

Mass Estimation for an Adaptive Trajectory Predictor using Optimal Control

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ABSTRACT

Air traffic predictability is paramount in the air traffic system in order to enable concepts such as Trajectory Based Operations (TBO) and higher automation levels for self-separation. Whereas in simulated environments 4D conflict-free trajectory optimisation has shown good potential in the improvement of air traffic efficiency, its application to real operations has been very challenging due to the current lack of information sharing between airspace users. Consequently, such operations are still very limited in scope and rarely attempted in dense traffic situations. Better predictability of other traffic future states would be an enabler for each aircraft to fly its user preferred route without decreasing safety in a self-separation context. But this is not an easy task when basic aircraft parameters such as aircraft weight, performance data or airline strategies are not available at the time of prediction. In this paper the authors propose to compensate this hindrance by continuously integrating the state of the surrounding traffic to improve the ownship's knowledge of other aircraft's dynamics. Specifically, conventional position (and velocity) messages, as coming from Automatic Dependent Surveillance Broadcast (ADS-B), are integrated at the ownship. Then, an optimisation problem is formulated, using optimal control theory, that minimises the error with the known states, having the parameters of study (i.e. mass) as decision variables. A scenario with two departing trajectories is used to demonstrate the effectiveness of this parameter estimation method. In it, the take-off mass of the potential intruder is estimated on-board the ownship and its impact to conflict detection and resolution is presented, demonstrating the big improvements in predictability and safety.

Keywords

mass estimation; trajectory prediction; trajectory optimisation; optimal control; self-separation

1. INTRODUCTION

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One of the major drivers for research and development in the SESAR and NextGen programmes is the improvement of air transport efficiency in terms of economic and environmental impact. New technologies and procedures for future air traffic management (ATM) and on-board systems and operations are being investigated and proposed. More and more, the air traffic system is seeking benefit from initiatives such as Continuous Climb Operations (CCO), Continuous Cruise Climbs (CCC), and Continuous Descent Operations (CDO), which propose good fuel reduction in specific phases of the flight. However, such operations are hugely dependent on multiple characteristics of each aircraft (such as aircraft performance, weights or operating procedures) and meteorologic conditions. This produces a great variety of *optimal* vertical and speed profiles that difficult the task of separating the traffic, ultimately impacting negatively on airspace capacity [1].

To prevent this negative impact in efficiency and/or airspace capacity, research has been performed on the integration of CDOs in dense TMAs [2, 3, 4, 5]. The Oceanic Tailored Arrivals program, currently in place at San Francisco airport, is another relevant example [6]. These arrivals are supported by the En-route Descent Advisor (EDA) developed by NASA-AMES, which is able to compute conflict-free optimal descent trajectories and satisfy a given arrival fix metering by issuing speed advisories to participating aircraft [7]. The literature on optimal arrival trajectories is very extensive when compared to that regarding optimised aircraft departures [8, 9, 10].

Most solutions, however, lack accurate aircraft performance data, since airlines do not publish what they consider is subject to confidentiality. This leads to uncertainties in the prediction of aircraft future states. A lot of effort has been put into enhancing the sharing of information between aircraft users [11, 12], although the specific contents are still subject of debate and the implementation of such paradigm is still far in the future. On the other hand, many techniques for trajectory prediction are available in the literature [13]. Furthermore research is being done with the purpose of using the aircraft past states to enhance ground based predictions [14, 15, 16, 17]. Most of these algorithms are based on analytical models that iteratively correct the aircraft weight estimation with each new received track data minimising the energy rate differences with the projected energy rate using a simplified dynamic model.

Along these lines, this paper presents a unified framework for trajectory optimisation, prediction and parameter esti-

mation with the purpose of enhancing predictability of air traffic operations whilst proposing optimal trajectories and conflict resolution in a dense traffic area. Following concepts described in [18], a continuous multiphase optimal control problem formulation is created. Given different spatial and temporal constraints along with the definition of specific objective functions for each purpose, the same problem formulation provides optimisation, prediction and estimation functionalities. The described framework builds upon previous research by the authors presented in [19, 20].

