Can Route Charging incentivise Environmentally-friendly Trajectories?

Green route charging

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***Abstract*—The way airlines plan flights is crucial, needing to consider route charges, fuel consumption, and expected delay on the route. However, their decisions also have important consequences for the climate, since choosing different routes can have very different impacts in terms of emissions of CO_2 and other types of pollutants, such as NO_x. Whilst, in general, low fuel consumption and low environmental impact go hand-in-hand, the different route charges set by the ECAC countries mean that cheaper routes have sometimes worse environmental impact. The Green-GEAR project is developing incentivisation frameworks to help re-align airlines' decisions with low(er) environmental impacts. In this article, we present this issue in more detail, the methodology of the project, the modelling aspects, a stated-preference survey, and the determination of climate hotspots. Further, we present the preliminary survey results obtained from test data from the consortium team, and a sample of climate hotspots. We use these test data to discuss the principles of the modelling of utility functions, and the integration of utilities and climate hotspots in a new route-charging scheme.**

***Keywords*—Green route charging; stated-preference survey; climate hotspots; meteorological data; airline decision-making**

I. INTRODUCTION

The European Green Deal [1] calls for achieving net-zero emissions by 2050, urging a shift towards sustainable mobility. Aviation needs to reduce emissions, and while development of electric or hydrogen-powered planes and sustainable aviation fuel will make a considerable difference, they will take time to have a full impact. To address a more immediate future, the Green-GEAR project [2] is exploring 'green' route-charging mechanisms to incentivise environmentally friendly flight path choices.

Route charges are paid by airspace users (AUs) to cover the provision of air navigation services. The route charges need to be non-discriminatory, transparent and cost-related [3], [4]. The current mechanism can result in unintended consequences [5], when a longer route through cheaper airspace is used to avoid more expensive airspace along a direct route, which results in cost savings for the AU, despite an increase in fuel consumption and higher CO_2 emissions, for example[1].

The 'green' route-charging (GRC) Solution proposes to address the emissions reduction in two steps: an 'initial' and 'full' Solution. The *initial* one proposes a novel route-charging mechanism aimed at reducing the horizontal inefficiency due to differences in unit rates as cited above (i.e., avoiding extension of route to save costs). In this paper we are focusing on the *full GRC Solution* that aims to incentivise the use of climate-friendly trajectories, when considering *both* CO_2 and non-CO_2 emissions. The idea is to explore a mechanism that 'rewards' the avoidance of climate sensitive areas (i.e., climate hotspots), while still leaving the flexibility of using the said areas, against a higher charge. A 'climate hotspot' is a volume of airspace where the atmospheric conditions are such that flying through it creates much higher climate impact than flying through other areas (e.g., a region where persistent warming contrails are very likely to get formed). Of course, the operational environment of such a solution is complex, as it involves stakeholders with very different operational goals (AUs, and air navigation service providers (ANSPs)), ATM infrastructure, and the state of the atmosphere. It is important for AUs not to be constrained to a single option, but to retain flexibility, as operational reasons such as avoidance of, or recovery from delays, may require different trajectories, which have differing environmental costs.

The design and assessment of a full GRC Solution requires a methodology including careful consideration of several factors (see Section II), but we will discuss only two factors in detail in this paper: AU behaviour in light of new charging mechanisms, and full inclusion of the impact of non-CO_2 emissions on route choice.

Historically, ATM has faced the challenge of predicting AU behaviour as a function of route charge changes, in particular, such as when one state changes its charges to such an extent as to cause unexpected overloads in neighbouring airspace, as was the case in 2015 when German ANSP raised their unit rate [7]. In this paper, we present a novel methodology for evaluating AU preferences when presented with a set of realistic, options set in a future context of route charges designed to discourage behaviour with strongly negative environmental impacts. To the best of our knowledge, this is the first time that a 'stated preference' (SP) survey will be deployed with AUs

[1]The analysis of possible application of common unit rate found that having the same unit rate could reduce up to 4400 tons of CO_2 emissions on a busy day [6], but the scheme would not necessarily be equitable.

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specifically to gauge their sensitivity to environmental impact when faced with difficult choices in operations. We explain the particular value of the SP approach, over other direct interview methods (e.g., directly inferring values from actual choices in 'revealed preference' surveys) and indirect inference (e.g., the relative common practice of deducing future choice probabilities from machine learning models). The design and validation of such a method are vital to its success, and are presented in this paper.

The climate impact of aviation's non-CO_2 emissions is rather difficult to assess and/or monitor. Aviation's radiative forcing[2] is composed, roughly, of one-third CO_2 impacts and two-thirds non-CO_2 impacts. The most significant contribution comes from contrails and contrail cirrus, albeit with considerable uncertainty, alongside effects from NO_x emissions [8]. Unlike CO_2 impacts, non-CO_2 effects are highly influenced by atmospheric conditions, thus they depend on the location, time and altitude of emissions. The FL4ATM and ALARM projects [9] developed a CLIMaCCF tool [10] that can give the location of volumes of airspace that are particularly sensitive to aviation non-CO_2 emissions, termed climate hotspots. Here, we analyse the usage of information on climate hotspots for the new route-charging mechanism.

