

A new modulation charging concept to reduce CO₂ and non-CO₂ emissions

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Abstract—Aviation accounts for approximately 3–5% of total anthropogenic climate forcing, with two-thirds of its impact from non-CO₂ emissions and effects. Provided that such emissions can be accurately measured, charging schemes can be designed to incentivise airlines to reduce them (in addition to CO₂). However, non-CO₂ emissions are more complex than emitted CO₂, because they depend on many factors: the chemical and physical state of the atmosphere, and engine type, in particular. Hence, dynamic pricing schemes have to be considered, but models that have to predict the appropriate levels of modulation are then hard to solve, due to the various sources of stochasticity, in particular the state of the atmosphere. In this paper, we present an analysis of the main characteristics that need to be taken into account for non-CO₂ emissions. We present a charging scheme that may be able to alleviate the non-CO₂ emissions problem, using a ‘climate hotspot’ concept. We present a simple model able to capture sources of stochasticity and find the appropriate levels of modulation, for given traffic forecasts.

Keywords—Route charges; environmental modulation of charges; non-CO₂ effects; climate impact; airline incentives; capacity

I. INTRODUCTION

The European Green Deal [7] strives to make Europe the first climate neutral continent, with the European ATM Master Plan setting the vision for making “Europe the most efficient and environmentally friendly sky to fly in the world” [6]. A key part of that vision is the reduction of aviation climate impact. Global air traffic amounts to approximately 3–5% of total net anthropogenic climate forcing. Aviation’s climate forcing originates from CO₂ and non-CO₂ emissions and effects, where the latter are responsible for roughly two-thirds of the total effective radiative forcing [17]. Non-CO₂ effects are comprised of NO_x-induced effects on ozone and methane, water vapour, particulates (soot and sulphates), and contrails that can develop contrail-cirrus. Contrail-cirrus have the highest effective radiative forcing (of all non-CO₂ elements), but are subject to considerable uncertainty [21]. Indeed, non-CO₂ effects are strongly influenced by atmospheric conditions [16] and as such depend on the location, time and altitude of emissions, which makes them complex to determine. Furthermore, the exact emissions depend on aircraft and engine type as well as on the fuel composition.

However, even if the estimation of emissions improves significantly in the coming years, how to best decrease their impact in practice is still an open question. Sustainable Aviation Fuels (SAFs) are already mandated for inclusion in the fuel mix [2]. SAFs are new types of fuel that capture as much CO₂ during their making as what they produce when burned, reducing overall CO₂ emissions. This type of fuel is in use already, but a reliable mode of production on an industrial scale is not present yet. Moreover, burning SAF still produces non-CO₂ emissions.

Another possibility is to tax emissions, as is already done through the Emissions Trading Scheme (ETS) introduced by the European Union. While the ETS is currently applicable only to CO₂, an update to the ETS regulation was introduced recently [8], by which all European airlines have to report their non-CO₂ emissions. The taxation of these emissions might then be introduced in the ETS, or a similar trading scheme.

Centralised methods for emission reduction also represent an alternative to the market-based ones. They have the advantage of being built directly into the system as it is today, with information flowing from ANSPs and Network Manager, and airlines reacting to it by choosing their flight plan, and strategic plans made in return by ANSPs and the Network manager.

Modulation of route charges¹ in particular represents an untapped potential. Indeed, en-route charges are collected from airspace users and are proportional to the costs of provision of en-route air navigation services, based on the route charging mechanism. One could thus introduce modulations that would result in the best trade-off between the reduction of overall environmental impact, and keeping the economic and capacity impact stable. The mechanism would reward avoidance of climate sensitive areas, while still leaving the flexibility for aircraft operators of using the said areas, against a higher charge, and keeping revenue neutrality for air traffic navigation service providers (ANSPs).

The present work introduces and explores such a mecha-

¹Modulation of route charges consists “of financial advantages or disadvantages and shall be revenue neutral for air traffic service providers.” [1]

nism, called Green Route Charging (GRC) mechanism and introduces a simple model to estimate the potential gains and trade-offs, on a simplified setup. More specifically, our work provides the following contributions:

- The definition of the GRC mechanism by which route charges are modulated on an OD basis, with a simple rule for redistribution.
- A definition and an analysis of climate ‘hotspots’, where emissions are notably higher than average if a flight goes through.
- A simple analytical model providing estimations of Climate Impact (CI) and other key performance indicators (KPIs), taking into account route charge modulations and airlines’ reactions.
- An analysis showing the central (and detrimental) role of congestion in the airspace on the mechanism, but highlighting the potential benefits of the mechanism and existing trade-offs.

The article is organised as follows. First, we give a quick overview in section II of the background on route charges. We then describe in section III a new concept based on ‘climate hotspots’ that may help mitigate the total emissions of flights. In section IV we present a pre-analysis of non-CO₂ emissions, which highlights the main challenges when dealing with them, followed by section V, where we present a simple model that enables initial estimations on the application of the concept. In section VI, we describe the scenario that we applied the model to, and the data used to build it. In section VII, we present the results obtained on this scenario, in particular in terms of climate impact savings. Finally, we present our conclusions on the limitations and the future of the concept in section VIII.

II. LITERATURE REVIEW/BACKGROUND

Current regulatory landscape around aviation climate impact includes climate and related air traffic management regulations. Recently, the EU revised its CO₂ emissions trading system (ETS) to support a 55% emission reduction by 2030 (Directive 2023/958 [8]), tightening aviation CO₂ allowances, and introducing Monitoring, Reporting, and Verifying (MRV) framework for non-CO₂ effects. The route charging is regulated by the Performance and Charging Scheme [15] (to be changed by the application of Regulation (EU) 2024/2803, also called SES2+ [1]), and the route charges are collected and disbursed according to the Multilateral Agreement on Route Charging, with 41 States adhering to it, implemented by EUROCONTROL’s Central Route Charges Office (CRCO). The route charge “is a levy that is designed and applied specifically to recover the costs of providing facilities and services for civil aviation.” [5]. Route charges are paid by all non-exempted flights, to each State crossed. SES2+ [1] introduces the possibility of the *environmental modulation of route charges*, if the feasibility is confirmed. Note that the unit rate for route charges is determined strategically, at the beginning of the reference period (that could be from 3-5 years), and updated once a

year (per regulations in force). This approach offers stable prices of air navigation provision to the airspace users. Any modulation rates will need to be applied in the same spirit.