Through this approach, firstly an aircraft trajectory is optimised upon own cost-objectives with a high accuracy model of dynamics. In current day air transportation density, it is most probably that this trajectory conflicts with other traffic. Consequently, given ADS-B intent information (e.g. list of fixes), the aircraft (ownship) predicts surrounding traffic future states using simplified dynamics model and assumptions (based on BADA¹). As the situation evolves, ADS-B state data is used to learn about other aircraft dynamics (e.g. initial mass). This information forms a trail of past states that the estimation model uses to converge to more accurate parameters. Accordingly, the prediction is continuously regenerated as the knowledge of the other traffic grows (i.e. longer trail). The ownship then uses this updated prediction to detect any potential conflict and generates a new conflict-free trajectory. It is shown how this enhanced prediction enables efficient conflict detection and resolution.

This paper is organised as follows. Section 2 describes a self-separation optimisation framework that integrates trajectory prediction, mass estimation and conflict-free optimisation. Section 3 lays out the dynamic model of the aircraft, the optimal control problem formulation and the trajectory modelling in multiple phases. Section 4 describes the scenarios and the success of the self-separation framework. Finally, section 5 presents the authors' conclusions.

2. SELF-SEPARATION FRAMEWORK

Conflict-free trajectory optimisation in dense traffic conditions has a very complex implementation due to many factors that introduce uncertainties at different levels. The research framework described in this paper tries to unify three main aspects in an effort to minimise such inaccuracies: trajectory prediction, mass estimation and trajectory optimisation. These functionalities work together interconnected in order to achieve better predictability for a safer and more efficient self-separated air traffic system. The concept of operations is summarised in figure 1 and the main modules described in the following subsections. The problem formulation of the optimisation engine, which provides core functionality of each module, is described in section 3. Its use for trajectory optimisation and trajectory prediction is almost identical, whereas some slight modifications occur for parameter estimation.

2.1 Trajectory prediction

Prediction methods in the literature are usually based on the integration of the aircraft dynamics model with specific assumptions in form of throttle setting, vertical speed, flight path angle, etc. [13]. In a different manner, our assumption for prediction purposes is that the aircraft of study is optimising on a cost functional as defined in equation 1:

$$J = \int_{t_0}^{t_f} [FF(\mathbf{x}, \mathbf{u})] dt. \quad (1)$$

As opposed to fix specific controls to integrate the prediction, this assumption allows for more complex predictions and can potentially provide more accurate results when many restrictions apply to a trajectory. Especially, when a flight plan is available that follows a defined lateral route or when multiple constraints have to be met at one fix (e.g. altitude and time). Particularly, the optimisation framework presented in section 3 is used to generate predictions. However, given the fact that a complete knowledge of the other traffic is unknown, the following restrictions apply:

- (a) Since we do not have an enhanced and accurate dynamics model of the other aircraft, assuming we can work out the type of aircraft, we use BADA to model the dynamics of the state variables and provide nominal parameters. Among this nominal parameters, there is the take-off mass, which BADA defines for each type of aircraft.
- (b) We assume that the aircraft intents are available in form of a list of geographical points that represent the lateral (and potentially vertical) route. Such information could be available in form of ADS-B messages or other concepts such as AIDL (Aircraft Intent Description Language) [21] and SWIM (System Wide Information Management) [12].

Given the potential big deviations between the predictions and the reference truth (mainly introduced by big parameter biases such as the aircraft weight), we propose a parameter estimation method to enhance the prediction model. With it, parameters such as the weight of the aircraft, the airline strategy (i.e. Cost Index), thrust and drag corrections (to compensate for small aerodynamic differences with the assumed case), etc. are inferred so predictions become more accurate. The scope of this paper is limited to estimate the mass of the aircraft only, as described in section 2.2.

2.2 Mass estimation

The core part of the parameter estimation framework is based on exploiting the known states of the intruder trajectory. Using ADS-B messages, the ownship can generate a trailing trajectory that positions the intruding aircraft along the time (in the past). The longer this trailing trajectory, the more can be extracted from it. Then, an optimisation process is performed that, as opposed to finding the cost-optimal trajectory as described in equation (3), finds the initial mass that produces a trajectory that minimises the error to this trailing trajectory.