A. *Current route-charging scheme*

EUROCONTROL's Central Route Charges Office (CRCO) implements the Multilateral Route Charging System and is responsible for the calculation, collection, and redistribution of route charges, and the charging system in the European Union is regulated by Implementing Regulation IR 2019/317, the Single European Sky Performance and Charging Scheme [4]. A route charge "is a levy that is designed and applied specifically to recover the costs of providing facilities and services for civil aviation." [3]. Each State needs to establish one or more 'en-route charging zones' – volumes of airspace that extend from the ground up, where en-route air navigation services are provided and for which a single cost base and a single unit rate are established. The *unit rate* is a unique tariff per service unit. The number of service units for a flight is determined by the product of the distance and weight factors.

The route charge for a flight is the sum of charges accrued over all crossed charging zones i.

$$R = \sum_i r_i, \quad r_i = u_i \times n_i,$$

where R is a route charge, r_i is the charge accrued in zone i, u_i is the unit rate for zone i, and n_i is the number of service units in zone i, which are the product of the distance (d_i) and weight (w_i) factors:

$$n_i = d_i \times w_i, \quad d_i = \frac{\text{GCD}}{100}, \quad w_i = \sqrt{\frac{\text{MTOW}}{50}},$$

The distance factor is proportional to the great-circle distance between entry and exit points to each of the charging zones, minus 20 km if the origin or destination airport is within a charging zone. The weight factor takes into account the productive capacity of an aircraft, where heavier ones are expected to pay more for air navigation services.

The Performance and Charging Scheme, IR 2019/317 [4] fosters long-term improvements in air traffic management (ATM) (as described in the European ATM Master Plan [11]), reduction of greenhouse gas emissions and optimum use of airspace. The regulation defines the following:

- Reference period, that is the period of validity and application of the Union-wide performance targets;
- Performance plans, which are taking into account future costs based on planned investments and forecast traffic, and also set the performance targets;
- route and terminal charging scheme (describing the charging zones and unit rates, obtained by dividing determined costs[3] by the traffic forecast);
- incentives that could be introduced in performance and charging schemes aiming to encourage better ATM performance. One form of incentives is the modulation of charges that can be used to reduce the environmental impact of flying or the level of congestion of the network in a specific area [4]); and
- the Network Manager performance plan.

Thus, the current route-charging scheme takes into account investments planned to improve ATM performance and the traffic forecast. The charging is based on the actual route flown (previously it was based on the last-filed flight-plan), and the charges are calculated and collected by the CRCO. The environmental impact is not taken into account; nor is the potential cost of delay or AU planning priorities.

B. *Literature review*

The work presented here builds on prior research activities both within and outside SESAR, and the research of behaviour forecasting (SP *versus* revealed-preference, etc.).

The optimisation of the individual trajectory under any objective is relatively easy. The optimisation of any factor (e.g., delay, capacity usage, environmental impact) involving the traffic in the network becomes harder, as it is subject to myriad constraints. It is even harder when flexibility needs to be an important ingredient of the system's operation. The economic incentives for traffic redistribution in the European ATM network have been studied in SATURN, ADAPT, COCTA, and CADENZA, all SESAR projects. SATURN studied the impact of peak-load pricing modulation of route charges [12] on the traffic redistribution, to avoid sector capacity overloads, while ADAPT [13] explored advanced prediction models aimed at enhancing flexible, trajectory-based operations, providing a basis for adaptive decision-making in air traffic management. The developed model offered a measure of flight flexibility [14], which is an important attribute for the AUs. The dynamically priced trajectory products, where the price and delay are taken

[2]Quantification of a change to the balance of energy flowing through the atmosphere.

[3]The costs that are to be financed by charges imposed on airspace users.

into account, and their application in the EU ATM network was analysed by [15].

The environmental impact of aviation is composed of CO_2 and non-CO_2 emissions. The CO_2 emissions are generally proportional to the distance flown [16], meaning that to decrease the impact of CO_2 one should strive to decrease miles flown. The longer routes can be caused by pure economic factors, such as the cost of the trajectory, but also by the airspace capacity overload. When a demand over a portion of airspace exceeds its capacity, air traffic flow management regulations are invoked that result either in flight delay (to smooth the demand) or flight re-routing, which is often longer than originally planned trajectory [17].

The emissions from aviation increase the overall radiative forcing from the atmosphere on the planet, more commonly known as the greenhouse effect. CO_2 is responsible for roughly one-third of this radiative forcing from aviation, while two-thirds come from non-CO_2 effects. The most significant contributor to aviation's radiative forcing arises from contrails and contrail cirrus, alongside effects from NO_x emissions [8]. As already mentioned, the non-CO_2 effects are highly influenced by atmospheric conditions, meaning they depend on the location, time and altitude of emissions. Climate hotspots can be determined through the use of the CLIMaCCF python library [10]. The hotspots are determined from the computation of individual and merged non-CO_2 algorithmic climate change functions (aCCFs) [9]. By leveraging these models, the Green-GEAR project aims to enhance the accuracy and effectiveness of its environmental impact assessments. Here, we will present the climate hotspot determination, and discuss the requirements for their operational use in the route-charging mechanism.