Several recent studies demonstrated the potential of operational measures to reduce the climate effects, which include flight path and altitude adjustments to avoid climate-sensitive portions of airspace like persistent contrail formation areas [3], [9], [10]. All show potential, at the same time facing operational (e.g. possible conflicts) and economic challenges (e.g. related costs). Moreover, most of the past work involves optimisation of individual flights, without taking into account the provision of air navigation services via availability of airspace capacity. In the following section we will show that the airspace capacity saturation has an impact, which in turn means that single-operator actions can do very little, individually, to reduce overall climate impact. Effective mitigation needs to be coordinated across stakeholders for the fuller effect. Price-based approaches include integrating non-CO₂ effects into the ETS [11] or applying aircraft-specific modulation of route charges for sensitive areas [12], [24]. In Green-GEAR project [24], two approaches to modulation were tested. One tries to reduce CO₂ emissions while respecting capacity, and the other looks at reduction of climate impact from all emissions. The CO₂ one shows that the modulation can help reduce the CO₂ around 1%.

Here, we explore in more detail this other approach, looking at intricacies of environmental route charge modulation that includes both CO₂ and non-CO₂ effects.

III. DESCRIPTION OF THE GRC MECHANISM

The core idea of the GRC mechanism is to reward (airlines) the avoidance of climate sensitive areas (that we call climate hotspots in the following). A ‘climate hotspot’ is a volume of airspace where due to the atmospheric conditions climate impact of emissions is much higher if flown through, compared to other areas. This could be for instance region where persistent warming contrails are very likely to be formed. More specifically, for a given flight/engine, a **climate hotspot** is any area in which the total emission impact per unit of time is in the X th top percentile. This percentile is computed on a distribution capturing the climate impact on several weeks and months.

For the purpose of the article, we chose $X = 99$, a period of time of one month, over the entire European area. Moreover, while the definition relies on a specific flight and type of engine, we actually consider averages for different flights and engines. See subsection V for more details.

The GRC mechanism process can be described in the following steps:

- At the start of a reference period (e.g. every year), the central planner determines the ‘climate impact modulation rate’ (CI rate). The central planner is a new function, that does not exist in the current route charging mechanism.
- X hours before a flight plan needs to be submitted (e.g. 6 hours, if taking the current frequency of the weather

forecast publication, as it is needed for calculation of non-CO₂ effects) the central planner computes environmental ‘hotspots’, as 3D volumes. Note that currently, a great majority of flight plans are submitted in the period 6 to 3 hours prior to the departure time.

- Any flight going through a hotspot has to pay a modulation of a route charge – an extra charge that is expressed as the product of the distance flown through the hotspot and the CI rate.
- Keep revenue neutrality by the uniform **decrease** of route charges enabled by extra revenue from CI modulations collected.

Note that the choice of keeping the total revenue constant for ANSPs is due to specific regulation requirement [1] (i.e. keep revenue neutrality). However, different options could be implemented. For example, keep the revenue per unit of service fixed, or apply another rule involving airlines. In the present mechanism, all the extra cost (positive in general) is born by the airlines, which may be unfair. The exact rule of redistribution has to be chosen by the policy-maker, in accordance with the high-level objectives of the public. This is a complex and highly political subject which is outside the scope of the present work. One can simply note that other rules of redistribution can be trivially added to the model presented here.

Note also that a slightly different process could be defined, which may be more accurate. Instead of defining hotspots, the total CI produced by flights (all flights) could be charged. We found that this variation of the mechanism is only slightly more efficient than the hotspots one, while requiring a lot more computation. See section VI for more details.

The route charging is a means of financing the air navigation service provision, subject to regulation [1], [15], as any route charging modulation would be. The inclusion of modulation in GRC mechanism involves and impacts the following stakeholders: airlines, ANSPs, states, and CRCO office. It would imply changes to the current route charging mechanism, through the introduction of environmental route charging modulation, which would require new functions to make it work: central planner and meteorological (MET) provision of environmental information. The central planner would collect the traffic and capacity forecasts, unit rates and run the GRC models to determine the CI rates. Furthermore, the planner would need to share the state-of-atmosphere forecast for the hotspot determination and collect the post-operational data for route charges assessment. The MET provision would need to issue weather forecasts for the determination of climate hotspots.

In order to seriously contemplate the change of the route charging mechanism, the environmental route charging modulation needs to show that it can incentivise the use of environmentally friendly routes, and that the benefits from the new mechanism (i.e. lower climate impact) overcome the costs of the implementation. To do that, we need to compute what the CI rate should be; what is the expected impact of the CI rate on the behaviour of airlines; and how much the CI

rate can reduce the environmental impact. Before describing the methodology to tackle these points, we present a pre-analysis on the climate hotspots, which drove the modelling process.

IV. PRE-ANALYSIS OF CLIMATE SPOTS

The non-CO₂ effects are strongly influenced by atmospheric conditions and depend on the location, time and altitude of emissions. Furthermore, the exact emissions depend on aircraft and engine type as well as on the fuel composition. To determine the hotspots, and the environmental impact distributions, we used the CLIMaCCF library [16], [18] on ERA5 data. ERA5 data² present the atmospheric reanalysis of the global climate, providing hourly estimates of a large number of atmospheric, land and oceanic climate variables.

CLIMaCCF is a tool that efficiently calculates individual non-CO₂ algorithmic Climate Change Functions (aCCFs), from water vapor, NO_x-induced ozone, methane depletion, contrail cirrus and, their merged totals. To merge aCCFs, all values are converted to a common physical unit using aircraft- and engine-specific data (e.g., NO_x emission indices, fuel burn per distance), provided for regional, single-aisle, and wide-body aircraft classes. Users can also select from various climate metrics. The analyses shown in this section are for single-aisle aircraft, using the aCCF merged (i.e. accounting for all non-CO₂ effects expressed via the average temperature response over 20 years (ATR20) metric. Note that this covers only one ‘average’ type of aircraft (single-aisle), using the generic engine emissions data.

The state of atmosphere is dynamic, which causes continuous movement and change of airspace volumes sensitive to climate impact (i.e. hotspots). These changes have a seasonal component, which is depicted in Figure 1 showing the values of aCCF merged for the airspace covering Europe, for pressure levels 400-150 hPa. The top graph shows the distribution across January and February of 2019 and the lower graph shows the same for May and June of 2019, where the values are in general lower in May-June period.

