form of constraints in the optimisation problem (Charnes et al., 1955; Charnes and Cooper, 1961). Then, any deviations from these aspiration levels are minimised. *Physical programming* maps general classifications of goals and objectives, and verbally expressed preferences, to a utility function. It provides a mean of incorporating preferences without having to conjure relative weights (Marler and Arora, 2004). Finally, *weighting* and *weighted Tchebycheff methods* can be considered as *a priori* methods when weights are set up beforehand.

3.2. Ranking phase: multi-criteria decision analysis methods

Many approaches have been considered to solve MCDA problems. An overview of their main streams of thought and state of the art can for instance be found in Belton and Stewart (2002) and Figueira et al. (2016). Again the *weighted sum model* (WSM), or *weighted linear combination* (WLC) or *simple additive weighting* (SAW), is a well-known and simple MCDA method for evaluating a number of alternatives in terms of a number of decision criteria.

Other MCDA methods are distance-based, such as the *VIKOR method*, which is a combination of compromise programming and a weighting method, and was originally developed to solve decision problems with conflicting and non-commensurable objective functions (Opricovic, 1998; Opricovic and Tzeng, 2004, 2007). VIKOR ranks alternatives and determines the solution named compromise (referring to an agreement established by mutual concessions) that is the closest to the ideal from an initial set of (given) weights. In the context of airline transportation industry, VIKOR was used, along with other methods, to rank the best performing companies on financial and operational performance aspects (Gudiel Pineda et al., 2018).

Outranking methods belong to another MCDA family, and consist in comparing all couples of alternatives and determine which are preferred by systematically comparing the alternatives for each criterion, trying to establish outranking relations based on for how many components the decision maker judges indifference, weak preference, preference or no preference. These decisions can be complemented, for instance, with veto thresholds, which prevents a good performance in some components of the objective vector from compensating for poor values on some other components. Popular examples of outranking methods are *ELECTRE* (ELimination Et Choix Traduisant la REalité) (Roy, 1968; Figueira et al., 2005; Govindan and Jepsen, 2016) and *PROMOTHEE* families (Brans et al., 1986; Behzadian et al., 2010).

A similar approach to outranking methods is the *analytic hierarchy process* (AHP), primarily based on the pairwise comparison of matrices that the DM uses to establish preferences between alternatives for different criteria and the rating methods (Saaty, 1994). This method includes both the rating and comparison methods. Rationality requires developing a reliable hierarchic structure or feedback network that includes criteria of various types of influence, stakeholders, and decision alternatives to determine the best choice (Saaty, 1994).

Once again, hybrid interactive methods can also be used in MCDA, such as for example the combination of VIKOR and AHP methods, San Cristóbal (2011).

4. Domain-driven selection of methods

As presented in Section 2.2, the multi-objective optimisation framework used for the generation and selection of a trajectory to be flown by the crew is divided in different phases. Each one of these phases has different characteristics, which means that the method used at that stage of the optimisation will be different. Yet, some of the characteristics of the problem apply to all phases. To consider this, the process, to select the method(s) followed a two-stage approach, using input from different sources (see Fig. 2):

1. *General filtering*: the characteristics of the problem (tactical trajectory optimisation) are considered with inputs from the technical definition and high-level requirements of the Pilot3 prototype. Pilot3 is a Clean Sky 2 innovation action, and as such receives feedback from an industrial organisation (Thales AVS France SAS). This input is also considered as part of the requirements for the tool. Finally, an Advisory Board composed by airlines, pilots, dispatchers, experts and a representative of the European Network Manager (Eurocontrol) has been composed and a workshop was held to discuss the use of a decision-support tool like Pilot3, including aspects related to flight operations

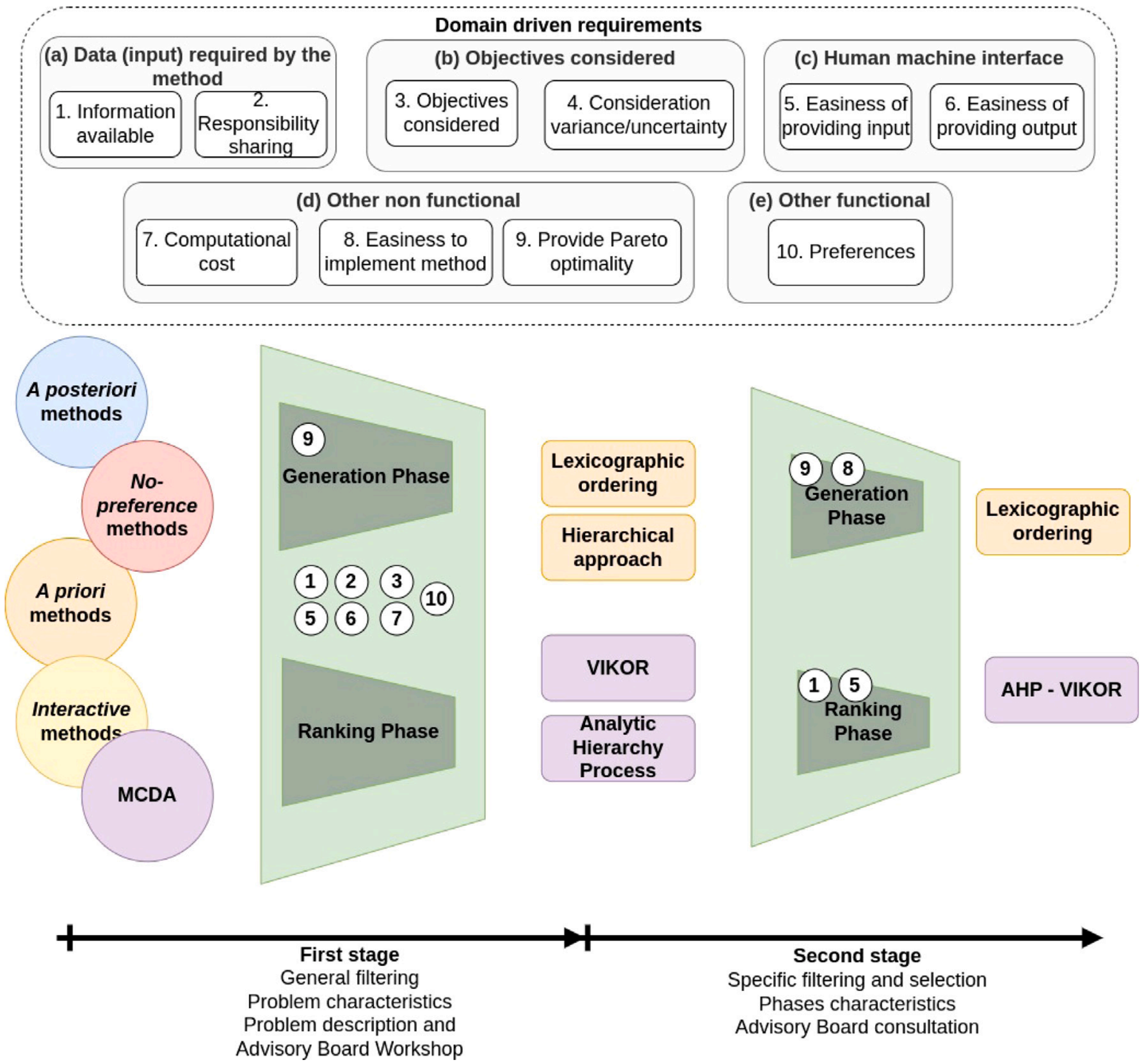

Fig. 2. Approach followed to select the optimisation methods for generation and ranking phases.

and performance monitoring, among others. Their input is considered in this first general filtering. This activity (detailed in Section 4.1) reduces the number of potential methods across all the optimisation (or decision-making) phases (generation, ranking and selection phase).

2. *Specific filtering and selection*: the specific characteristics of each phase are then considered. A follow-up consultation with the Advisory Board was conducted to validate the approach followed by Pilot3 on the definition of objectives, how the information is presented and available, etc, including as well views from pilots. After this process, a final benchmarking and selection of method process per phase was conducted. Section 4.2 presents in detail this selection process.