Finally, the GRC mechanism would involve a new way of charging that takes into account the complete climate impact of emissions in the pricing. The efficient tool for prediction of future choices can be found in SP surveys [18]. A rare application of SP surveys in aviation can also be found earlier in the CADENZA project, with a novel assessment of potential future scenarios for trajectory pricing [19].

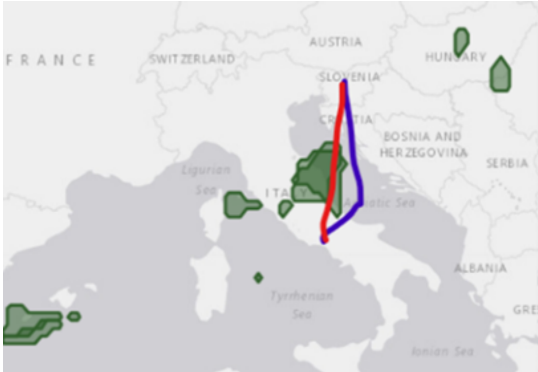


Figure 1. Example of climate hotspot and trajectories with different environmental impact.

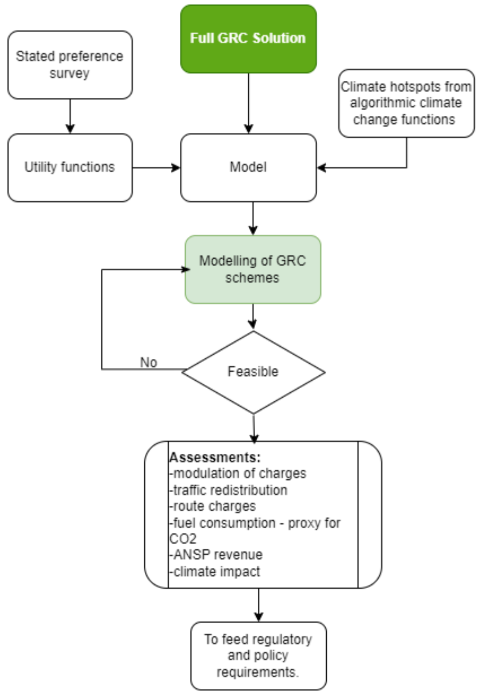


Figure 2. Full GRC Solution methodology.

II. Methodology

The goal of the full GRC Solution lies in finding the airlines' willingness to pay in the hypothetical situation where the full GRC Solution would be implemented, where the crossing of a climate hotspot would entail an increase of route charges (e.g. a penalty) and avoidance would entail some form of compensation ('award') in terms of lower route charges for avoiding the hotspot (which also might bring higher fuel costs and delays). Figure 1 gives an example of the environmental impact of two trajectories. The blue one mostly avoids climate hotspots (depicted in green), and thus creates a 'low' environmental impact. The red trajectory crosses a climate hotspot and thus has a 'high' environmental impact.

In order to design the full GRC Solution, and to assess it, we will apply the methodology depicted in Figure 2. Two components of the methodology are of the utmost importance: the SP survey, and climate hotspots, that are described in the following subsections. The results of the survey, the AUs' utilities in the case of green route charging, and the climate hotspots will then be included in the optimisation framework to model the GRC scheme. The optimisation framework will take into account the route charges, flight operational costs, AUs' willingness to pay, subject to ANSPs' revenue neutrality and airspace and airport capacities. As with any optimisation model, we need to test the feasibility of the proposed formulation, taking into account the size of the problem, which needs to be sufficient for the required assessment. Another element will need to be added to the optimisation framework that is still under development, and that is the penalty/award scheme to be applied for crossing/avoidance of the climate hotspots, which will be discussed with the ANSP and AUs representatives in a planned workshop. The results of the optimisation model runs will be used to assess the Solution from the feasibility and performance points of view. As the Solution is still under development, here we focus on the SP survey and the climate hotspots, which are described next.

A. Stated preference (SP) survey and design

The method deployed is known as 'stated preference' because respondents state their values / preferences, rather than the researcher inferring values from actual choices ('revealed preference'). The survey will be used to assess airlines' willingness to pay (WTP) for the avoidance of climate hotspots, and/or their sensitivity to arrival delay and costs, and the associated uncertainty. SP is much stronger than the practice of solely inferring preferences from *post hoc* (machine learning) models, which have the combined disadvantages of being:

- typically based on executed trajectories (e.g. in response to extant delays);
- weakly capable of evaluating future choice sets;
- based on weaker inference.