Furthermore, the aCCF merged accounts for different components of non-CO₂. Lee et al. [17] describe that persistent contrail formation areas contribute the most to the radiative forcing.

In the analysis presented in this paper, the hotspots are determined as a 99th percentile of the value of aCCF merged (over a month of ERA5 data - September 2019), expressed in K/kg fuel, for single-aisle, generic engine aircraft. Figure 2 shows the movement of hotspots along one day, on one pressure level. The yellow areas correspond to midnight, orange to 6AM, red to noon, and purple to 6 PM.

The hotspots and values of aCCF merged described here are used further in this work, see next section for description.

V. MODEL DESCRIPTION

The GRC mechanism requires a way of computing the modulation of route charges, i.e. the CI rate, and the assess-

²The data are available here <https://cds.climate.copernicus.eu/>

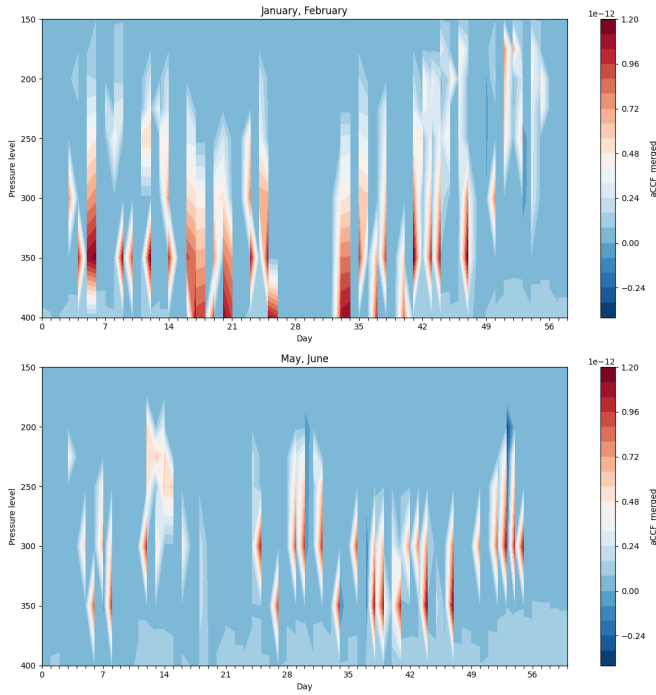


Figure 1. Values of aCCF merged across non-CO₂ emissions for 4 months of 2019.

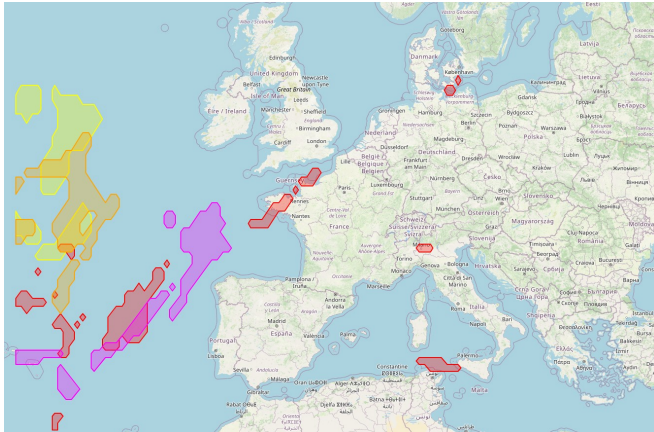


Figure 2. Hotspot movement on one pressure level, for one day, shown at each 6 hours.

ment of its impacts on a number of performance indicators (PIs). The non-CO₂ effects are complex to determine, and the fact that the climate sensitive areas move with the state of the atmosphere, adds to the complexity of devising the new mechanism. We start by describing the performance indicators considered in this work, followed by the model used to determine various estimations and the CI rate.

A. Performance indicators

In order to estimate the impact of the mechanism, we select several indicators. The most important one is the Climate Impact, or CI, for which we choose the “Average Temperate Response at the 20 years horizon” (ATR20). This

is the typical increase in temperature expected in 20 years, expressed in nK. The second indicator that we are tracking is the number of capacity violations. Our model features a soft constraint in capacity, which means that one can track the violations of capacity as indication of how much the system is under stress. The third indicator we track is the extra fuel consumption, expressed in kg of fuel. Note that this value also gives us a direct estimation of the CO₂ emissions, as these are directly proportional.

In order to have direct comparability with other studies, in particular in the context of SESAR, we also computed following five indicators, reflecting the important dimensions of the air traffic system, in a typical scenario. The first four are computed following the exact definition from the SESAR JU’s Performance Framework [26]:

- **FEFF1**: flight efficiency, average fuel burnt per flight (in kg).
- **TEFF6**: time efficiency, average flight time (in minutes).
- **AUC3**: direct operating costs for an airspace user, here taking into account route charges, environmental modulation and fuel costs (in 2014 euros).
- **CAP2-like**: capacity saturation in challenging airspace per unit time. This indicator is slightly different from the CAP2 as it indicates how much of the declared airspace capacity is consumed by the demand.
- **ATR20**: climate impact, expressed as average temperature response (in nK) over a 20 years horizon.

These performance indicators were selected because they represent the most important dimensions of the problem: the flight efficiency, the cost for the airspace user, the congestion in the network, and the climate impact.

B. Problem statement

As stated previously, we now need a way of computing the impact of a given value of the CI rate on the system. This problem, mathematically speaking, is highly non-trivial, because of:

- the stochasticity of the system, mainly in terms of the hotspot location;
- the airlines’ decisions, trying to find the least costly paths, given route charges, delay, etc.

The first point is absolutely crucial. Indeed, one cannot simply predict where and when the hotspots will be one year in advance, and decide which CI rate to implement. In fact, one year ahead, all areas in Europe are pretty much indistinguishable from the climate impact point of view, because they will all be subject to hotspots at some point in time, fairly uniformly³. This is in contrast to CO₂ alone, where one can predict the average CO₂ production on a given trajectory, since the latter is only a function of the fuel burnt⁴.

This means that, in principle, one has to set a CI rate ‘blindly’, which is applied on the day of operation, without

³Even though there might be slight differences, for instance between northern Europe and southern Europe.