To do so, we use a slight modification of the optimisation framework described in section 3. This parameter estimation framework is thus based on the same basic structure, state and control variables, and only some additional constraints and a different cost function are proposed to achieve the specific objectives. Specifically, the constraint on the initial mass of the problem has to be removed (in section 3 all state variables are bound at the initial value), so the optimiser is free to find aircraft take-off mass that minimises the cost functional. Additionally, a fixed throttle setting is assumed throughout the climbing phase.

¹Base of Aircraft Data, v3.9, Eurocontrol

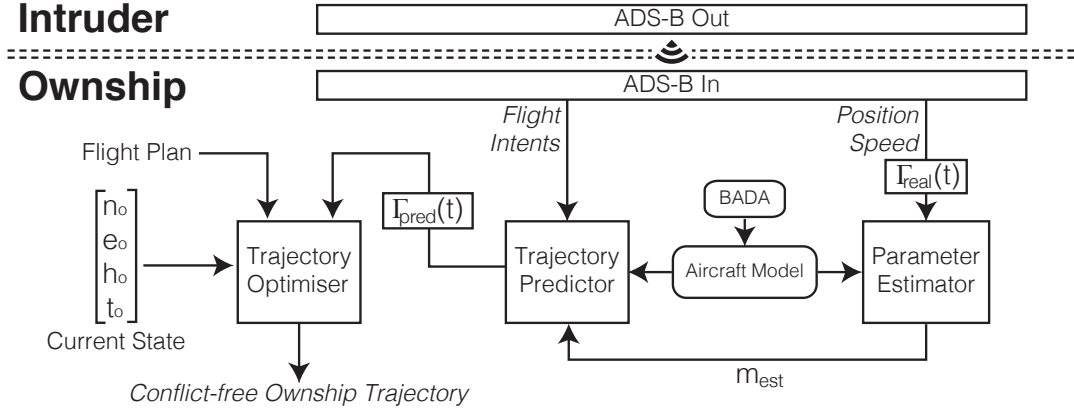


Figure 1: Self-separated optimisation framework concept diagram.

Because the optimisation solver requires all variables to be modelled as twice-differential continuous functions, we model the intruder's trailing trajectory following polynomials that depend on the time [22]. To this end, we store the current and past states (from ADS-B) to form a trailing trajectory, which is then approximated with curves represented by basis splines (B-splines). A cubic B-spline is a continuous function twice-differentiable represented by piecewise polynomials of order three. As opposed to higher degree polynomials, these provide an accurate fitting and have been demonstrated to perform well with NLP optimisation [23, 19] as they can be very smooth. Effectively, this solution has proven very reliable, robust and performant in our simulations as shown in the results section. With such process, our problem creates three splines that represent the ownship's north and east coordinates and altitude over time ($\Gamma_{real}^{(n)}(t)$, $\Gamma_{real}^{(e)}(t)$ and $\Gamma_{real}^{(h)}(t)$ respectively).

At the parameter estimation process, the solver will iteratively call these curves that represent the geographical position over time, to minimise error of these to the n , e and h variables in the state vector over t . This has been implemented in the cost function of the optimisation problem so as to minimise the root mean square (RMS) of the deviation as follows:

$$J = \text{RMS}(\Gamma_{real}(t) - \mathbf{x}_e(t)). \quad (2)$$

where \mathbf{x}_e is the state vector subset of the mass estimation model containing north and east coordinates and altitude (complete set is defined in section 3).

Finally, we relax some other constraints of the problem with the purpose of helping find a feasible and optimal solution. Given the fact that the trailing trajectory is the most accurate information we have about the intruder, other constraints on time, altitude, position, etc. (as could come from the published flight intents) are removed. Furthermore, using BADA model could mean that some of these constraints are unfeasible with regards to exactly following the lateral and vertical trailing trajectory as defined by $\Gamma_{real}^{(n)}(t)$, $\Gamma_{real}^{(e)}(t)$ and $\Gamma_{real}^{(h)}(t)$. Doing so really helps the optimisation problem on finding the mass that produces a trajectory that is the closest to what the aircraft has actually flown.