The SP survey is composed of a set of choice-based questions representing a series of hypothetical choices between trajectories with different characteristics. We use the Lighthouse Studio platform for survey design and on-line implementation. The survey adapts to participants' preferences as they provide feedback, enabling us to gather detailed insights into what participants value most in their choices. We are interested in assessing the preferences over four trajectory characteristics, or 'attributes'. Each attribute has several values to be included in the variation of choices. Below are the key attributes along with the number of levels they encompass:

- Cost sensitivity: fuel and route charges (with 7 levels);
- Short arrival delay aversion: 50^{th} percentile delay time, i.e., there is a 50% chance that the flight will be delayed by less than X minutes on arrival (with 3 levels);
- Long arrival delay tolerance: 90^{th} percentile delay time, i.e., there is a 10% chance that the flight will be delayed by more than Y minutes on arrival, (with 4 levels);
- Environmental consideration: environmental impact (with 3 levels).

For example, the attribute environmental impact, with levels of 'high', 'medium', and 'low', refers to the climate impact a flight can cause by flying through, or avoiding, a climate hotspot.

The survey presents the following sets of questions, where sets 2-3 are adaptive ('adaptive' because the choices offered in each subsequent question are based on respondent's previous choices):

1) Introduction and demographics: participants are introduced to the survey's purpose and provide basic demographic information.
2) Screen (10 tasks) and attribute identification tasks: these tasks involve screening questions designed to filter out irrelevant choices and ensure that only the most relevant options are considered. The participants should assess the offered choices as 'I would consider' or 'I would consider in the most extreme case'. The selected choices are transferred to the 'choice tasks'. The choices are further filtered with 'unacceptable tasks', where the participants need to identify unacceptable choices. Therefore, unacceptable, and screen tasks are iterative and interconnected, used to down-select from all possible combinations ((7x3x4x3).
3) Choice tasks (up to 15 tasks): participants face the choices filtered down via the previous set of questions. The offered choices are characterised by varying levels of key attributes.

Based on the description above and as a part of the design concept, it was important to formulate choices presented to AUs with as realistic choices as possible. For example, to use accurate estimates of fuel and route charges. The design also includes appropriate contextual description in the survey introductory material, underlining that the offered, sometimes challenging (realistic) choices reflect 'the types of trade-offs required in our congested European airspace'. Underpinning the adaptive approach, it was also important to clearly explain what is meant by 'unacceptable' attributes. Choices of attribute levels, indicated by respondents as only acceptable 'in the most extreme case' were thus checked downstream in the survey logic against whether a flight would actually be *cancelled* in such an 'extreme' case, before inclusion or exclusion from subsequent choices.

It should be noted here that our SP approach was not trying to find some optimal solution (which would be trivial: cheap trajectories without delays or environmental impacts!), but to determine realistic operational constraints in which future regulatory measures are more likely to be workable.

The first version of the SP survey is currently being tested for coherency and proper interpretation of the questions with the project's Advisory Board volunteers. After this initial feedback, the survey will be circulated to more than sixty European airlines, with the help of Advisory Board members.

The obtained data will be analysed to determine the utility of the four attributes, when faced with the choice of avoiding climate hotspots, *inter alia*. The analyses will be performed using an algorithm incorporated in the Lighthouse Studio platform, and the Biogeme Python library [20]. Biogeme is a library dedicated to estimating discrete choice models and analysing the preferences and decision-making processes of participants.

As already mentioned, the design and validation of the survey are vital to its success. In order to validate the method, here we use test data collected via the first version (currently under review by AU representatives) of the SP survey, where the respondents were recruited from the consortium team. There were four respondents that completed the survey playing roles of network, regional and low-cost carriers. For some runs, the role included high environmental concern sensitivity. The test data used has 20 responses.

B. Climate hotspots

The CLIMaCCF Python library [10] is easy to install and use. It provides different options for the quantification of the climate impact of aviation. The library can be used to calculate the individual and merged non-CO_2 aCCFs[4], taking the actual meteorological situation into account, and using that information to determine the spatial and temporal resolution of climate hotspots.

In order to determine hotspots, the user needs to specify the threshold values of interest. It is important as "if the merged aCCF exceeds a certain threshold value of the merged aCCF the region is defined as a climate hotspot" [9]. The authors advise using a dynamic determination of the threshold "for every time step and flight altitude over a certain geographical region." For example, if the 95th percentile is chosen, the library calculates this percentile over all grid points spanning the chosen geographical region, and if the merged aCCF is above the chosen percentile, that region is defined as a climate hotspot, for that percentile.

In order to determine the climate hotspots, meteorological data are needed as input. The ERA5 high resolution re-analysis data, available from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/) is used for input. The library requires two input datasets, one containing data at each pressure level, and another one the data provided on a single pressure level (e.g., surface layer). The data needed for calculation and their physical units is presented in Figure 3, which lists the input parameters and their physical units[5].

Parameter	Short name	Units
Pressure	pres	$[K.m^2/Kg.s]$
Potential vorticity	pv	$[K.m^2/Kg.s]$
Geopotential	z	$[m^2/s^2]$
Temperature	t	$[K]$
Relative humidity	r	[%]
Top net thermal radiation	ttr	$[J/m^2]$
TOA incident solar radiation	tisr	$[J/m^2]$

Figure 3. Meteorological input parameters needed to calculate aCCFs within CLIMaCCF, taken from [9] .