The filtering and benchmarking of the MOO and MCDA methods was conducted using 10 different criteria, grouped into 5 categories:

(a) Data (input) required by the method

1. the input needed for the method to function should be available
2. share of responsibility between users (dispatcher, pilot) to provide required inputs

(b) Objectives considered

3. ability to deal with high/low number of objectives
4. consideration of variability/uncertainty

(c) Human-machine interface considerations

5. easiness of providing the input required
6. easiness of providing the output required

(d) Other non functional considerations

7. computational cost of the method
8. easiness to implement the method
9. the method should provide a necessary and sufficient condition method for Pareto optimality

(e) Other functional considerations

10. other general preferences expressed by stakeholders

Some of the above ten criteria used in this selection apply to all phases and significantly restrict the number of possible candidate methods to be used, while others have been used to further discriminate among methods for a specific phase.

4.1. General filtering

This filtering of potential methods is based on the characteristics of the problem and applied to classes and specific methods. Some of the criteria used to select the method(s) to be implemented significantly restrict the number of potential methods that could be considered (see *First Stage* in Fig. 2). This filtering is organised in three categories: the characteristics of the objectives to be considered (Section 4.1.1), the data required for the optimisation method (Section 4.1.2) and the other considerations (Section 4.1.3).

4.1.1. Objectives considered

First, in order to analyse the most suitable MCDM methods to be used, it is crucial to understand which are the objectives that should be considered and their characteristics (see selection criteria b.3 *ability to deal with high/low number of objectives*).

When an airline is operating its flights, their flight policies are reflected in their airline Operations Manual (OM), which serves as a communication tool that conveys the airline flight policy, aviation department's goals and procedures to the entire company. Information given in the OM is communicated to the crew and flight dispatch personnel through different internal training programmes and communication channels of the airline. This OM will define (and limit) some of the actions to be performed when flights are disrupted.

Although flight policies may vary significantly from one company to another, there is a general consensus among the Advisory Board that these depend highly on:

- the airline network structure (hub-and-spoke network vs. point-to-point network),
- the characteristics of a particular flight (long-haul flight vs. short-haul flight), and
- the type of passengers served (individual-end consumers vs. high-end business travellers).

For instance, for an airline operating hub-and-spoke network, a viable connection of its transfer passengers is of the utmost importance. On the other hand, flight policies of airlines operating point-to-point networks are rather oriented towards fuel saving. However, airlines generally allow for certain level of flexibility in their flight policies in order to accommodate for some characteristics of the particular flight reflected in parameters such as, the seasonal traffic characteristics, specific flight requirements, and pilot's decision (to a limited extent).

The objectives defined in flight policies are translated into operations through the CI. Most policies have a standard component (*e.g.* default CI set to a given value for all flights), plus a variable component defined as a function of the flight/event/situation (*e.g.* override CI to a higher value). Note that CI is used as a proxy to manage/estimate the flight in order to meet the airline's objectives.

During a workshop with the Advisory Board, the most relevant performance indicators (PIs), which are considered when selecting the major aspects of airlines' objectives and policies, were identified. Six main indicators were selected as the most important ones (ordered by relative importance):

1. Fuel cost,
2. On-time performance (OTP),
3. Passenger missed-connections,
4. Time in holding,
5. (Cost) of passenger disruption, and
6. Crew and maintenance cost.

Fuel cost indicator is relevant as fuel costs still constitute a large portion of total operating costs. Although the sensitivity to fuel costs could vary significantly among airlines with different business models, there is still a clear consensus that fuel costs will play an important role in the future. Note that a tool such as Pilot3 will focus on the extra fuel cost used or saved tactically due to the management of the trajectory.

Passenger missed-connections are of high importance for airlines operating very complex and large networks, as it affects both hard-costs due to compensations (*e.g.* European Regulation 261) and soft-costs by directly altering the airline reputation (Cook and Tanner, 2015): passenger disruption costs are a direct monetisation of the cost due to passenger disruptions, including both connecting and non-connecting passengers. Passenger missed-connections were therefore identified as a proxy to the cost of passenger disruption due to their large contribution on these costs for flight where these missed connections arise. However, these two indicators can be grouped into IROPs (Irregular Operations) costs.

In addition to fuel cost, airlines are also keen to minimise other costs, such as crew and maintenance costs. Airlines may apply a variety of policies regarding crew wages and salaries. However, most of them acquire hourly-based policy, in which a pilot is paid based on the hours spent in the air or/and on the ground. With strict policies regarding pilot working hours in place, disruptions may lead to increased crew costs and additional scheduled inefficiencies. Additionally, regular aircraft maintenance checks are performed after predefined flight hours, requiring a large majority of the aircraft's components to be inspected and/or replaced (Cook and Tanner, 2015).

The time in holding is usually out of the control capabilities of airlines. However, the prevalence of holdings and sequencing and merging procedures (*e.g.* tromboning) could lead to sub-optimal decisions (*e.g.* speed up a flight to recover delay to end up in a holding stack). This is therefore not an indicator that airlines can act to reduce, but a parameter that should be considered when optimising the trajectories as part of the uncertainty in the system. For this reason, in the Pilot3 framework, it is part of the indicators estimated by the operational ATM estimator.

In addition to fuel costs, airlines are also concerned about the on-time performance, as this indicator is very often used to reflect the level of service provided to passengers. Nowadays, OTP is being monitored on a flight basis by most airlines in order to verify compliance with OTP targets defined in their respective airline flight policies.

After this analysis of the different indicators, it was deemed that four of them (fuel cost, passenger missed-connections, cost of passenger disruption and crew and maintenance costs) could be directly translated into cost. On-time performance is a binary indicator, which was difficult to monetise and therefore is kept independently. Finally, time in holding, is considered as part of the uncertainty in the optimisation: the trajectory generator deterministically computes the trajectory until reaching FL100 in the arrival descent, but the final cost function is calculated with respect to the arrival time at gate. Therefore the cost of delay function should take into account the processes and uncertainty between this point and the gate (holding, sequencing and merging and taxi-in time).

It has thus been established that the main high-level objectives relevant for an airline can be reduced to only two:

- Cost: complex objective built from the aggregation of three KPIs:
  - cost of fuel,
  - cost of IROPs, including hard and soft passenger costs (considering connecting and non-connecting passengers), and
  - other costs, which account for extra crew and maintenance costs, but most importantly for reactionary costs.
- On-Time Performance: considered as a binary variable (*i.e.*, achieve arrival delay $\leq$ 15 min or not).

From an optimisation point of view, two objectives (cost and OTP) are therefore considered. Note that to estimate the cost objective, its components need to be estimated and to this end, low level indicators (*e.g.* number of passengers missing connections) will need to be estimated too. This is the role of the performance indicators estimator.

The characteristics of these two objectives have a significant impact on the Pareto analysis of the solutions. By definition (it is generally

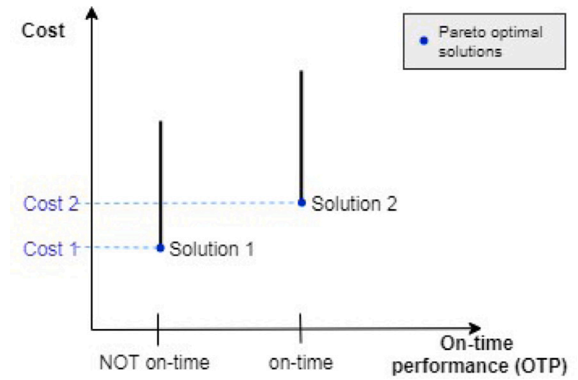

Fig. 3. Pareto optimal solutions example total cost vs. on-time performance.

accepted that a flight meets OTP if it arrives before its scheduled in-block time + 15 min[6,7]), OTP is a binary objective function, thus the problem yields to 0, 1 or 2 possible Pareto efficient solutions. It could happen that the given constraints on the trajectory make the optimisation infeasible. However, this should not be the typical situation, unless the pilot is interacting with the system, asking for potential solutions while setting different operational constraints in altitude, speed, etc. In some cases, it would not be possible to tactically recover enough time to achieve OTP. Therefore, only one Pareto efficient solution would exist and the decision-support tool should focus on minimising the total cost. In other cases, a trade-off may exist between achieving OTP and reducing the cost.