2.3 Trajectory optimisation

Finally, the trajectory optimiser module generates a conflict-

free trajectory given the (enhanced-)predicted trajectories of surrounding traffic (see section 2.1) whilst minimising the following cost functional:

$$J = \int_{t_0}^{t_f} [FF(\mathbf{x}, \mathbf{u}) + CI] dt. \quad (3)$$

The Cost Index (CI) scalar relates the cost of time to the cost of fuel (FF) and takes into account different airline policies. Moreover, the value of t_f is a decision variable itself and will be fixed by the optimisation algorithm.

Additional constraints in this optimisation problem ensure that the minimum required separation between aircraft is maintained. Again, splines are used to model the intruder's predicted trajectory ($\Gamma_{pred}^{(n)}(t)$, $\Gamma_{pred}^{(e)}(t)$ and $\Gamma_{pred}^{(h)}(t)$) [19, 20]. Specific details about the optimisation framework are found in section 3.

3. OPTIMISATION FRAMEWORK

Aircraft trajectory optimisation has been a subject widely researched in the last decades. A mathematical approach to formulate such problem is as a continuous and constrained optimal control problem. Although several references on its resolution can be found in the literature, realistic aircraft trajectories are hardly possible to solve analytically due to the important non-linearities in the different equations. Thus, a wide variety of numerical solutions have arisen [24, 25]. One of the most relevant ones converts the infinite-dimensional original problem into a finite-dimensional non-linear programming (NLP) problem with a finite set of decision variables in the time interval $[t_0, t_f]$. To do so, a direct transcription or collocation strategy is applied, being Euler, Trapezoidal or Pseudospectral among the most used [26].

Let $\mathbf{x}(t) \in \mathbb{R}^{n_x}$ be the state vector describing the trajectory of the aircraft over time t and $\mathbf{u}(t) \in \mathbb{R}^{n_u}$ the control vector that leads to a specific trajectory. The goal is to find the best trajectory that minimises a given cost functional defined over the whole time period $[t_0, t_f]$:

$$J(\mathbf{x}(t), \mathbf{u}(t)). \quad (4)$$

We have formulated an optimal control problem, the solution to which minimises the objective defined in Eq. (4) with the state and control vectors defined as follows:

$$\begin{aligned} \mathbf{x} &= [v \ \gamma \ \chi \ e \ n \ h \ m] \\ \mathbf{u} &= [n_z \ \phi \ \pi] \end{aligned} \quad (5)$$

In order to guarantee a feasible and acceptable trajectory, as a result of this optimisation process, several constraints must be considered. In particular, the dynamics of the system (dynamics of the state vector) expressed by non-linear differential equations. Furthermore, additional algebraic constraints either at the initial/final points or all along the trajectory must be specified. Next sections describe the mathematical formulation of these constraints.

3.1 Aircraft dynamics

In this paper, a point-mass representation of the aircraft is used, where forces apply at its centre of gravity. A situation without wind in a flat non-rotating earth has been assumed. The equations of motion are written as follows [27]:

$$\begin{aligned} \frac{dv}{dt} &= \dot{v} = \frac{1}{m}(T - D - mg \sin \gamma) \\ \frac{d\gamma}{dt} &= \dot{\gamma} = \frac{g}{v}(n_z \cos \phi - \cos \gamma) \\ \frac{d\chi}{dt} &= \dot{\chi} = \frac{g \sin \phi}{v \cos \gamma} n_z \\ \frac{de}{dt} &= \dot{e} = v \cos \gamma \sin \chi \\ \frac{dn}{dt} &= \dot{n} = v \cos \gamma \cos \chi \\ \frac{dh}{dt} &= \dot{h} = v \sin \gamma \\ \frac{dm}{dt} &= \dot{m} = -FF \end{aligned} \quad (6)$$

where n and e represent the spatial location of the aircraft in north and east coordinates respectively, h is the geometric altitude, v is the true airspeed, γ the aerodynamic flight path angle, χ the heading and ϕ the bank angle. Furthermore, we model the dynamics of the mass of the aircraft m . The load factor (n_z) is defined as the relation between the aerodynamic lift force and the aircraft weight.

Regarding the atmosphere, a set of polynomial approximations of real weather data predictions have been implemented to define the density ρ , pressure p and temperature τ magnitude as functions of the altitude and geographic location.