Our intention is to assess the climate hotspots obtained from the library in terms of the area coverage (both geographical area and altitude levels), and the rate of change during the day, to try to determine the impact on stakeholders' operations. Here, we show the climate hotspots obtained from one week from March, June, September and December of 2019, for 95th and 99th thresholds.

III. Preliminary results

A. SP runs

1) Survey results, value of time, risk aversion: We present here the method by which the project will build the utility functions used in the model, using the SP survey results. We illustrate the methodology by applying it to the test data, as described, and highlight the assumptions and next steps.

The raw output of the survey is composed of different options presented to the respondent and the choices they made. Note that because of the adaptability of the survey, respondents in general have different options presented to them, and even a different number of questions. The goal is to regress their behaviour by assuming that they make their decision based on a utility function taking into account the dimensions of the survey presented to them. As described in II-A, there are four variables (i.e., attributes) on which respondents will base their answers: cost sensitivity, short arrival delay aversion, long arrival delay aversion, and environmental impact.

The two delay thresholds test the adversity of airlines to short, relatively certain delays and long, quite uncertain ones. However, we are also interested in reporting their value of time. The concept of value of time is in general applied to passengers, to capture the fact that they might prefer shorter journeys (in time) by paying a certain price. For airlines, it is assumed that this parameter is somehow explicit in their decision, since they are able in principle to compute the actual cost that a given arrival delay has implied in the past. Here, we can capture it by checking decisions made by the airlines, and compare it to the 'real' cost of delay, as determined by [21], [22].

In order to do this, we have to assume a certain shape for the distribution of delay. The concept of the value of time assumes a comparison of an expected arrival delay compared to a certain value of cost. The two variables present in the survey are the median and the 90th percentile, and do not prescribe the average of the distribution, which would be the delay expected by perfectly informed agents. For the purpose of this article, we assume an *ad hoc* exponential delay distribution, as justified below.

Once we have chosen the distribution of delay, we can compute not only the average but also other characteristics, such as the variance of the distribution, and test if the respondents are sensitive to them. Thus, in the following, we perform a regression using the standard deviation of the delay as one of the variables (on top of the mean) and compute the corresponding coefficient that we call 'risk aversion', with reference to the fact that even with the same expected arrival delays, airlines might be averse to the uncertainty of the distribution[6].

This risk aversion links closely with previous work we have conducted in this area, highlighting the importance of uncertainty in day-to-day operations, and the need to take it into account to properly assess the cost of delay for AUs [23]. This work reviewed the limited state of the art on assessing the disutility of uncertainty, and defined a cost of uncertainty using estimates also based on [21]. The article showed that

[4]aCCFs "provide spatially and temporally resolved information on aviation's climate effect in terms of future near surface temperature change." [9]

[5]The step by step guide is available in the CLIMaCCF library Manual.

[6]As they should, given that in general, the cost of delay is highly non-linear with delay duration. Note also that risk aversion is in general defined very precisely as a coefficient that drives the behaviour as a function of the variance of the utility, not the delay itself. Hence we use this term more generically here.

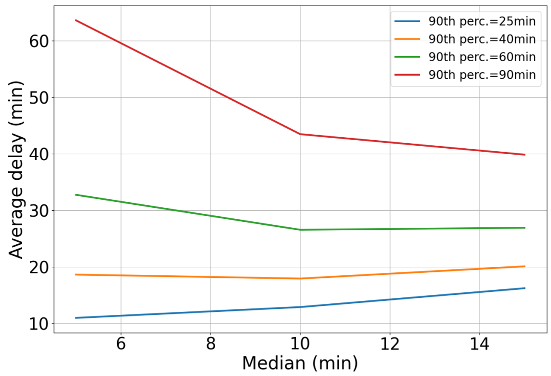


Figure 4. Evolution of mean of log-normal distribution with its median, for different values of the 90^{th} percentile.

uncertainty is also important in the formulation of buffers for airlines (and provided a simple model to estimate the optimal assignment, using real data, to compute the optimal value at different airports). The link with the current work, set in the route-charging context, is clear, in that the risk aversion we calculate is essentially the disutility of consuming notional buffers that AUs associate with route planning, which are a hidden function of generic factors such as the route and airline type, and specific factors, such as passenger load and connectivities.

2) Ad hoc distribution of delays: The *ad hoc* distribution we use for the arrival delays had to be prescribed by two parameters, since the survey fixes two of them: the median and the 90^{th} percentile. Hence, once we fix the form of the distribution, we back-compute the mean and standard deviation thereof, based on the options presented to the respondents.

The distribution itself can have many different forms (albeit with only two free parameters), however some distributions may raise issues, especially in how the respondents intuitively picture the underlying distribution. An example of such an issue can be seen in Figure 4. To produce this figure, we assumed a log-normal distribution of delay, and computed the parameters of the distributions based on the different values of the median and the 90^{th} percentile. We then plot the mean of the distribution (in the figure as a function of the median, for different values of the 90^{th} percentile).