Fig. 3 presents an example of one case where such trade-off exists. There is a set of trajectories that do not achieve OTP, each one of them with an expected different cost; and a second set of trajectories meeting OTP, with another set of costs. The two highlighted points of Fig. 3 are the Pareto optimal solutions.

A follow-up consultation with the Advisory Board confirmed that providing to the pilot information on the 'extra-cost' of achieving OTP with respect to the minimum cost, which does not respect the OTP, *i.e.*, difference in cost between Solution 2 and Solution 1 in Fig. 3, would be desirable and of great interest for airlines. Therefore, it is considered that there is no preference from the DM between the two objectives.

Due to the nature of the MOO problem, with only two objectives and up to two possible Pareto optimal solutions, the way to address this becomes almost trivial and straightforward: the multi-criteria support-decision tool will first optimise the trajectory considering only cost. If OTP is not achieved with the optimised solution, then the alternatives generator will try to impose achieving OTP as a constraint, to compute the extra cost that it would represent (*i.e.*, finding Solution 2 from Fig. 3), in case this is achievable.

Finally, note that even if the problem has been reduced in terms of objectives, trade-offs might still occur with respect to the KPIs composing the cost objective (*i.e.*, cost of fuel, IROPs and other costs), and that irrespectively of these potential trade-offs, more than one trajectory/solution could lead to a statistically equivalent total cost. To allow the alternatives generator to generate several alternatives, and avoid getting only the solution leading to the absolute minimum total cost, cost buffers (from 10 to 300€, see Section 5.3) have been considered. To do so, if we consider A the set of all trajectory alternatives α_i (including all possible arrival times and total costs), $C(\alpha_i)$ the total cost of alternative α_i, and b the allowed economic buffer, the set of alternatives considered to have equivalent total costs, (within the margin of the cost buffer) is obtained as:

$$\{\alpha_i \in A \,|\, C(\alpha_i) \leq \min(C(A)) + b\} \tag{1}$$

These *cost equivalent* alternatives will then be ranked based on KPIs preferences. Note that the generation of alternatives, even with these cost buffers, will produce a small set of trajectories due to the nature of the trajectory generators used, as presented in the example of Section 5.3 (Dalmau et al., 2018).

4.1.2. Data required

Once KPIs and objectives are identified, it is important to capture the preferences of the airlines of how to provide the input necessary to the optimisation, in order to ensure the appropriate MOO method to be selected (see criteria a.1 *input needed for the method to function should be available*, a.2 *share of responsibility between users (dispatcher, pilot) to provide required inputs*, c.5 *easiness of providing the input required* and e.10 *other general preferences expressed by stakeholders*).

Experiments in psychology show that the amount of information provided to the DM has a crucial role (Kok, 1986). Though more information may increase the confidence of the DM in the solution obtained, it may also lead to less percentage of the information used, and thus it might worsen the quality of the solution. In this context, some considerations on the visualisation of the results should also be considered (criteria c.6 *easiness of providing the output required*). The graphical representation of alternatives and the human machine interface with the DM plays an important role and constitutes an important challenge itself.

While airlines generally have a clear idea that OTP is important for them, and they can easily perceive that arriving early/late is not desirable, they acknowledge it is very hard to quantify this in terms of cost, since the implications of arriving early/late are many (*e.g.* waiting for gate, implications to handling processes, delay for passengers, crew management, etc.). For this reason, OTP has been kept as an independent objective (not monetised). This also implies that it is difficult to compare cost and OTP in a quantified manner.

Further consultation with the Advisory Board was conducted to identify if priorities could be established among the sub-objectives (criteria) and indicators of the total cost. It was identified that alternatives such as target setting, or quantification of goals was not suitable for the criteria of cost (cost of fuel, cost of IROPs and other costs). On the contrary, *ranking* their relative importance was the only easily available input for the DM, *i.e.*, indicating the order of importance of the sub-costs if the total cost is kept constant, for example, if cost of fuel can be traded for cost of IROPs. This ranking should be defined as part of the configuration of the Pilot3 prototype (*e.g.* at dispatcher or strategic level).

4.1.3. Other considerations

Despite current computational capabilities available, finding an acceptable solution to the MCDM problem may still be a limiting factor, especially for (quasi) real-time applications and/or large problems with many objectives and constraints. For real-time calculations needed in this type of tactical decision-support tool, the computational cost of *a posteriori* method is assumed to be prohibitive (criteria d.7 *computational cost of the method*). This, and the fact that the DM would have difficulties selecting from a large panel of Pareto solutions (criteria c.6 *easiness of providing the output required*) were important enough reasons to disregard *a posteriori* methods for the present application.

Based on these considerations, *a priori* MOO methods seem suitable for the generation phase, where flight policies are set up beforehand, whereas MCDA methods could be of used for ranking and selection phases, where additional input from the decisions makers could be obtained.

[6] OAG, On-time performance, https://www.oag.com/on-time-performance-airlines-airports.

[7] Bureau of Transportation Statistics, 2021, Airline On-Time Performance and Causes of Flight Delays, https://www.bts.gov/explore-topics-and-geography/topics/airline-time-performance-and-causes-flight-delays.

4.1.4. Shortlist of optimisation methods

Within the available MOO *a priori* methods described in Section 3.1.2, goal programming combines the drawbacks of not always leading to Pareto solution (criteria d.9 *the method should provide a necessary and sufficient condition method for Pareto optimality*), and the fact that, though goal-setting seemed at first to be an understandable and easy way of making decision, feedback from the Advisory Board showed that it was not easily available for the airlines, even at planning level (criteria a.1. *input needed for the method to function should be available* and c.5 *easiness of providing the input required*).

After a follow-up consultation with the Advisory Board, it was made clear that airlines would not be able to provide numerical targets for KPIs, nor numerical bounds, nor relative weights of importance between KPIs. Only ranking of importance would be an available input from the DM.

Taking into account these restrictions, the following optimisation methods were identified as suitable candidates, for *a priori* methods:

- *Lexicographic ordering*: DM arranges objective functions according to their absolute importance. Then the most important objective function is minimised (or maximised). If the problem has a unique solution, it is the solution of the whole MOO problem. Otherwise, the second most important objective function is minimised, but adding a new constraint in the problem to guarantee that the most important objective function preserves its optimal value found in the previous step.
- *Hierarchical approach*: Modification of lexicographic ordering, where the upper bounds obtained when minimising the most important objective function are relaxed by so-called worsening factors. These relaxations allow to trade off higher prioritised objectives in front of lower prioritised ones, exploring in this case, a widest area of the Pareto front containing solutions that can be more interesting to the DM.

These methods could be used in the generation phase of the optimisation process: from airline flight policies obtained in the configuration phase of Pilot3, prioritisation of cost or of OTP is decided (with or without trade-off) and a (reduced) subset of alternative trajectories is generated by the alternatives generator.

After this phase, several alternative trajectories may have been obtained, leading to equivalent values of both objectives (cost and OTP), but showing differences with respect to other KPIs such as cost of fuel, IROPs, etc. Once this set of alternatives has been generated, ranking and selection is performed by the performance assessment module in interaction with the human-machine interface. The ranking of alternatives is based on airline preferences in term of cost of fuel, IROPs and other cost. In the ranking phase, using additional input from airline policies and in the selection phase, where the pilot would have a mechanism allowing to compare and rank the optimal solutions, the following MCDA methods may be used:

- VIKOR: combination of compromise programming and weighting method. VIKOR ranks the set of available alternatives and determines the solution named *compromise*, that is the closest to the ideal from an initial set of (given) weights. Though initial weights of relative importance of the attributes would be needed, and that in our case they seem impossible to obtain directly from airlines, these weights may be computed using a process similar to AHP, which is described next.
- Analytic Hierarchy Process: generates a weight for each criteria according to the DM pairwise comparisons of criteria: the higher the weight, the more important the corresponding criteria. Next, for a fixed criteria, AHP assigns a score to each alternative solution according to pairwise comparisons of the alternatives based on that criterion provided by the DM: the higher the score, the better the performance of the option with respect to the considered criteria. Finally, AHP combines the criteria weights and the alternative scores, thus determining a global score for each alternative, and a consequent ranking. The global score for a given alternative is a weighted sum of the scores it obtained with respect to all the criteria. It can either be used alone or combined with the VIKOR method. This approach is applicable to our case given that the number of considered criteria and available trajectories would be limited; indeed, for problems with many criteria and available alternatives, it may require a large number of evaluations by the user.