All aerodynamic and engine parameters are represented by continuous polynomials, that ensure continuity for the first and second derivatives as it is required for the numerical solvers used here. Details on the modeling of aerodynamic Lift (L) and Drag (D) forces, and engine thrust (T) and fuel flow (FF) are described in [19].

3.2 Operational constraints

Besides the equations of motion described above, the problem is further constrained by additional equations that take into account several operational restrictions. Since the operating speeds are always expressed in calibrated airspeed (v_{CAS}), an extra constraint equation to relate this speed to the true airspeed (v) is added:

$$v_{CAS} = \sqrt{\frac{2p_0}{\mu\rho_0} \left[\left(\delta \left(\left(\frac{\mu v^2}{2R\tau} + 1 \right)^{\frac{1}{\mu}} - 1 \right) + 1 \right)^{\mu} - 1 \right]} \quad (7)$$

where $\mu = \frac{\gamma_a - 1}{\gamma_a}$, γ_a is the specific heat ratio of the air and R the perfect gas constant.

Some other constraints are specified as a function of the along path distance (s), which although it is not a state variable its dynamics are modelled as:

$$\frac{ds}{dt} = \dot{s} = \sqrt{\dot{e}^2 + \dot{n}^2} \quad (8)$$

Table 1 depicts the constraints considered in the optimisation problem. Many of these are operational constraints, either to stay within the flight envelope or comply with ATM constraints such as CAS profiles and ground obstacle avoidance. Additionally, bounding constraints on n_z and ϕ are defined following civil aviation standards. More information on optimal control formulation and resolution techniques used in this research can be found in [23].

Table 1: Constraints in the optimal control problem

Constraint	Definition
Operating airspeeds	$V_{MCA} \leq v_{CAS}(t) \leq V_{MO}$
No deceleration allowed	$\dot{v}_{CAS}(t) \geq 0$
No descent allowed	$\dot{h}(t) \geq 0$
Minimum climb gradient	$h(t) \geq 0.033 s(t)$
Load factor	$0.85 \leq n_z(t) \leq 1.15$
Bank angle	$-25^\circ \leq \phi(t) \leq 25^\circ$

Furthermore, specific constraints are set for the state variables at specific nodes to represent the initial and final state of the optimisation problem as well as intermediate restrictions (such as waypoints, RTAs, etc.).

Finally, an aircraft departing trajectory comprehends different flight phases, each with specific performance and geographical constraints. Specific details on the formulation of these phases into the problem is found in [20]. Some collocation and link equations ensure that the different state nodes (collocation points) within a phase are correctly linked to the previous phases in compliance with the dynamic models, and that the phases relate to the time continuum they represent.

4. NUMERICAL EXAMPLE

For the purpose of this paper, we have prepared a scenario following close-to-real life operations in two major airports in the Catalonia region. An aircraft departs from Reus airport (LERS) to the east, but instead of flying the standard departure BCN1S, it is guided through a more fuel efficient route, convenient to its destination. At the same time, another aircraft departs from Barcelona airport (LEBL) to the west through the GRAUS3W SID. Figure 2 shows the lateral routes as resulting from the optimiser, overlaid to the charts defined in the AIP [28, 29].

In the depicted case, if both aircraft were to fly their optimal trajectories, the separation between them would not be kept to the required minimum of 3NM horizontal and 1000ft vertical throughout the flight. This situation could be estimated just before take-off, since every aircraft has a (fairly-)accurate prediction of its own future states. However, due to the very limited degree of information sharing between airspace users, it is much more difficult from an