Interestingly, for some values of the 90^{th} percentile, the mean **decreases** with the median. Hence, if a respondent was presented with these two options (median, 90^{th} percentile):

- (5, 60) and (10, 60).

then choosing the first option would mean that they opt for the option with the **higher arrival delay on average**. This is particularly counter-intuitive and we do not think that respondents would choose that option if they knew about the average.

Other distributions display the same kind of behaviours, at least for some values of their parameters. For example, a normal distribution with a cut-off, while others may raise other issues (for instance, normal distributions are not bounded in the low values). For the purpose of this article, we thus used a simple but well-behaved distribution: the shifted exponential. This distribution has two parameters, λ and l, and it is easy to show that the mean of the distribution always increases with the median and any percentile. The standard deviation of the distribution also increases with the 90^{th} percentile when the median is fixed, and decreases with the median when the other percentile is fixed, which is the behaviour respondents will look for intuitively.

Hence, whilst using the shifted exponential for the purpose of this article, the work continues to formulate a fully 'appropriate' distribution to use to infer the mean and the standard deviation, in order to compute the value of time and the risk aversion of participants. It is interesting to note that, while historical distributions do matter in this case, in the sense that participants may have an implicit knowledge of them, we would ideally like to have access to the distributions intuitively used by participants, or, more specifically, to the rule by which they convert the two initial percentiles to average delay and width of distribution (triggering risk aversion). It might also be that the entire concept of value of time is not valid in the context of this survey and respondents' choices are triggered directly by the initial percentiles (e.g. the median and 90^{th} percentile).

3) Estimation: For the purpose of this article, we have used test data, generated by the members of the consortium, as described above. We illustrate the survey, the knowledge that we can gain from it, and how the results will be used in the model. First, we compute the expected arrival delay and the risk aversion. We then use different models with a logit regression:

- I: cost + expected delay;
- II: cost + expected delay + uncertainty;
- III: cost + expected delay + uncertainty + environmental impact;

The results of the estimation of these models can be found in Table I. All models seem to capture the same trends, with all variables – delays, costs, and environmental impact being negative for respondents. All coefficients are statistically significant at least to a 1% threshold.

TABLE I. RESULTS OF THE ESTIMATION OF DIFFERENT MODELS.

Model	Coefficients	Value	Std err	p-value
I	α_{cost}	-1.1e-3	1.6e-4	4.9e-12
	α_{exp}	-3.3e-1	3.7e-2	$\leq$ 1.0e-13
II	α_{cost}	-1.1e-3	1.7e-4	2.4e-11
	α_{exp}	-2.9e-1	4.1e-2	4.7e-12
	α_{std}	-8.5e-2	2.5e-2	5.6e-4
III	α_{cost}	-9.8e-4	1.7e-4	1.5e-8
	α_{exp}	-3.0e-1	4.2e-2	2.0e-12
	α_{std}	-8.6e-2	2.5e-2	4.9e-4
	α_{env}	-5.7e-1	1.9e-1	3.4e-3

Table II shows the resulting estimation of the value of time and risk aversion, which are computed as the ratio between the cost coefficient and the expected arrival delay coefficient on one hand, and the ratio between the expected delay coefficient and the uncertainty coefficient on the other hand.

The values for the value of time seem to fall roughly between €200 and €400 per minute, taking into account the errors on the values. These values, interestingly, are of the same order of magnitude as the actual cost per minute computed by [21], even though the latter is closer to €100 per minute on average[7]. It is interesting to recall that these values emerge from the respondents that are not computing the cost of delay explicitly, or even being given any kind of a scale (apart from the questions themselves). The respondents, although they were not from airlines, were exposed to these kinds of values in the past and have thus an intuitive idea of the orders of magnitude of costs implied by delays. Of course, this will be compared afterwards with the results from the real respondents (AUs), and once again compared to the expected value of time for the respective types of airline.

TABLE II. RESULTS OF THE ESTIMATION OF DIFFERENT MODELS. ERRORS ARE COMPUTED BY PROPAGATING STANDARD ERRORS.

Model	Value of time (euros per minute)	Risk aversion
I	308 ± 79	N/A
II	253 ± 75	0.29 ± 0.13
III	302 ± 96	0.29 ± 0.13

The computation of the risk aversion is also interesting, because it indicates that respondents roughly consider the width of the distribution three times less important than the expected delay. The fact that this coefficient is not null is a good indication that respondents somehow take into account that large arrival delays are proportionally more harmful than small ones for airlines, a fact that is very well known by the respondents: all members of the team are exposed to the inner logic of decisions based on cost of delay over many years.

One can also run the model on a specific subset of answers. In Table III we show a comparison of three type of answers: those that were emulating expensive network carriers, those that were playing regional carriers, and one that was playing a regional carrier with a strong environmental concern. In order to measure the latter, we also defined the 'environmental concern' indicator, as the coefficient for the environment variable divided by the sum of all coefficients[8].