4.2. Specific filtering and selection

Focusing on the particularities of the different phases of the optimisation process, and after obtaining further feedback from the Advisory Board, a selection of methods is performed for each of these phases, and illustrated on the *Second Stage* of Fig. 2.

4.2.1. Generation phase

This phase aims at generating a (reduced) subset of alternative trajectories based on the main two objectives to consider from the optimisation point of view: cost and OTP. This will enable the possibility to tactically assess (either by the crew or by the dispatchers) the trade-off between extra cost (*e.g.* by burning extra fuel) and achieving on-time performance.

Based on this feedback and considering that the MOO problem can present up to two different Pareto points, we propose, for the generation phase, to compute both (if they exist). Lexicographic ordering will be used to generate these Pareto optimal solutions. Since one of the objectives considered is binary (achieving or not OTP), using lexicographic ordering allows us for an easy exploration of the Pareto front (d.8. *easiness to implement the method*), as in an *a posteriori* method, with no relaxation factors needed (d.9 *the method should provide a necessary and sufficient condition method for Pareto optimality*). An *a posteriori* lexicographic ordering is thus used in this case, where the two possible combinations of the objective rankings are considered:

1. Consider as first objective the total cost and as second objective achieving OTP. This will provide at least one possible trajectory (note that several ones could lead to equivalent total costs), which minimises the total cost (first objective); if OTP is reachable with that cost, only trajectories meeting this objective will be generated (second objective). This strategy is, therefore, robust against potential local minima issues: in situations presenting a flat Pareto front (*i.e.*, Fig. 3 with cost 1 = cost 2) ensuring that the selected solution minimises cost and also achieves OTP.
2. If OTP is not achieved during the first step, then a possible trade-off might exist between cost and OTP. To generate this possible point, achieving OTP will be set as a constraint (first objective fulfilled) and cost will then be minimised (second objective). The computed trajectory(ies), if any, will be kept as a trade-off alternative(s) to the one(s) generated in the first step (*i.e.*, they will have a higher cost than the previous ones but will achieve OTP). Note that in some cases this might not be possible: *e.g.* no trajectory can ensure OTP as the delay is already too high.

The generation phase thus aspires to provide several alternative trajectories leading to equivalent minimum total costs or at a higher cost but allowing reaching OTP.

4.2.2. Ranking phase

When starting the ranking phase of the optimisation process, several alternative trajectories have been generated (all Pareto points) and the objective is to rank and select them following the preferences of the airlines. The MCDM problem is now a MCDA problem, involving a limited number of alternatives.

This ranking phase will aim at disaggregating the total cost into sub-costs (or criteria), and at providing ranking of the alternative trajectories based on preferences established by airline policies. Depending on how these preferences can be expressed, different optimisation methods could be selected. It is thus fundamental to capture if and how airlines can share these preferences (see criteria a.1 *input needed for the method to function should be available*). It was already established that ranking of KPIs was the only easily available way of sharing preferences, but further consultation with the Advisory Board indicated that it should be possible to rate the most important KPIs two by two. For example, they should be able to decide what cost component is more important between fuel and IROPs:

- fuel is the more important; or
- IROPs is the more important; or
- fuel and IROPs are equally important.

A more detailed grading of relative importance (*e.g.* indicating if this importance is moderate, strong, very strong), or numerical relative importance on a scale (*e.g.* from 1 to 5), were deemed too complex.

Based on these characteristics for the ranking phase (possibility to provide a simple ranking between criteria but no specific weights; and having a limited number of criteria, see c.5 *easiness of providing the input required*), we propose to use a compromise ranking method (AHP-VIKOR). Both methods (AHP and VIKOR) are combined following a similar process as in San Cristóbal (2011).

The VIKOR method is an effective tool in multi-criteria decision making, particularly in situations where the DM is not able, or does not know how to express her preference at the beginning of system design. Even if airlines are able to express their preferences, when coming to cost components it is not always an obvious decision to decide which one is the overall most important (if any). When combining VIKOR with AHP, their properties allow to solve problems with the following characteristics, which match ours:

- Compromising is acceptable for conflict resolution: at this stage of the problem, this is the case, else, if a single KPI overpasses all others, the selection of the corresponding trajectory is obvious.
- The DM is willing to approve solution that is the closest to the ideal (ideal or utopia point would correspond to the minimum possible value of each cost KPI).
- The criteria are conflicting: *e.g.* going faster to decrease IROPs cost will increase fuel consumption.
- The alternatives can be evaluated according to all established criteria: here, all KPIs can be computed for each trajectory.
- The DM's preference is expressed by weights, given or simulated: here, given that the weights cannot be directly given by the DM, the two-by-two preferences between KPIs will allow to assign weights of relative importance of KPIs, using AHP.

For our optimisation problem, in some cases all alternatives will achieve OTP, in others none will, a third possibility will be to solve two separated problems: rank the best options for OTP and rank the best options for minimising the total cost. In each case, the J alternative trajectories are denoted as $\alpha_1, \alpha_2, \ldots, \alpha_J$. For alternative α_j the rating of the ith attribute is denoted by f_{ij}. Thus, f_{ij} is the value of the ith objective function for the alternative α_j. Finally let us define n as the number of criteria, 3 in our case. Then, the resulting compromise ranking algorithm AHP-VIKOR has the following four steps.

Step I: Identify the criteria and compute the best (f_i^*) and worse (f_i^-) values of each criterion.

Step II: Compute $s_j = \sum_{i=1}^{n} w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-}$ and $r_j = \max_i \left[w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \right]$ for $j = 1, 2, .., J$, where w_i are the weights of criteria, expressing the DM's preference as the relative importance of the criteria. The weights of relative importance of the attributes can be assigned using AHP (Saaty, 2000). The steps for obtaining the weights w_i are explained below and partly follow the approach from Rao (2008):

1. Find out the relative importance of the different criteria. To do so, one has to construct a pairwise comparison matrix using a scale of relative importance. The judgements are usually entered using the fundamental scale defined in AHP. A criterion compared with itself is always assigned the value 1 so the main diagonal entries of the pairwise comparison matrix are all 1. The numbers 3, 5, 7, and 9 would correspond to the verbal judgements "moderate importance", "strong importance", "very strong importance", and "absolute importance". Recall that, after surveying a panel of DM (airlines, pilots, etc.), it was made clear that defining such a differentiated judgement to compare the kinds of cost would not be possible. Thus only one level of relative importance is kept: "more important", and the value 3 is assigned. Note that higher values could be used, but they lead to lower consistency results, see sub-step 3 and Section 5.5, where the impact of the value of relative importance is also discussed. For example, here, we consider ranking preference input obtained from the airline policies (pre-flight) under the following form:
   - IROPs cost (attribute 2) is more important than cost of fuel (attribute 1).
   - Cost of fuel (attribute 1) is more important than other costs (attribute 3).
   - IROPs cost (attribute 2) is more important than other costs (attribute 3).