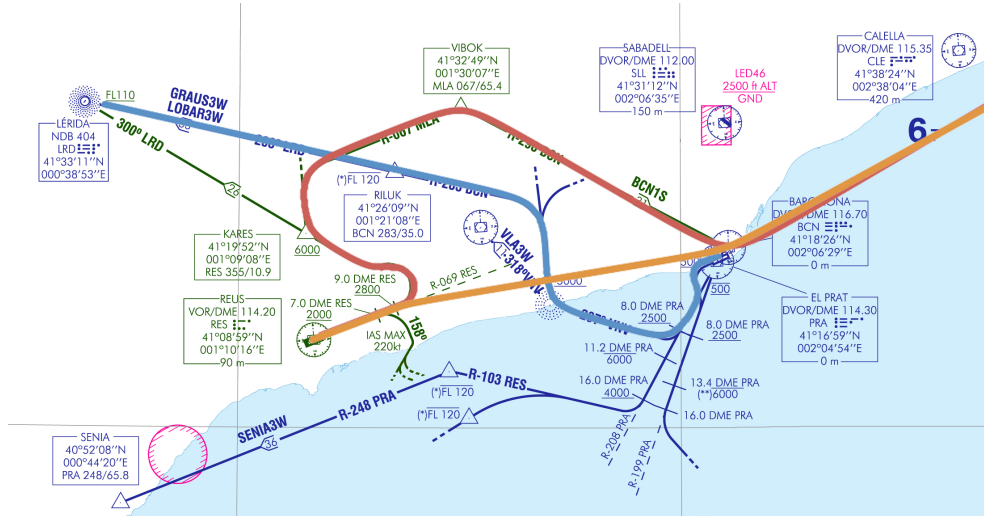


Figure 2: Published standard instrumental departures for Barcelona (blue) and Reus (green) and optimised trajectories for Barcelona departure GRAUS3W (light blue), Reus departure BCN1S (red) and proposed direct route (orange).

external entity (e.g. another aircraft) to synthesise such accurate predictions of other traffic: sensitive data such as aircraft weight and performance data remain unknown.

To reflect this issue, we simulate the situation where the ownship (BCN, flying from LEBL) predicts the intruder (RES, flying from LERS) trajectory. As already said, the ownship knows very little about the intruder. The following subsections deliver results on different situations and aspects of the problematic presented by this scenario.

4.1 Vertical predictability

In [20], the authors presented a case where a bad assumption of an intruder's mass would produce very inaccurate trajectory predictions. To cope with the issue, a conformance monitoring algorithm was presented that would relaunch a new prediction every time the errors jumped over a specific threshold. However, due to unchanged wrong assumptions, the new predictions would quickly deviate again. The main scope of this paper is to present an estimation process that, using the past known states of the intruder, enhances the accuracy of each new prediction.

Following the scenario described in 4 and depicted in figure 2, this section presents results on the effectiveness of estimating the mass of the intruder towards prediction accuracy. To do so, two cases are presented as follows:

Case A: Without parameter estimation

The ownship uses the BADA performance model to predict the intruder trajectory. The required unknown parameters are filled with the nominal values of the intruder's aircraft type in BADA. The intruder's flight intents (flight plan) is shared through an ADS-B message as a list of fixes (geographic coordinates). Besides, each aircraft broadcasts the current state (position and velocity) through an ADS-B message.

Case B: With parameter estimation

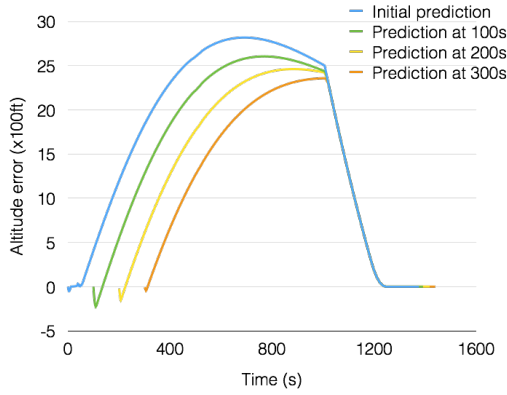
Same as case A, but once the aircraft takes-off, the ownship uses the intruder's past and current state (from

ADS-B) to infer a more accurate value of the intruder's aircraft mass for subsequent predictions.

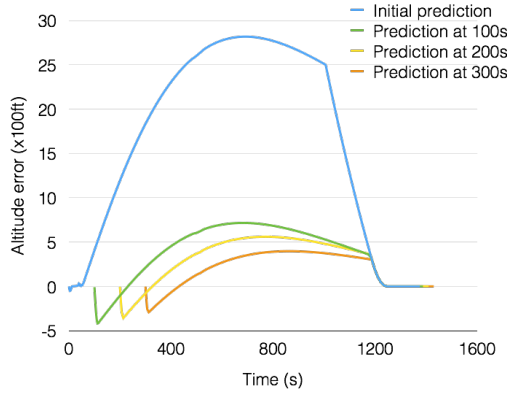
In all cases, the ownship generates an initial prediction of the intruder trajectory with the said assumptions and assuming both aircraft start flying at $t = 0$ s and do not deviate from their own individually cost-optimal trajectory (i.e. without self-separation). After take-off, a new prediction is generated every 25 s with the following updated values: current intruder's state (position and velocity, as coming from ADS-B) and, if applicable, updated parameters (i.e. mass in case B).