⁴And even then, the winds and their impact on fuel burn might be tricky to estimate.

knowing beforehand how the airlines will react. In order to compute the impact, one in principle would need to use the following method:

- 1) fix a CI rate⁵,
- 2) draw at random the relevant variables (position of hotspots, delays that day, etc),
- 3) compute the cost of each trajectory,
- 4) run a model where airlines choose the best trajectory,
- 5) compute relevant KPIs for that day,
- 6) iterate steps 2-5 and compute averages of KPIs,
- 7) possibly change the CI rate to another value to see the impact, starting from step 1.

Steps 2-5 describe a Monte-Carlo simulation, particularly heavy computationally speaking, especially if there are many sources of randomness. Even though this Monte-Carlo optimisation (to find the ‘best’ CI) could be done in a slightly smarter way, we turn to a simpler form of model in order to catch at least the magnitude of the impact of the GRC mechanism on the PIs, and high-level insights like the presence and magnitude of trade-offs.

The simpler model we turn to computes analytically the mathematical expectations of the climate impact in particular (in V-C), for a single OD pair. Then we add a simple optimisation process to enforce capacity (in V-D). Finally, we add another level of optimisation to find the optimal CI rate for the system in a given scenario (in V-E).

C. Mathematical expectations

Mathematically speaking, we are trying to compute the expectations of performance indicators given various probability distributions and parameters. These distributions capture the randomness that one can expect over a period (e.g. year) of operations, for various variables. They are, in general, computed on historical data, and can even be regressed to known distributions for analytical purposes (like the exponential distribution, see below).

Given the complexity of the problem, we compute the expectations analytically, at least partially, in a simplified setup:

- Each flight, when filing a flight plan (a few hours before departure), has the choice between exactly two routes (labelled A and B in the following).
- When choosing a route k , the flight is subject to two random variables: a delay t_k , and the CI c_k associated with that route.
- The cost P_k of a route k is determined by 3 components: the route charges q_k , i.e. the charges fixed by the current rules, the cost of fuel f_k (assumed constant for a given OD pair and route), and the extra CI modulation, if any. The modulation is computed as the CI impact on this

route, c_k (a stochastic variable), times the CI modulation rate λ . In the following we denote as p_k the deterministic part of the price of a route, i.e. $p_k = f_k + q_k$. Hence, $P_k = p_k + \lambda c_k$.

- The flight always chooses the route which yields the maximum utility: $u = -\alpha P - \gamma t$. α and γ are the behavioural (positive) parameters of the utility function, which is deterministic. In the following we also assume that $\gamma = 1$ without loss of generality⁶.
- Delays t follow an exponential distribution, specific to the OD pair, but not to the route.
- CIs c follow an empirical distribution, computed from data.
- Delays are independent of each other on each route and so are CIs. Delay is also independent of CI.

The goal is now to compute several averages, in the form of mathematical expectations over the two distributions (delay and CI). For instance, the expected CI can be expressed as:

$$\tilde{c}^* = \int dt_A dc_A dt_B dc_B p_t(t_A) p_c(c_A) p_t(t_B) p_c(c_B) c^* \quad (1)$$

where c^* is the CI resulting from the choice of the flight, i.e.:

$$c^*(p_A, p_B, c_A, c_B) = c_{\arg\max_{k \in \{A, B\}} (u(p_k, c_k))},$$

i.e. the value of the CI on the route with the maximum utility. Integral (1) can then be computed analytically, assuming an exponential distribution for the delays and empirical discrete distribution for CI. More specifically, if $p_c(x) = \sum_i w_i \delta(x - c_i)$, where the weights $\{w_i\}$ and the values of CI $\{c_i\}$ are empirical values, and δ here is the Dirac distribution⁷, then one can compute the expectation as:

$$\begin{aligned} \tilde{c}^* &= 2\tilde{c} - \sum_{i,j} w_j w_i c_j [W(\alpha(p_A - p_B + \lambda(c_j - c_i))) \\ &\quad + W(\alpha(p_B - p_A + \lambda(c_j - c_i)))] , \end{aligned} \quad (2)$$

where $\tilde{c}$ is the mean of the CI distribution, and $W(x) = \int dy p_t(y) F_t(x+y)$ is a pure function depending only on the distribution of delay, computable offline or even analytically in the case of exponential distributions. From this expression, one can prove that $\tilde{c}^*$ is monotonically decreasing with λ and that $\tilde{c}^* = \tilde{c}$ for $\lambda = 0$, which means that applying the CI modulation *always* decreases the CI.

A similar expression can be derived for instance for the occupation of routes A and B (i.e. the average probability that a flight will choose this route):

$$\begin{aligned} \tilde{o}_A^* &= 1 - \sum_{i,j} w_j w_i W[\alpha(p_A - p_B + \lambda(c_j - c_i))] \\ \tilde{o}_B^* &= 1 - \sum_{i,j} w_j w_i W[\alpha(p_B - p_A + \lambda(c_j - c_i))] , \end{aligned} \quad (3)$$

from which most other indicators such as fuel consumption, or capacity infringements, can be derived.

⁵Note that in our model the CI rate is expressed in Euros/nK, not in Euros/NM or Euros/km. This is because, in practice, one is equivalent to the other. The hotspots are defined at the certain fixed threshold, and we consider that the flight is producing a certain amount of emissions above it, which is a fixed amount per unit of distance. Hence, one can always translate a CI rate per unit of distance in a CI rate per unit of temperature.

⁶Because we are only comparing relative levels of utility, so we can always normalise the function by γ .

⁷The Dirac distribution allows to write discrete distributions as continuous ones, going from integrals over a continuous variable to sums over specific values seamlessly. For instance, $\int \sum_i x \delta(x - c_i) dx = \sum_i c_i$.

These simple expressions get a lot more complex when airspace capacities and diversity of airlines (in terms of behaviour, i.e. utility functions) are introduced. Keeping the model simple, we assume that:

- there are two kinds of airlines, with different utility functions, i.e. distinct coefficients α_1 for airline 1 and α_2 for airline 2,
- each route can only hold a certain number of flights κ_A for route A and κ_B for route B .