   Assuming n attributes, the pairwise comparison of attribute i with attribute j yields a square matrix $\mathbf{A}_{n \times n}$ where a_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$. For our 3-attribute case, we thus obtain $\mathbf{A} = \begin{pmatrix} 1 & 1/3 & 3 \\ 3 & 1 & 3 \\ 1/3 & 1/3 & 1 \end{pmatrix}$
2. Compute the weight vector $\mathbf{w} = [w_1, w_2, .., w_n]$ from the pairwise comparison matrix $\mathbf{A}$: first, $\mathbf{A}$ is normalised, into a new matrix, $\mathbf{A}_{norm}$, then w_i is computed as the average of the entries in row i of $\mathbf{A}_{norm}$. Here we obtain: $\mathbf{w} = [0.29, 0.57, 0.14]$. That is, in this example, and as expected, the highest weight is assigned to IROPs cost, followed by cost of fuel and finally other costs. Note again that if the airline was willing to, it could give more details on the level of the relative importance (*e.g.* cost of fuel is strongly more important than other costs, IROPs cost is moderately more important than cost of fuel, etc.) or rate them with a numerical scale, in order to obtain a finer tuning of the relative weights of the KPIs.
3. Check the consistency of the pairwise comparison matrix $\mathbf{A}$ and obtained weights w_i, see San Cristóbal (2011) for the details. Here we obtain a satisfying consistency value.

Step III: When applied to a given set of alternatives, the obtained compromise solution aims to provide a maximum group utility of the majority (by minimising the weighted sum of the differences between KPI values and their respective minima), and a minimum individual regret of the opponent (by minimising the maximum difference between a KPI value and its minimum).

To that end, we compute $q_j = v \frac{s_j - s^*}{s^- - s^*} + (1 - v) \frac{r_j - r^*}{r^- - r^*}$, where $s^* = \min_j s_j$, $s^- = \max_j s_j$ and respectively for r^* and r^-, and v is introduced as a weight for the strategy of maximum group utility, whereas $(1 - v)$ is the weight of the individual regret. The solution obtained by $\min_j s_j$ corresponds to a maximum group utility ("majority" rule), and the solution obtained by $\min_j r_j$ to a minimum individual regret of the "opponent". Normally, the value of v is taken as 0.5, which is the value chosen here. However, v can take any value from 0 to 1, and the sensibility of the method to the choice of v is checked in Section 5.5.

Step IV: Rank the alternatives, by sorting the values s_j, r_j, and q_j in increasing order into three ranking vectors $\mathbf{s}$, $\mathbf{r}$ and $\mathbf{q}$. Propose as a

Table 1
Flight characteristics.

Aircraft	Origin	Destination	SIBT	Number of passengers	Connecting passengers	Nominal CI	Cruise flight level
A320	Madrid (LEMD)	Frankfurt (EDDF)	9h10	171	65	10 kg/min	FL380

compromise solution the alternative $\alpha^{(1)}$, which corresponds to the best ranked by $\mathbf{q}$ ($\mathbf{q}(1)$, the first position of $\mathbf{q}$, is its minimum value), if the following two conditions are satisfied:

(1) Acceptable advantage: $\mathbf{q}(2) - \mathbf{q}(1) \geq D_J$, where $D_J = 1/(J-1)$;
(2) Acceptable stability in decision-making: alternative $\alpha^{(1)}$ must also be the best ranked by $\mathbf{s}$ or/and $\mathbf{r}$.

If one of the conditions is not satisfied, then a set of compromise solutions is proposed, which consists of:

- Alternative $\alpha^{(1)}$ and $\alpha^{(2)}$ (second best ranked by $\mathbf{q}$) if only condition (2) is not satisfied, or
- Alternatives $\alpha^{(1)}, \alpha^{(2)}, \ldots, \alpha^{(M)}$ if condition (1) is not satisfied. $\alpha^{(M)}$ is determined by looking for the maximum value of M satisfying the relation $\mathbf{q}(M) - \mathbf{q}(1) < D_J$.

If neither condition is satisfied the set of solutions would be the complete initial set.

4.2.3. *Selection phase*

The final phase of the decision-support tool consists in interacting with the crew. This selection phase will be conduced via HMI. The crew (or dispatchers) will be able to obtain the different ranked alternatives and explore the trade-offs and cost components. When deciding if operating a given trajectory, many other tactical and operational parameters beyond the airlines objectives are considered by the crew. Examples of these include expected workload, interactions with ATC required, other tactical information not available to the decision-support system, such as the presence of weather turbulence at a given flight level, etc.

It could be possible to envisage a system capturing all these operational aspects and translating them into criteria to be considered as part of the MCDM problem. However, this was deemed not practical, as in some cases these parameters are difficult to assess and might vary crew to crew. Instead, the decision-support tool will calculate some operational indicators that might be relevant to the crew (*e.g.* number of flight level changes, location of top of descend) and present this information along the description of the trajectory. The crew will then have an enhanced understanding of the impact of different alternatives on the airlines goals, but they will also be able to assess the suitability of the solutions and reject inadequate solutions.

If desired, operational constraints can be introduced by the crew, *e.g.* do not descend, maintain top of descent after a given waypoint. These constraints will feed the alternatives generator (see Section 2.2.2). New trajectories will be generated as described in the generation phase (see Section 4.2.1) and added to the pool of trajectories still under consideration by the crew. This will trigger the ranking phase and a further interaction with the crew via the HMI.

5. Example of application

A flight is modelled in this section to describe the application of the MCDM framework. Assuming different initial delays, several case studies are defined presenting the trajectory alternatives that would be generated and ranked. The configuration required for the AHP-VIKOR algorithm are maintained as defined in Section 4.2.2, that is, considering IROPs as moderately more important than fuel and other costs for airlines, and setting the algorithm tuning parameter ν to 0.5.

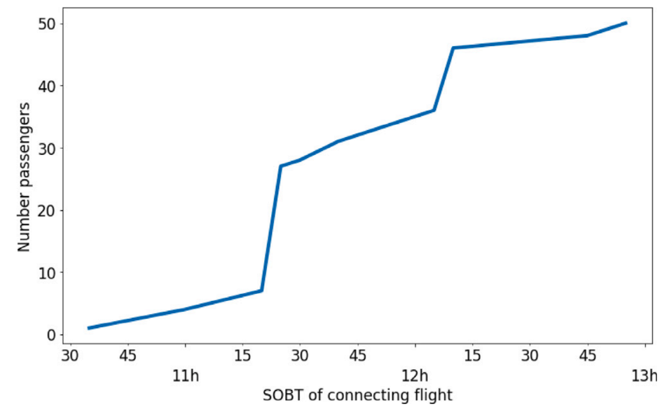

Fig. 4. First 50 passengers with connecting fights with the SOBT of on-going connection.

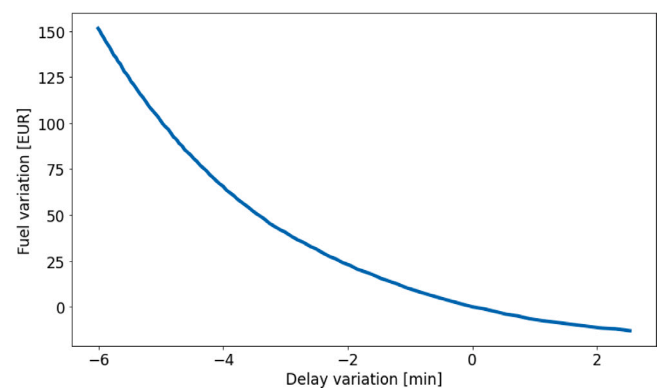

Fig. 5. Possible fuel and delay variations with respect to nominal flight plan.

5.1. *Flight characteristics*

The characteristics of the flight, an Airbus A320 flight between Madrid (LEMD) and Frankfurt (EDDF), are presented in Table 1. It is an early flight scheduled to arrive to Frankfurt at 9h10 UTC with 38% of passengers with further on-going connections. Fig. 4 represents the first 50 passengers with connections as a function of the schedule off-block time (SOBT) of their intended connection. Note that, in Frankfurt the domestic minimum connecting time is 45 min, and 60 min for international passengers. This means that passengers need at least that time to ensure their connection.

5.1.1. *Fuel and delay recovery estimation*

Fig. 5 represents, for this flight, the variation in fuel and time that can be achieved optimising the trajectory by selecting a different CI with respect to the planned one (*i.e.*, CI of 10 kg/min). These fuel and delay trade-offs are computed using the trajectory optimiser DYNAMO, an in-house aircraft trajectory prediction and optimisation tool developed by UPC for research and development purposes (Dalmau et al., 2018).