TABLE III. COMPARISON OF PARAMETER VALUES FOR DIFFERENT TYPES OF PLAYERS.

Type of players	VoT	Risk aversion	Environmental concern
Expensive network carrier	1743 ± 1332	0.11 ± 0.16	0.58 ± 0.43
Cheap regional carrier	158 ± 98	0.61 ± 0.49	0.58 ± 62
Environmental friendly regional carrier	73 ± 65	0.74 ± 0.82	0.82 ± 0.81

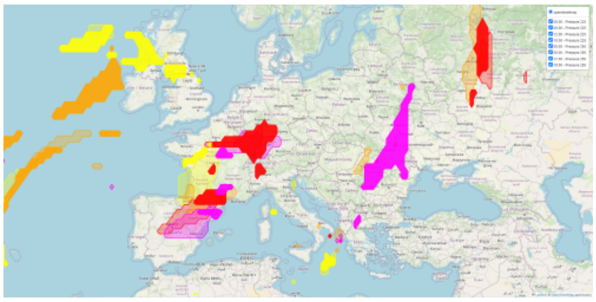
The comparison of the values of time shows that, as expected, it is very high for the players emulating an expensive (highly cost-sensitive) network carrier, and much smaller for regional airlines. The risk aversion seems also quite different, even though the error bars are too high to have a definitive answer. If the fact that regional airlines have higher risk aversion but smaller values of time is confirmed in the results of the survey, it would be interesting to look for the behavioural reasons behind this. Finally, the environmental concerns are hard to assess because of the error bars, but it looks that they tend in the right direction, with the environmental friendly carrier having the highest value.

[7]European-wide average, including all types of airlines.

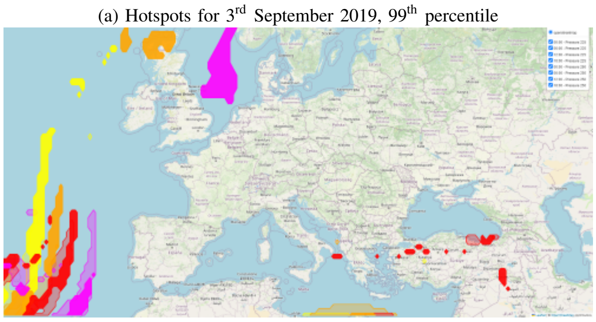
[8]Note: the data have not been standardised in input, so the absolute value of this metric is meaningless.

B. Climate hotspots

In this preliminary analysis, we run the CLIMaCCF library on ERA5 data for four chosen weeks, to have a better picture of how much and how fast the climate hotspots change. Figure 5 shows, as an example, the evolution of the hotspots along two days, one in September 2019 (Figure 5a), and another in December 2019 (Figure 5b). Different colours denote different times in the day – yellow shows hotspots at midnight, orange at 06:00, red at 12:00, and magenta at 18:00, so we can see how the hotspots move around with the atmosphere. Only two flight levels – FL340 (250 hPa) and FL360 (225 hPa) [24] are presented, the hotspots on the latter level being more transparent. The hotspots are calculated for all flight levels, but we show only two flight levels to ease the visualisation.



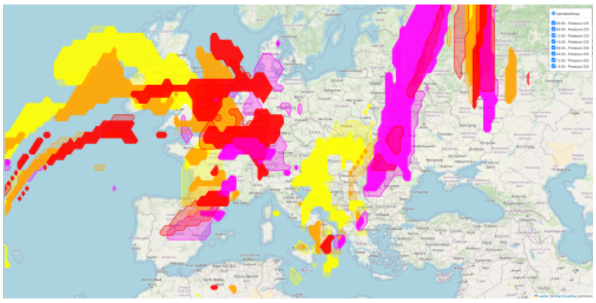
(a) Hotspots for 3rd September 2019, 99th percentile



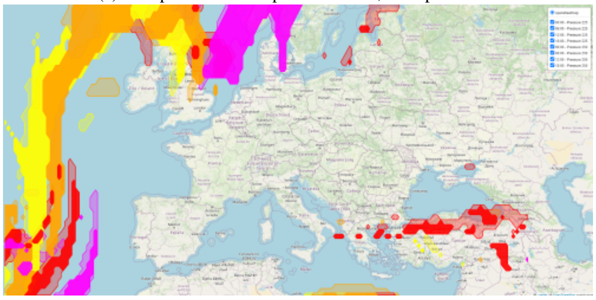
(b) Hotspots for 3rd December 2019, 99th percentile

Figure 5. Daily evolution of hotspots, for FLs 340 and 360, 99th percentile.