In this case, the expressions for the mathematical expectations are far more complex, but can be written as:

$$\tilde{c}^* = 2\tilde{c}o^+ + (-o^+ + o^1)\mathcal{Z}_{\leq,2} + (o^- - o^2)\mathcal{Z}_{>,2} + (o^- - o^1)\mathcal{Z}_{\leq,1} + (-o^+ + o^2)\mathcal{Z}_{>,1}, \quad (4)$$

where o^+ , o^1 , o^2 , and o^- are simple numerical expressions dependent on the number of flights m_1 and m_2 respectively for airline 1 and airline 2, and on the capacities of the routes. For instance, assuming the same capacity κ on each route, if $\kappa < m_1 + m_2 \leq 2\kappa$, then $o^+ = m_1 + m_2$, $o^- = 0$, $o^1 = m_1$, and $o^2 = m_2$. The expressions for $\mathcal{Z}$ are more complex but similar to the previous case:

$$\begin{aligned} \mathcal{Z}_{\diamond,l} = & \sum_{c_i - c_j \diamond (p_A - p_B)/\lambda} w_i w_j c_i W[\alpha_l(p_A - p_B \\ & + \lambda(c_i - c_j))] \\ & + \sum_{c_i - c_j \diamond (p_B - p_A)/\lambda} w_i w_j c_i W[\alpha_l(p_B - p_A \\ & + \lambda(c_i - c_j))], \quad (5) \end{aligned}$$

where the sums run on i, j but only on values that fulfil the condition below, where $\diamond$ represents any operator of comparison (like $<$), and where k is the index of the airline (either 1 or 2). A similar expression can be obtained for $\tilde{o}_A^*$ and $\tilde{o}_B^*$.

These expressions, valid for one OD pair and two routes, are hard to generalise to more OD pairs, because capacity issues create dependencies between several OD pairs (the dependencies are hidden in the o^+ , o^1 , o^2 , and o^- coefficients). Instead of deriving analytical expressions, we set up a numerical optimisation process to solve congestion in a multi-OD environment.

D. Numerical optimisation for congestion solving

Now we consider the following setup and assumptions:

- a number of OD pairs co-exist;
- volumes of airspace are defined, crossed by routes, and each has a maximum capacity (maximum entry count);
- capacities are computed per time window (one hour), similarly to what is done in reality;
- entries are counted probabilistically, using the previous expressions $\tilde{o}_A^*$ and $\tilde{o}_B^*$;
- flights can be shifted (forward) in time, i.e. can be delayed in order to keep the entry count under the capacity threshold; the shift is made through a modified probability of delay (adding to the mean).

On top of adding a delay to the distribution, we also cut it at the end the time window, which represents the fact that flights which are too late can be pushed to the next time window.

We now setup an optimisation routine. We use delays in each time window for each airspace as variables, noted as Δ . The most penalising delay along a route is selected to set the delay distribution for the flights on this route, in a manner similar to how air traffic flow management delays are assigned. We define the following objective function, to be minimised:

$$O_c(\lambda, \Delta) = \sum_l \sum_i \sum_{k \in i} (o_{l,k,e}^*(\lambda, \Delta) - \kappa_i), \quad (6)$$

where the first sum is carried over all time windows, the second over the airspace volumes, the third over the routes crossing that airspace, where $o_{l,k,e}^*$ is the expected occupancy for that route at that time window, known analytically via the model described in the previous section (and a function of Δ through its dependency on the distributions of probabilities p_t). While the optimisation process can be long, because the problem is highly non-linear with real-value variables, the estimation of the objective function is fast thanks to the analytical expression derived in the previous section.

The result of this procedure is a set of delays that minimises the congestion in airspace, given a CI rate λ and the internal optimisation of the airlines.

E. Numerical optimisation for environmental impact

Finally, to be able to introduce the new environmentally friendly route charging mechanism, we are interested in minimising the environmental impact via the CI rate, while keeping the revenues of the ANSP constant. There are different ways of ensuring ANSP revenue neutrality (for instance, assigning a fixed revenue per service unit). In this article we simply ensure that the total amount of revenue is fixed, i.e. that the extra revenue is covered by a decrease of the price of the ANSP services, uniformly.

Hence, on top of the delay variables, the optimisation problem now has two additional ones: λ , the CI rate, and μ , a new variable that decreases the usual route charging rates by multiplying them by μ .

The objective function now has two more components, linked to the revenue constraints, and to the ‘real’ objective, the CI itself:

$$\begin{aligned} O(\lambda, \mu, \Delta) = & \sum_l \sum_k \tilde{C}_{l,k}^*(\lambda, \Delta) \\ & + v_r \sum_l \sum_k q_k (\mu \tilde{o}_{l,k}^*(\lambda, \Delta) - \tilde{o}_{l,k}^*(0, 0)) \\ & + v_c O_c(\lambda, \Delta) \end{aligned} \quad (7)$$

with v_r and v_c two weighting parameters. These are chosen so that the revenue constraints are prioritised, then the capacity constraints, and then the environmental impact.

VI. SCENARIO DEFINITION AND DATA

Due to the complexity of the problem the GRC mechanism and associated modelling is applied on a *medium-sized scenario*, represented by the 10 busiest airports in Europe, and all the origin-destination (OD) pairs which were serviced in the time period chosen for the analysis (see Figure 3). The time period covers AIRACs 1909 and 1910⁸, chosen to represent busy months in 2019, as a busy pre-COVID traffic, the levels of which are just now being reached (see EUROCONTROL's Daily Traffic Variation dashboard). The design and analysis of environmental modulation of route charges requires diverse input data, which are described below.



Figure 3. Depiction of the scenario used to run the model. Blue shapes represent sectors, solid black lines are 'routes A' and dotted black lines are 'routes B'.

Typical trajectories for each origin-destination (OD), which are obtained via clustering from historic data (DDR2 data [13]). The clustering was applied on all the possible trajectories in the data. Two most representative trajectories for each OD were chosen for the solution scenario (routes A and B in Figure 3).

Airspace configurations, to be able to take the airspace capacity into account (DDR2 data). A simplified configuration is used: one configuration, at noon on the 19 September 2019 (chosen as a busy day without significant disruptions). The maximum entry count per sector is taken to represent the nominal capacity. As the scenario is limited to only 10 airports, to make up for the missing traffic, a modulation factor for the capacities is introduced, which allows the decrease (or increase) of all capacity values by the same amount.

Fuel consumption and CO₂ emissions along each trajectory (which depend on aircraft type, and load factor) are determined using OpenAP [23], while **route charges** along the chosen trajectories are sourced from DDR2 [13].

Distribution of delays (historic), defined as the difference between planned and actual arrival times. These are fitted for

⁸Aeronautical Information Regulation And Control (AIRAC) 1909 and 1910 cover 56 days, 28 each, from 15 August to 9 October 2019.

each OD pair, using an exponential distribution. For all the airports in the scenario, the regression was sufficiently good to validate this assumption.