Figure 3(a) shows the vertical deviation between each prediction and the reference truth for case A. It can be seen how at each new prediction (for visualisation purposes not all recalculations are shown), the magnitude of the error decreases slightly, mainly because each time the current position and velocity is corrected and the remaining trajectory is shorter. However, the new prediction deviates rapidly, with a similar rate than the previous calculations. This is expected, since each new prediction has the same parameter assumption errors.

This behaviour is, to some extent corrected with case B, as seen in figure 3(b). As expected, the magnitude of the error for the initial prediction is the same as in case A, since no further information about the intruder is available yet (before take-off). However, the subsequent calculations have remarkably lower altitude errors. This is thanks to a better estimate of the intruder's mass (see figure 4). See how this estimation becomes better and better for later predictions and is confined to vertical errors lower than 700ft (and better) for the whole climbing phase (more than 15 minutes look ahead time). This is due to the fact that a bigger amount of information is available when the parameter estimation process is run (longer trajectory trail), and thus a better mass estimation is produced. Even if globally the vertical error decreases highly, the moments immediately after the recalculation are actually worsened. This is due to the fact that the prediction model (based on optimisation) finds lower



(a) Case A



(b) Case B

Figure 3: Vertical deviation between the intruder predicted trajectory and the reference truth after each recalculation for cases A and B.

costs at higher speeds (i.e. compared to current intruder's speed from ADS-B) with the new inferred mass and BADA model. Therefore, the predicted trajectory initiates with an acceleration segment that repercuts negatively on the vertical rate, resulting into a big momentary vertical deviation. This could be easily compensated at the prediction side by applying conventional climb rules, or by expanding the estimation process to further assumptions (besides mass), to enhance the dynamic model and its parameters as a whole. Surely enough, when such parameter deviations are completely removed, and only the mass is wrong (i.e. the utopic case where the aircraft dynamics model of the intruder is very accurate), we have tested that the mass is immediately estimated with no error at all.

It is worth mentioning that this parameter estimation model is actually not intended to infer the real value. As said, this process produces an estimated value that minimises the error between the real trajectory trail and a predicted trajectory with BADA. The intrinsic inaccuracies of this model, bias the estimation process. The effort is then to enable sufficient correcting parameters, which can be estimated, to allow for a prediction model that can be brought closer to the reference truth. This paper sets the grounds for the authors to continue researching on this matter.

4.2 Along track predictability

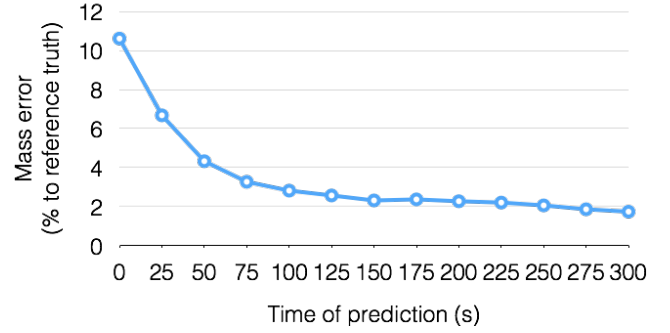


Figure 4: Predicted mass error at each recalculation time.

Surprisingly, despite the proved gains in vertical predictability, figure 5 demonstrates that along track predictability is not ameliorated with the estimation of the mass alone.

The main reason for this is the difference in flight dynamic models and the way we synthesise the trajectory prediction (which assumes optimisation in fuel). Consequently, BADA model prefers to fly at faster speeds given the fact that these provide lower fuel consumptions at the given estimated mass. To cope with this issue, the parameter estimation model should be enhanced to account for the errors in the calculation of dynamic forces such as drag and thrust and also the fuel flow dynamics. Alternatively, improved flight intents sharing between aircraft could also help with this issue, as presented in section 4.4.