It can be seen that the hotspot areas are not the same on different levels, meaning that sometimes the avoidance of high climate impact could be obtained by the FL change. Further, as can be seen in Figure 6, the hotspot areas are much larger at the 95th percentile, which points to the need to agree on the appropriate threshold, i.e. percentile, to be used in a route-charging scheme. The intention is to discuss with the

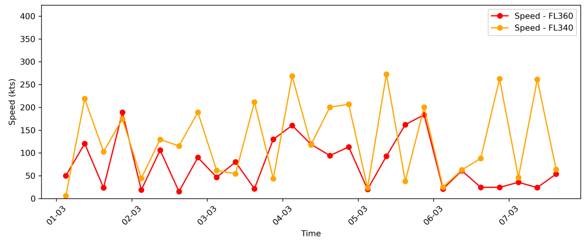


(a) Hotspots for 3rd September 2019, 99th percentile

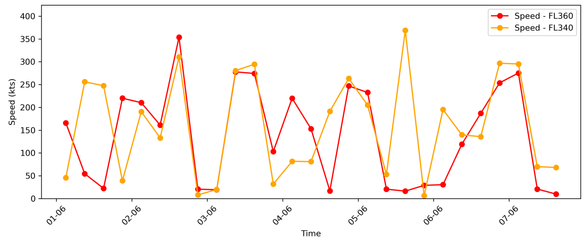


(b) Hotspots for 3rd December 2019, 95th percentile

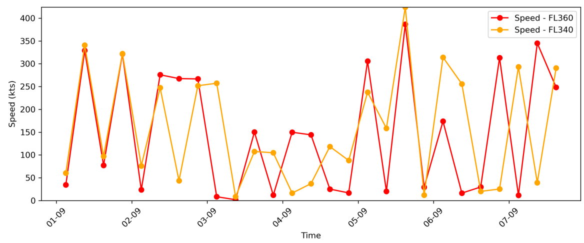
Figure 6. Daily evolution of hotspots, for FLs 340 and 360, 95th percentile.



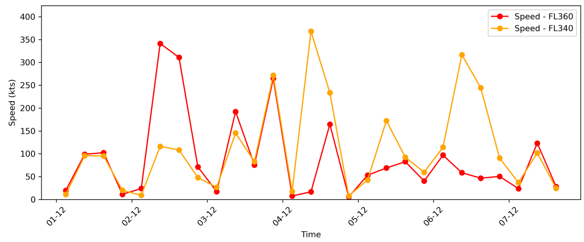
(a) March 2019



(b) June 2019



(c) September 2019



(d) December 2019

Figure 7. Speed of climate hotspot movement across 4 weeks in March, June, September and December 2019

scientists, AUs and ANSPs, during the planned workshop, to be able to find a potential compromise, based on the trade-offs between climate impact and operational needs (flight and capacity planning).

Figure 7 shows the speed of the hotspot movements across the days (locations taken at every 6 hours) of a week in March, June, September and December of 2019. Speeds of hotspot movements range from tens to hundreds of knots (measured at 6 hour intervals), pointing to a rather dynamic, and not easily predictable situation. By means of visual inspection, the four graphs seem to indicate different speed patterns, with lowest speeds in March, and highest in September. The speeds also differ across the chosen FLs. More in depth analysis of larger time period is needed to be able to determine if the hotspots demonstrate patterns that can be of operational use in ATM.

Furthermore, the requirements for any route-charging mechanism are that the charges are non-discriminatory, transparent and cost-related. The determination of climate hotspots depends on the weather forecast data (i.e., its resolution) and the choice of other parameters (as described in the corresponding manual). As the charges need to be transparent, there is a need for all stakeholders to use the same information. This new source of information would not only imply changes in the route-charging mechanism, but also a need for a *new service* that would source, calculate and share the information with all stakeholders.

IV. Conclusion

The quest for an environmentally friendly air transportation system passes through the optimisation of the existing processes under the prism of any potential climate impact. One of these processes is to make sure that flights are planned in such a way that they minimise their environmental impact. The full GRC Solution is addressing the total climate impact (both CO_2 and non-CO_2 emissions), which introduces complexities when compared to the current route-charging system as the non-CO_2 emissions depend on the location, time and altitude of emissions.

The full GRC Solution needs to capture not only changes in the charging scheme but also the reactions of airlines to these changes. The first step thus lies in setting up an SP survey to collect responses from AUs. The survey is designed to capture high-level weights of the decision-making processes when it comes to cost, delay, uncertainty, and environmental impact. Using the test data generated by the team, we illustrate the challenges of the analysis, in particular, how we will infer values of time and risk aversions from the survey results. The results presented here are exploratory in nature, but the team is interested to see if the actual respondents will demonstrate values similar to the test, and, if the values align with AUs' actual costs of delay, as expected.

The definition of the environmental hotspots is also crucial. Our first analysis points to the following issues:

- a potential difficulty to agree on the definition (in terms of percentiles),
- the fact that a hotspot may be very easily avoided by changing the trajectory FL,
- the fact that hotspots are particularly dynamic, which presents a challenge to the incentive scheme, especially taking into account that the current route-charging scheme is static, and simple in comparison.

The regression performed with the survey and the climate hotspots will be integrated into the overall GRC model, which will be used to estimate the impact of a new incentive scheme, both in terms of environmental impact and overall efficiency of the system.

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