Behavioural parameters for airlines as they pertain to costs and environmental impact, are results of a survey performed within the project [4]. The parameters are bundled into two categories, one for 'legacy' airlines, with high sensitivity to delays, and one for 'low-cost' airlines, with higher sensitivity to cost.

Distributions of climate impact on each OD pair. To obtain this, a month of ERA5 data (September 2019) was used to compute the environmental impact for each of the actual daily atmospherics, for each route of each OD. This allows us to have a prior distribution of environmental impact. After that we 'binarise' this distribution. We consider the CI value that defines the hotspots (the 99th percentile in general, as explained in section III), and set all values to 0 below this threshold, and to X over the threshold, with X being computed so that the average CI is the same in the binarised and non-binarised version. This distribution represents the CI that is taken into account in the flight planning route choice (i.e. flying through a hotspot or not). Note that the initial, non-binarised version of the distribution can also be used if one wants to apply a different 'flavour' of the GRC mechanism, described in section III, where the flight pays for all its emissions instead of a per-hotspot basis. From the mathematical point of view, the only difference between the two flavours is the type of distribution used in the model. The binarised version is however vastly more efficient from the computation point of view, because the sums over the values of the distributions for instance in equation 5 have only 2×2 terms.

VII. RESULTS

In this section we present the results of the analytical model run over the scenario described in section VI. Note that the hotspot avoidance in this scenario is available only via choice of different route, which is a limitation. We start by showing the impact of an increasing CI rate – initially in an ideal situation with infinite capacity, then applying capacity constraints only. We then show how the model is able to predict the optimal CI rate for the system, keeping ANSP revenues constant and capacity violations under control.

A. Effect of environmental modulation and capacity on the system

Figure 4 shows the evolution of the expected climate impact, as given by equations 4 and 5 and the capacity optimisation (eq. 6). This represents the average CI that one would get with the atmospheric conditions considered in the data and the airline choice of the minimum cost route.

As expected, the climate impact decreases when the CI rate increases, as airlines avoid routes with high CI because they are more costly. The gains also naturally reach a plateau when the CI is so high that all flights use the most environmentally friendly trajectory. In this scenario, one could obtain

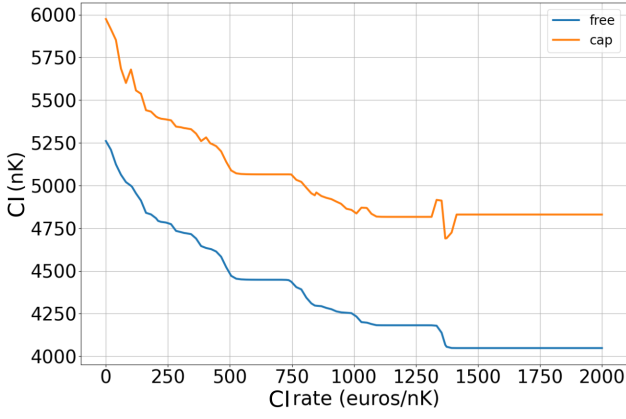


Figure 4. Total environmental impact as function of the CI rate, without capacity constraints (blue) and with capacity constraints (orange).

approximately a 22% reduction of CI, if the modulation rate is high enough. This is to be compared to about a 1% decrease possible with only CO₂ measures [22], highlighting the very high potential of the non-CO₂ charging scheme for the environment. Nonetheless, When the capacity is enforced, the available gains are much smaller (gap between blue and orange lines in Figure 4), even if the CI still decreases significantly when the modulation rate is applied.

Figure 5 shows that the model is behaving as expected, as capacity infringements are registered when capacity is not enforced, contrary to when capacity is enforced (showing the success of the optimisation process). Note that the number of capacity infringements does not vary monotonously with the modulation rate, which is entirely driven by whether or not low CI routes go through sectors at capacity.

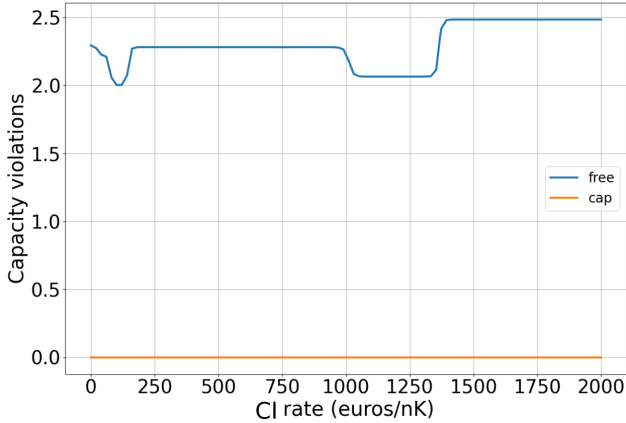


Figure 5. Average capacity violations as a function of the CI modulation rate, without capacity constraints (blue) and with capacity constraints (orange).

Note that the application of the CI modulation increases the airline costs, even without accounting for the cost of modulation itself. Figure 6 shows how fuel consumption increases with the CI modulation rate. This is due to the fact that the avoidance of the hotspot is available only by choosing

a different route, which is a limitation, useful for exploration of trade-offs the new mechanism would create. The scenario and mechanism setup has two separate consequences. First, the airlines' cost will increase already with the modulation, unless the ANSPs decrease unit rates sufficiently. We discuss this fact in the conclusions, but it is part of a 'no free lunch' effect whereby the system is naturally more costly if one minimises CI instead of cost.

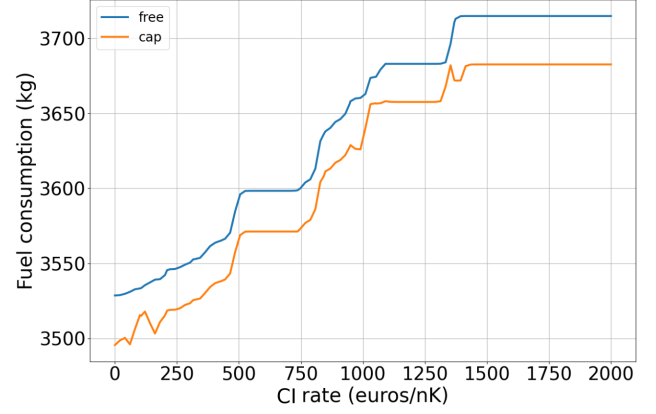


Figure 6. Total fuel consumption as a function of the CI modulation rate.