As observed, in this case, the flight can recover up to 6.4 min by selecting a higher CI (100 kg/min), using in this case 154€ extra of cost of fuel (308 kg of fuel at a fuel cost of 0.5€ per kg of fuel (Delgado et al., 2021)). The flight could also consider slowing down, increasing its

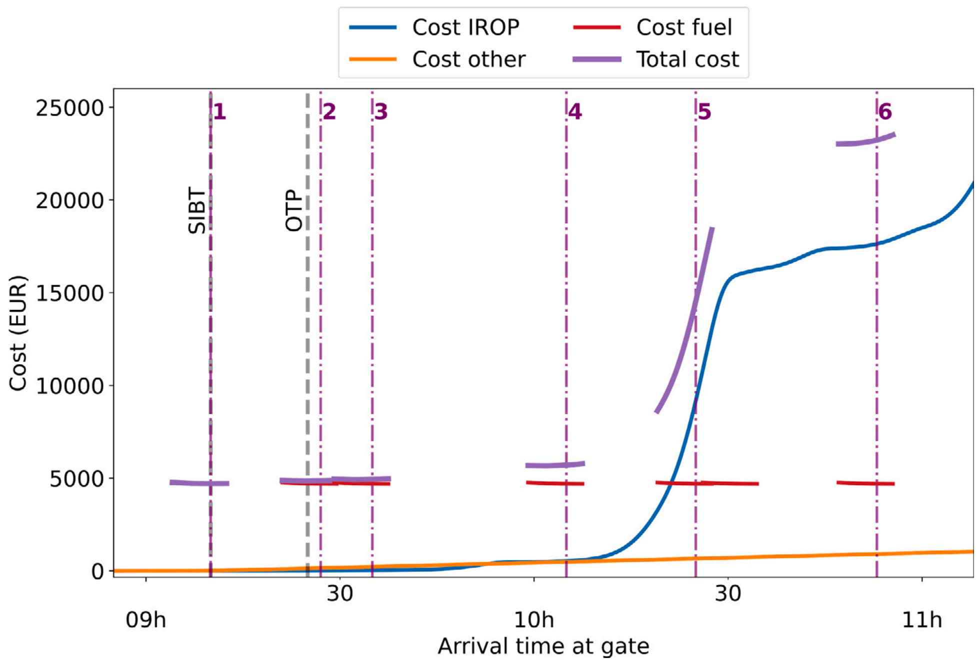

Fig. 6. Expected costs as a function of arrival time with case studies indicated.

delay by up to 2.2 min with a saving of 20€ of fuel. Note that a different optimiser could be used as part of the trajectory alternatives generation. In this case, this range of delay and extra fuel would determine the possible alternatives for the flight.

5.1.2. *Cost of delay*

As previously indicated, besides cost of fuel (see Section 5.1.1), airlines consider passenger related costs (IROPs), which include compensation, duty of care and costs generated due to missed connections, and other costs (*i.e.*, crew, maintenance, reactionary). For IROPs costs, if passengers arrive to their final destination later than 180 min with respect to their scheduled in-block time (SIBT), it is assumed that they are entitled to economic compensation as regulated by Regulation 261/2004 (European Commission, 2004).

Fig. 6 represents the variation of all the different costs of delay as a function of the arrival time at the destination gate. The cost of delay function could be deterministic, or consider uncertainties related to the operational environment, *e.g.* uncertainties associated with taxi-in time or holdings at arrival, and intrinsic uncertainties to the processes which generate the costs, *e.g.* missing a connection that depends on stochastic parameters such as the probability that the connecting flight is still available at a given time. The costs presented in Fig. 6 include the integration of these uncertainties and therefore represent the expected cost as a function of the arrival time. This generates smoother cost functions instead of sharp transitions for IROPs and other costs. Note that the fuel cost function of Fig. 5 is applied for each considered arrival time, leading to a total cost specifically defined only for each case study (see Section 5.2). For more information on the construction of the stochastic cost function, the reader is referred to Delgado (2020, 2021). Finally, note that in this example reactionary delay costs are not considered.

5.2. *Case studies*

Six different case studies are defined to represent different operational situations of interest for the application of the MCDM framework:

1. Case 1: Flight arriving at SIBT. In this case, OTP would always be reached but the trajectory could still be optimised considering trade-offs between fuel and cost of delay.
2. Case 2: Small expected arrival delay of 17 min, which would present the opportunity to recover enough delay to meet OTP.
3. Case 3: Small expected arrival delay of 25 min, which would not allow to meet OTP.
4. Case 4: High expected arrival delay of 55 min, with low variability of delay cost around expected arrival time.
5. Case 5: High expected arrival delay of 75 min (expected in-block time 10h25). As shown in Fig. 4, a significant amount of passengers have a connecting flight before 11h25 (27 passengers). This means that once the minimum connecting time is considered, an initial delay of 75 min generates a high probability of missing connections producing a high cost increment around that arrival time (high variability of cost).
6. Case 6: High expected arrival delay of 103 min: the passengers considered in the previous case would already missed their connection, and even if cost of delay continues increasing, this increment is not as steep. Note however, how in this case, the cost of delay would dominate over the cost of fuel.

5.3. *Generation of alternatives*

The expected total cost of a given trajectory is obtained by adding the expected costs of delay and fuel of this trajectory. Therefore, as shown in Fig. 6, given an expected arrival time at the gate, the possible available alternatives that the system will consider are obtained based on the variations of time and fuel as indicated in Fig. 5.

If only total cost is minimised, due to the characteristics of the cost of delay curve, only one alternative is generally found. Therefore, to be able to consider more than one alternative, some buffer (extra cost) should be used, as commented in Section 4.1.1 and presented in Fig. 7, which shows the number of alternatives obtained, as a function of the expected arrival time to the gate, and for different values of buffer (parameter b in Eq. (1)). With small buffers, *e.g.* 10€, several alternatives can already be obtained. For example, if the flight is expected to arrive at its SIBT (Case study 1), a range of 5 min can be considered, for which all solutions lie within a maximum of 10€ of extra total cost with respect to the minimum total cost alternative. However, if the initial expected delay is 75 min (Case 5), even with 300 € buffer, *i.e.*, considering that all solutions up to 300 € more than

Table 2
Potential solutions from Generation phase — Case 2. For each trajectory, the difference of minutes (extra delay) with respect to the initial solution is shown, as well as the total cost and sub-costs and their difference in Euros (Δ) with respect to the solution with the lowest cost.

Alternative trajectory	Extra delay [min]	Total cost (Δ) [€]	Cost of fuel (Δ) [€]	IROPs (Δ) [€]	Other costs (Δ) [€]	OTP
Trajectory$_1$	−6	4872 (25)	4767 (79)	8 (0)	97 (0)	Yes
Trajectory$_2$	−5	4858 (11)	4743 (55)	9 (1)	106 (9)	Yes
Trajectory$_3$	−4	4849 (2)	4725 (37)	10 (2)	114 (17)	Yes
Trajectory$_4$	−3	4847 (0)	4713 (25)	11 (3)	123 (26)	Yes
Trajectory$_5$	−2	4849 (2)	4705 (17)	12 (4)	132 (35)	No
Trajectory$_6$	−1	4852 (5)	4698 (10)	13 (5)	141 (44)	No
Trajectory$_7$	No	4858 (11)	4694 (6)	14 (6)	150 (53)	No
Trajectory$_8$	1	4864 (17)	4690 (2)	16 (8)	158 (61)	No
Trajectory$_9$	2	4872 (25)	4688 (0)	17 (9)	167 (70)	No