Second, the amount of CO₂ produced in the air traffic network *increases* with the modulation rate, as a consequence of increased fuel burn, in this scenario. However, as non-CO₂ climate effects can be markedly higher than CO₂ ones, in some cases it might be beneficial to fly more fuel-intensive routes in order to avoid climate sensitive zones. Note that the altitude change could also be used to avoid hotspots, which would require less fuel.

Note that, counter-intuitively, applying capacity constraints decreases fuel consumption in this case. The capacity constraints limit the availability of alternative routes, and this in turn reduces the distance flown and consequently fuel burnt.

B. Optimal modulation level

We now explore the results where the CI modulation rate is set using the optimisation process, with the objective function given by equation (7). To visualise the results, we choose to vary the capacity levels, in order to explore the effect of congestion on the network.

In figure 7 we show that the CI is decreasing when capacity reserves are higher. This is the generalisation of the results shown in figure 4, where one can quantitatively estimate the impact of congestion. In this scenario for instance, the shortfall due to congestion when the capacity modulation is at 70% is roughly 400nK, i.e. around 6% of the emissions in the infinite capacity case.

Moreover, the graph shows that applying the CI modulation can decrease the CI, while keeping the capacity infringements under control (see figure 8 for the capacity violations). Thus, the CI modulation can have a significant effect, but the congestion decreases the relative efficiency of the modulation. In

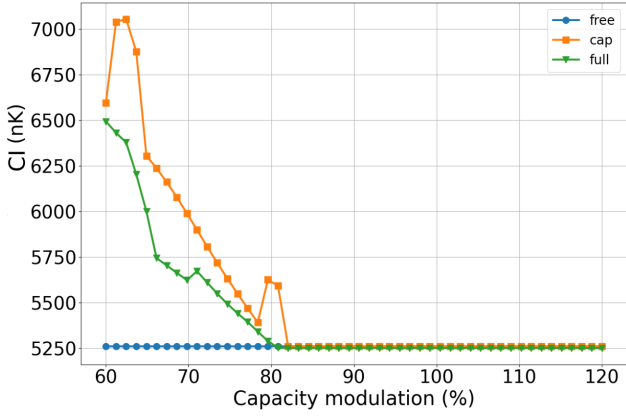


Figure 7. Total climate impact as function of the capacity modulation: without capacity constraints (blue), with capacity constraints (orange), and with capacity constraints + climate impact minimisation (green).

other words, when the airspace capacity is close to saturation, the alternative routes cannot be used without infringing the capacity of neighboring airspace.

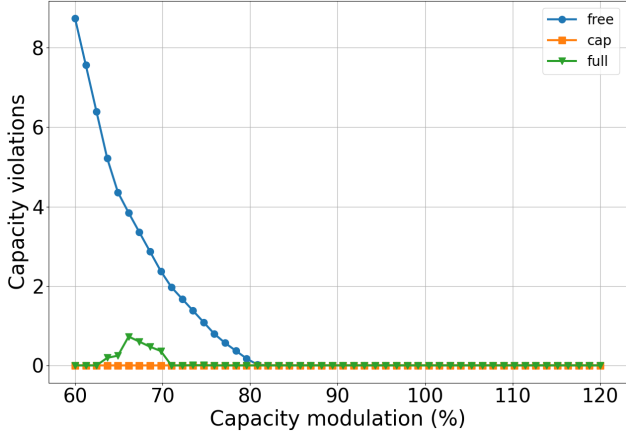


Figure 8. Average capacity violations as a function of the capacity modulation, without capacity constraints (blue), with capacity constraints (orange), and with capacity constraints + environmental impact minimisation (green).

Figure 9 shows the values of λ and μ at the optimal points. Note how a relatively small amount of revenue from the ANSPs is enough to offset the high modulation, while keeping a significant effect on CI. Note also that smaller capacities convert into the need to have higher CI modulations to encourage adoption of the ‘greener’ routes.

Most KPIs (CAP2, AUC3, FEFF1 and TEFF6) increase (i.e., worsen) when the CI is applied, compared to the nominal case (the case where only capacity is enforced). However, ATR20 decreases by 6% in this case, which is significantly higher than any gain expected on (charging) measures taking into account CO₂ only [22]. The KPI increases are fairly small (especially FEFF1 and TEFF6). This suggests that a charging scheme for non-CO₂ emissions may yield important environmental gains, while maintaining good network

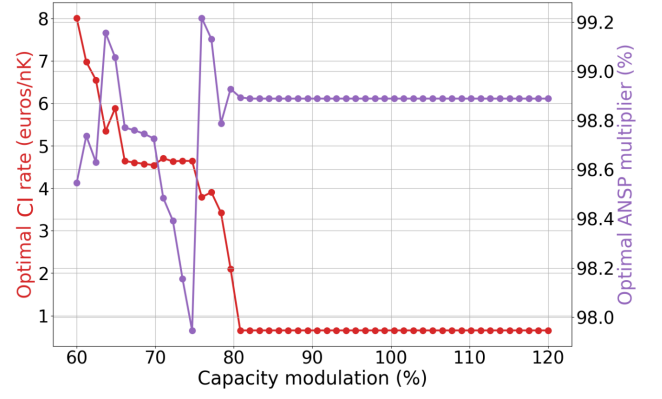


Figure 9. Optimal level of the CI modulation rate - λ (red) and the ANSP revenue multiplier μ (purple).

functioning conditions. This conclusion, however, relies on several hypotheses, that we discuss in the next section.

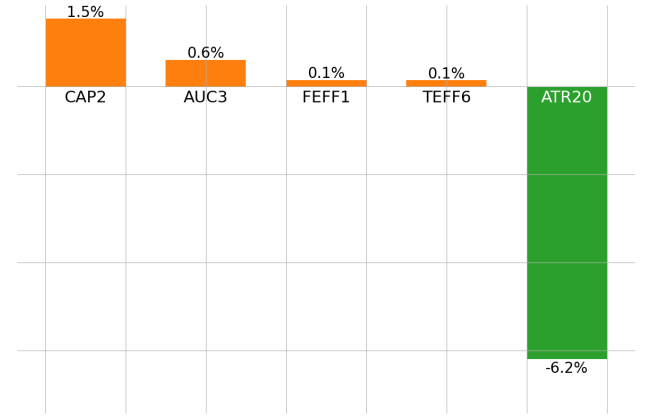


Figure 10. Change of value in KPIs between the constrained case and the constrained case with CI optimisation for a capacity modulation of 70%. An orange colour denotes a deterioration in the KPI, a green one shows an improvement.

VIII. DISCUSSION AND CONCLUSIONS

A. Discussion

The analytical model presented here is an original alternative to the usual integer programming optimisation processes, and particularly suited to the high degree of stochasticity of the system. It shows excellent computational performance for small scenarios, able to produce estimations of KPI expectations in seconds, but it scales badly with the number of OD, and even worse, with the number of routes per OD. Moreover, it relies on several core hypothesis that may be hard to relax, and may lead to an overestimation of the gains from the CI modulation. Here are the main assumptions:

- The *emission estimates are accurate enough* to define hotspots. If this assumption fails, then by definition, ANY solution taking non-CO₂ emissions into account will fail.
- Each OD pair has *only two routes* available. This is due to the fact that the number of terms grows exponentially

with number of routes available. Analytical computations are required in each case. This assumption is near impossible to relax with capacity constraints on top.

- CI distributions are considered independent across routes, but proximal routes are more likely to be in a hotspot together, in practice. In that case, it might not be possible to find a route with low CI. Correlations across routes can be easily added to the model.
- Airlines choose route based on a linear deterministic utility function, as we try to capture the sensitivity of airlines to delay and costs independently. We use deterministic utility function to simplify the integrals. Linearity could be relaxed via more complex analytical expression. Deterministic aspect could also be relaxed using numerical methods for the integral estimation.
- Fuel consumption and emissions are estimated using a typical aircraft engine included in the CLIMaCCF library. We decided to use single aisle estimation only, as this work is only exploring the high-level feasibility of the mechanism. This assumption is hard to relax with the current modelling approach, but could be relaxed in a simulation setting.
- Delays experienced by flights are exponentially distributed, as exponential distributions allow us to compute analytically some of the terms. Note that evidence that delays are either exponential or normal are numerous.
- Behaviours of airlines are bundled in two categories. The two categories notionally represent low-cost and network carriers. This allows higher diversity of choices of routes when faced with high delays (due to congestion) or high costs (due to hotspots).

This model should thus be considered as a means to estimate the magnitude of the climate impact savings produced via ‘climate hotspot’ modulation of route charges.

Operationally, the GRC mechanism would provide a choice of routes for airlines slightly more dynamic than it is today⁹. The impact on ANSPs would be two-fold. On one hand, the route choices based on the environmental impact will have an impact on required capacity provision, but it might also make it a bit more predictable than it is today, if the hotspot forecast is shared with all the stakeholders. On the other hand, the impact is administrative, and it would be preferable that the ‘accounting’ of modulation charges stays as simple as possible. Indeed, the current route charging formula is very simple, even if the process behind the calculation of traffic, service unit and cost forecast is much less so. The determination of the modulation rate would not be more complex, and would require a set up of a new function, and the adjustment of the current verification system (which impacts CRCO).

This work has explored the avoidance of hotspots through a simple mechanism of route switching. This is a first attempt in the direction of estimating the benefits of converting non-CO₂

climate emissions into financial penalties to change airspace users’ behaviours. One can however go beyond this simple scheme. Two mechanisms in the particular will be studied further.

The first one is a more continuous trajectory optimisation process, done during the execution phase. The added benefit of this would be to rely on the latest weather update for micro-decisions, instead of making a choice of route based on a forecast a few hours before. This idea will be explored in the newly founded SESAR3 Exploratory Research Project FAIRSKY, starting in July 2026. Note that this mechanism is fully compatible with the previous one: an airline can choose the route with the lesser likelihood of emissions at flight plan submission time, and then adapt slightly the trajectory en-route. Note also that continuous trajectory optimisation will only be doable in certain areas where traffic is sufficiently sparse to be handled by controllers.

The second one is the simple idea of making changes to the vertical profile instead of or on top of the horizontal one. Indeed, there is multiple evidence that contrails in particular are concentrated in a small layer that could easily be avoided. Hence, one could give the opportunity to airlines, at flight plan submission, to change their cruise speed by one or two levels in certain areas. This would be in general less disruptive for the system than horizontal changes and it can also be easily combined with the latter. The present model is in fact able to make predictions for this kind of mechanism, and preliminary results show very promising impact.

B. Conclusions

The model and the charging scheme presented here assume that information on the non-CO₂ emissions is reliable enough to be used on the day, i.e. that a flight will indeed cross a hotspot if the system forecasts so. This issue is crucial for the mechanism implementation and efficiency, and it depends on the atmospheric models used to compute emissions. Further research initiatives are planned to estimate the uncertainty linked with the results of such models, which can then be incorporated into the model presented above to estimate the drop in efficiency.

The GRC mechanism presented in this article indicates that a significant drop in the CI can be expected from even a small CI modulation, with only moderately negative impact on other important PIs. Moreover, it shows two other crucial facts. First, airline costs increase in general with the CI modulation *even when the latter are not considered in their costs*, due to the fuel consumption increase, which highlights a trade-off between CO₂ and non-CO₂ emissions. This raises the issue of who is going to pay for the extra cost that the climate impact minimisation is introducing, as discussed previously. Second, the overarching issue for decreasing CI is congestion (i.e. capacity available). Higher levels of congestion translate into reduced flexibility for the flights to avoid climate hotspots. Even so, the climate sensitive hotspots can be located in a rather thin layer, and could be avoided by changing the flight level [3], which would require much

⁹Note that even in the current system, different operational constraints pop-up constantly (e.g. weather related regulations, capacity disbalance).

less additional fuel consumption than the re-route around the affected area.

However, the modelling of non-CO₂ effects is still subject to significant scientific uncertainty, these stemming from weather forecasts, climate response, and aircraft performance (as it pertains to emissions in the atmosphere). The accuracy of the models, the dynamicity of the atmosphere, and the heterogeneity of the aircraft and engines flying in Europe imply that any mechanism based on these considerations has to make extra effort to determine the acceptable level of uncertainty. A significant research effort in this area, first to reduce the uncertainty and then to manage it more rationally, is needed. This is an important part of assessing the efficiency of the environmental modulation of route charges, and stakeholder consensus creation.

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