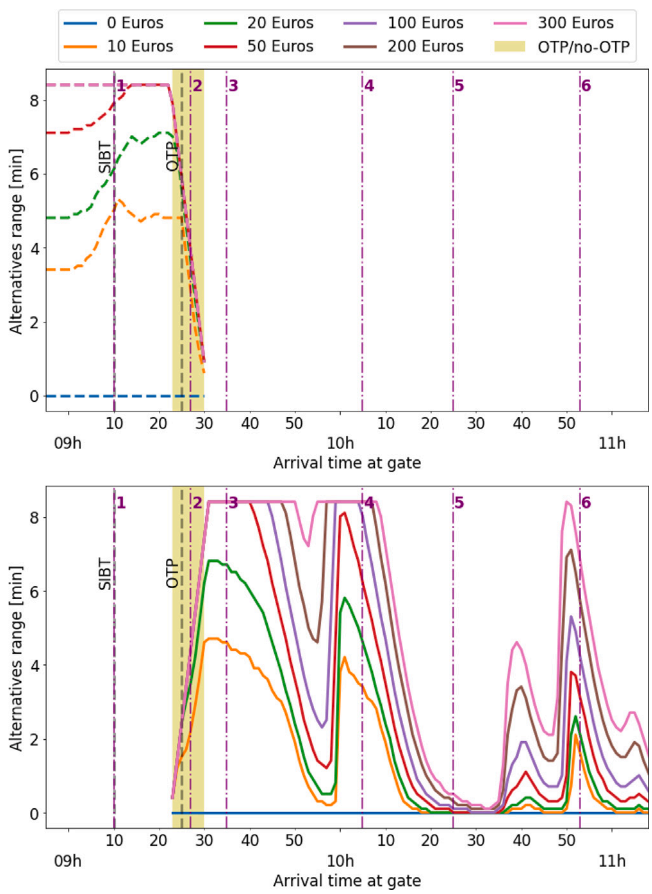

Fig. 7. Range of equivalent solutions as a function of buffer (in euros) and expected arrival time. Top: meeting OTP, bottom: not meeting OTP.

the minimum total cost should be retained by the generation phase, less than one minute can be used for an alternative trajectory. This is due to the fact that cost of delay grows very fast and even a few minutes of extra delay represent a very high extra cost. Therefore, the optimal trajectory is recovering as much delay as possible, and the savings on fuel obtained with other solutions are lower than the extra cost of delay generated, despite considering this 300 € margin.

Fig. 7 also shows how there is a time range (close to arriving to destination at OTP) where a trade-off between achieving OTP or not is possible. As shown in Fig. 5 only a maximum of 6.4 min can be recovered and extra 2.2 min can be accrued by slowing down. This means that if the flight is expected to arrive later than 6.4 min after OTP it will not be possible to meet OTP, and if the flight is expected to arrive earlier than 2.2 min before OTP then it will always meet OTP.

Table 2 shows the details of all the possible alternatives for Case 2 (expected arrival delay of 17 min): four trajectories reach OTP, and five do not. The costs of these trajectories are disaggregated into sub-costs (KPIs) and can be presented in the so-called performance matrix. As seen in Fig. 5, as some delay can be recovered at the expense of higher fuel cost, Table 2 shows for each alternative trajectory the difference of minutes (extra delay) with respect to the initial solution, and the total cost and sub-costs and their difference in Euros (Δ) with respect to the solution with the lowest cost. Recall that the number of alternatives retained will vary as a function of the cost buffer used.

5.4. Ranking of alternatives

Table 3 shows the results obtained for each case study when applying the ranking algorithm described in Section 4.2.2. It presents the ranked solutions, indicating the difference on arrival time with respect to the expected arrival time of the flight. In each case, several cost buffers are considered generating different numbers of possible alternatives (see column 'Number of available options' in Table 3). Note that there is a maximum buffer per case study, since at some point the maximum number of alternatives will be reached and there will no further benefit of increasing the cost buffer. For example, in the case study presented in Table 2, once the buffer is ≥25€ all alternatives are already considered. Note that this table shows all trajectories that will be kept after the ranking of the alternatives, that is, it can be seen how as a decision aid tool, it will help the pilot by presenting for example the three best options out of nine available ones. The pilot would be provided with these ranked options, and the information of whether they are OTP or not. These trajectories present trade-offs, or differences among their sub-objectives (or criteria), fuel, IROPs and other costs, which make them 'equivalent' (with no acceptable advantage, see Section 4.2.2), while dominating all other alternatives.

For example, in Case study 1, with a buffer of 20€, a total of 6 alternatives are generated (considering this buffer) and after applying the ranking only three solutions (recovering 1, 2 or 3 min of delay) are kept, being 1 min of recovery the preferred option. Note that, all options reach OTP, as the flight was expected to arrive at its SIBT. Therefore, it should be expected that fuel cost is the only cost and thus that slowing down to save fuel should be the only possible option. However, as indicated in Section 5.1.2, the cost function considers uncertainties linked to operations, *e.g.* holdings, missed connections. This means that IROPs costs, even if low, are not null. It can be seen that if cost buffer is low, the ranked solutions are close to SIBT (first ranked solution recovers only 1 min), while when the cost buffer increases, increasing the number of available options, slightly earlier options are proposed (recovering 3 min) in order to lower the IROPs costs (considered here as the most relevant cost).

In some cases, increasing the number of alternatives can change the ranked solutions even though the new alternatives are not kept. This is because VIKOR algorithm looks for a compromise solution, which is the closest one to the utopia point, and that adding alternatives usually changes the location of this point.

Case 2, whose details of costs are available in Table 2, presents the possibility of reaching, or not, OTP. As indicated in the methodology, these alternatives are treated independently. Depending on the cost

Table 3
Results (ranked solutions) as a function of allowed cost buffer after applying the ranking algorithm.

Case studies	Ranked solution (Extra delay [min])	Allowed cost buffer	Number of available options	OTP
1	−1, 0, −2	10€	5	Yes
	−1, −2, −3	20€	6	
	−3, −2, −1	50€	8	
	−3, −4, −2	100€	9	
2 (OTP)	−4	10€	2	Yes
	−5, −4	20€	3	
	−5, −6	50€	4	
2 (non-OTP)	−2, −1	10€	3	No
	−1, −2	20€	4	
	−1, −2	50€	5	
3	−4, −5, −3	10€	5	No
	−4, −3	20€	7	
	−4, −5, −3	50€	9	
4	−5, −4	10€	3	No
	−5, −6, −4	20€	5	
	−4, −5, −3	50€	7	
	−3, −4, −2, −5	100€	9	
5	−6	–	1	No
6	−6	10€	2	No
	−6, −5	20€	3	
	−5, −6	50€	4	
	−5, −4, −6	100€	5	
	−4, −5, −6	200€	6	
	−4, −5, −3	300€	7	

buffer considered, the OTP alternatives will recover between 4 and 5 min of delay, while the alternatives not meeting OTP will recover between 1 and 2 min. These alternatives will be presented to the crew independently, with information on the cost difference required to meet OTP.

Case 3, which does not allow to reach OTP solutions, shows that arriving 4 min earlier is the best ranked solution for all possible cost buffers (a cost buffer of 50€ includes all possible alternatives), and it is just one minute earlier than the absolute minimum of total cost (obtained for recovering 3 min), which is also included in the ranked solutions.

Case 4, which has a delay of 55 min, sees IROPs costs increase more rapidly than in the previous cases. As a consequence, if the airline only allows a low cost buffer, the solutions that are kept aim at recovering as much delay as possible. By increasing the cost buffer, new alternatives, corresponding to lower fuel cost, are kept and made available to the crew, but since they lead to higher IROPs costs, which is the most important cost considered here, in all cases, ranked solutions aim at recovering almost as much delay as possible (4-5 min). If cost buffer is very large, the compromise solution, to not penalise fuel cost too much, is found with a recovery of 3 min.

Case 5 shows a point in the cost of delay function where a significant amount of passengers have a high probability of missing their connection. As costs of delay are computed considering their associated uncertainties, instead of a high discrete step (which would force solutions before the discontinuity), cost of IROPs increases with a high gradient with respect to delay, as the likelihood (and hence expected cost) of missing connections increases over the arrival delay. For this reason, no alternative trajectory can be found, even within a cost buffer of 300€. The cost of delay increases so rapidly that only recovering as much delay as possible (6 min, which would allow expected saving of 6000€) is retained as a possible solution by the alternatives generation phase, and no ranking algorithm is used.

Finally, Case 6, corresponding to 103 min of delay, shows high and rapidly increasing IROPs costs (some more passengers have a higher likelihood of missing their connection). However, a high amount of IROPs cost has already materialised and cannot be recovered. In this context, if cost buffer is low the optimal solution consists in recovering as much time as possible (up to 6 min). When increasing the cost buffer, as IROPs cost does not grow as fast as in the previous case over time, some compromise solutions are proposed by the ranking algorithm. Note that in this case, and as IROPs costs still increase significantly over time, the maximum cost buffer considered (300€) only allows to get seven alternatives (out of a possible maximum of nine).

5.5. *Sensitivity of the ranking phase*

As indicated in Section 4.2.2, two parameters need to be tuned within the execution of the combination of AHP and VIKOR algorithm used in the ranking phase.

First, recall that in the determination of the weights of the criteria, AHP was used by creating a matrix $\mathbf{A}$ representing the relative importance of one criteria to all others. Since level of relative importance (corresponding to “moderate”, “strong”, “very strong”, and “absolute” importance) could not be precisely specified by the DM, moderate importance was considered, leading to a constant numerical value of 3 in $\mathbf{A}$. We found that choosing a higher value led to inconsistent weights, due to the fact that the same level of relative importance is set between all pairs of attributes. Higher values are thus discarded. We have also tried to set the constant value in $\mathbf{A}$ to 2. The resulting weights obtained with AHP in this case ($\mathbf{w} = [0.31, 0.49, 0.20]$) are consistent and logically more alike for each attribute. When comparing results between both sets of weights in the 23 cases where the ranking algorithm was applied, we observed either the same results are kept (in 44% of the cases), a change of order of ranking (26%), or an additional alternative is proposed by the algorithm (30%). The choice of the value of the relative importance parameter in $\mathbf{A}$ has thus some influence on the results, but it can be considered as limited since, it does not drastically change the results. We recall that in most of the cases, the preferred alternative is not considered as superior enough to the others to be the only one offered, and that the objective is to provide to the crew a list of options (which remains the same in 70% of the cases and includes one more or one less option in the remaining 30%). The final option will be selected by the pilot in the selection phase.

Then a second tuning parameter v, corresponding of the weight of the strategy of maximum group utility versus of the individual regret, was set to a “neutral” value of 0.5. In this example, changing this value does not affect the results, unless extreme values (≤ 0.1 or ≥ 0.9) are chosen. It is thus considered that maintaining the commonly used value of 0.5 is adequate.

6. Conclusions and further work

During a flight, the crew may contemplate modifying their planned trajectory, considering new available information. Trajectory modifications will be translated into changes on expected fuel and flying time, which will impact the airline’s relevant performance indicators, leading to a complex MCDM problem. Pilot3, a project from the Clean Sky Joint Undertaking 2 under European Union’s Horizon 2020 research and innovation programme, aims to develop an objective optimisation engine to assist the crew on this process. This article details the domain-driven approach followed to select the most suitable MCDM methods within this optimisation framework.

This article presented the relevance of a domain-driven approach to select the most adequate methods for trajectory optimisation considering airlines’ preferences and needs. Current systems simplify flight trajectory optimisation by translating the multi-objective problem of considering airlines’ needs into a minimisation of trip fuel and time combined, with a pre-defined weight (cost index), into a single objective optimisation. The research described in this paper contributes to the identification of the actual objectives that are relevant by the airlines, defined with the support of an Advisory Board composed of aviation experts (representing industry, airlines, pilots, dispatchers): meeting on-time performance (OTP) and reducing the total operating cost. Trip time (and hence cost index) is just a proxy used for convenience. Further analysis has identified that cost is composed of three sub-components: fuel, IROPs (passenger related) and other costs.

The MCDM framework described in this article enables the development of trajectory optimisers that move away from the use of proxy variables (such as the cost index) and that can directly use the criteria of relevance of the airlines. The optimisation of the trajectory becomes part of a MCDM framework that considers multiple objectives. The particularities of the problem (and the domain) enable the possibility of the exploration of Pareto solutions, as the set of alternative trajectories is limited. Consulted experts indicated that different operations might require the prioritisation of *equivalent* solutions as a function of the different components of the total cost. As only three sub-objectives (criteria) are identified, qualitative pair-wise preferences can be defined. With these considerations and as demonstrated in this article, an optimisation architecture composed of a *lexicographic* optimisation to identify the Pareto solutions, followed by an AHP-VIKOR algorithm is suitable for such a MCDM framework.

The MCDM process consists of two phases: first, Pareto optimal solutions are generated with an *a priori* MOO method (lexicographic ordering), as total cost is deemed the most important factor. Assessing the potential trade-off required to achieve OTP is also relevant for airlines and therefore, if OTP is reachable, trajectories meeting OTP while minimising the extra cost are generated. An economic buffer can be established to identify *equivalent* total cost solutions. Second, the set of optimal alternative trajectories is filtered and ranked using a combination of MCDA methods (analytic hierarchy process and VIKOR). This is possible as two-by-two ranking of sub-cost components can be provided by airlines as a set of preferences.

The example of an Airbus A320 flight between Madrid and Frankfurt shows the applicability of the process. It can be seen how in different cases, representing different scenarios when the flight could arrive on time, or with some delay, a ranked reduced set of options, with equivalent total costs, is offered to the crew to help them choose the most adequate one. In the hypothesis considered here, where IROPs costs would be more important for the airline, the optimiser tends to propose options recovering time, but the fastest alternative is not necessarily always selected, since the solutions aim at a compromise between all sub-costs and in some cases the required fuel cost will be considered too high for the benefit obtained on the expected IROPs costs. In general, the total delay that can be recovered, with the used trajectory generator, is low. This means that the number of alternatives for which a trade-off between meeting OTP or not exists is very low. With a relatively low economic buffer (10€), the number of alternatives kept by the filtering phase is already larger than the one minimising the total cost. This depends significantly on the evolution of the expected cost of delay as a function of the arrival time.

The effect of the choices of the two tuning parameters of the AHP-VIKOR algorithm used for the filtering and ranking of alternatives has been found to be rather limited, proving the robustness of the optimisation framework proposed.

This framework has been integrated into the Pilot3 prototype, which provides dynamic cost functions (Delgado et al., 2022). The trajectory generator used in this article considers modifying the CI as the only control variable, providing a rather low range of arrival times (Prats et al., 2022). A full trajectory optimiser, allowing also the consideration of operational constraints provided by the crew could be used. This will increase the range of alternatives with a larger trade-off between fuel and delay recovered. Further work should be performed on the assessment of the most suitable HMI to present the information and facilitate the exploration of alternatives to the crew.

At the time of conducting this research, the environmental impact of aviation was not considered an independent objective to be optimised, as it was not deemed relevant for tactical flight operations by the experts of the aforementioned Advisory Board. The environmental impact of a flight was directly linked to CO_2 emissions, which is already accounted by fuel cost (and consumption), as CO_2 emissions are proportional to fuel burn. However, the importance of non-CO_2 aspects of aviation on the environment is gaining relevance (Dahlmann et al., 2023; Thor et al., 2023) and the mitigation of these aspects might require the adjustment of trajectories in a more complex manner, *e.g.* with route or flight level changes (Matthes et al., 2018; Simorgh et al., 2022). The addition of this objective as part of the ranking of solutions should be still feasible with the AHP-VIKOR algorithm. The total number of indicators considered is still small and the pair-wise ranking could still be defined for all of them. Note that this definition of preferences could be done strategically, at dispatching and/or at pre-departure, therefore not having an impact on crew workload.

Yet, if the environmental impact of the flight is considered as a general objective to be minimised (as the total cost and meeting OTP), the generation of trajectories would not necessarily present solely two Pareto trajectories, as it is the case in the work described in this article. Therefore, other approaches instead of aiming at generating all Pareto solutions might be used, such as computing the trajectories with an Interactive Evolutionary Multiobjective Optimisation (Branke et al., 2008; Xin et al., 2018). This highlights the importance of the domain-driven analysis of the problem when selecting the optimisation algorithms. The methodological approach described in this article to select the most suitable method could be reapplied with these new considerations.

Data availability

Data will be made available on request

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