Nevertheless, this does not hamper the effective detection of the conflict and its resolution as explained in section 4.3.

4.3 Impact to conflict detection and resolution

The main issue with a bad intruder's trajectory prediction is that it adds a big deal of uncertainty to the detection of possible conflicts in the future. Figure 6 shows the potential conflict geometry at different prediction times, assuming both aircraft start flying at $t = 0$ s and do not deviate from their own individually cost-optimal trajectory (i.e. without self-separation). S_h depicts the minimum horizontal distance between aircraft, and $S_v|_{S_h < 3 \text{ NM}}$ the minimum vertical separation when the horizontal separation is not granted (i.e. less than 3 NM).

Effectively, due to the big errors in the initial prediction, the ownship presumes that the vertical separation is maintained throughout the flight (even if the horizontal minimum separation is not). However, from the real situation (the reference truth) we know this is not so. In case A, soon after take-off a new prediction is generated, without much difference as seen in figure 6(a): the ownship does not see a loss of separation. Effectively, this situation continues until the recalculation at $t = 200$ s, that the ownship realises the situation. Dramatically, this is only 106 s before entering into loss of separation with the intruder.

In comparison, when using a mass estimation process (figure 6(b)), even if the initial prediction is equally erroneous, case B rapidly corrects for the mass inaccuracies and soon after take-off the ownship predicts that a loss of separation will occur (in the example, this happens at $t = 50$ s, but with a higher recalculation rate this would have been noticed even

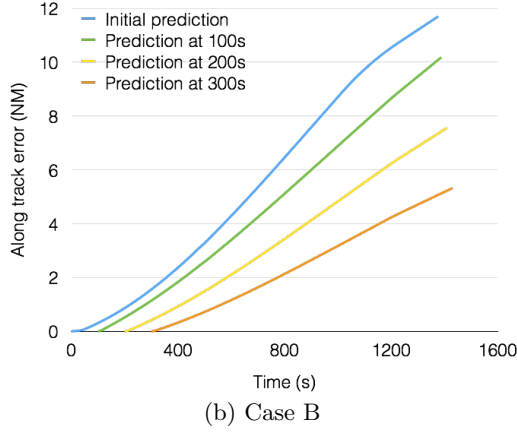
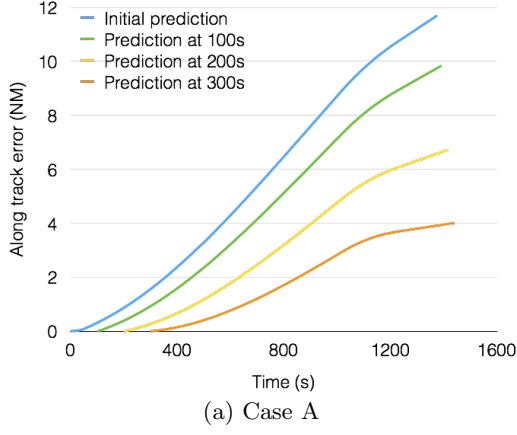


Figure 5: Along track deviation between the intruder predicted trajectory and the reference truth after each recalculation for cases A and B.

before). Therefore, this leaves more room for efficient resolution of the conflict: more than 256 s.

Moreover, the impact on the conflict resolution is also huge. Figure 7 repeats cases A and B but now, at each recalculation (in this simulation, every 50 s), the ownship generates a new trajectory that removes all conflicts from the predicted trajectories. Effectively, in case B BCN starts deviating soon during the flight, resulting in an efficient resolution that only increments the total fuel burned with 5.4 kg. As expected, in case A the reaction comes very late and results in an unavoidable loss of separation.

4.4 Enhanced flight plan data

In section 4.2 one of the conclusions is on the difficulty of enhancing horizontal predictability. To cope with this issue, in this section we propose two new cases (C and D) that provide different type of information in the shared flight intents, to help in the trajectory prediction. Such information is extracted from the Flight Management System (FMS) reference trajectory. At this moment, the uncertainty of such data has been deliberately kept out of the study to isolate the effectivity of the presented concept from other external factors. Additionally, each of these situations will test with

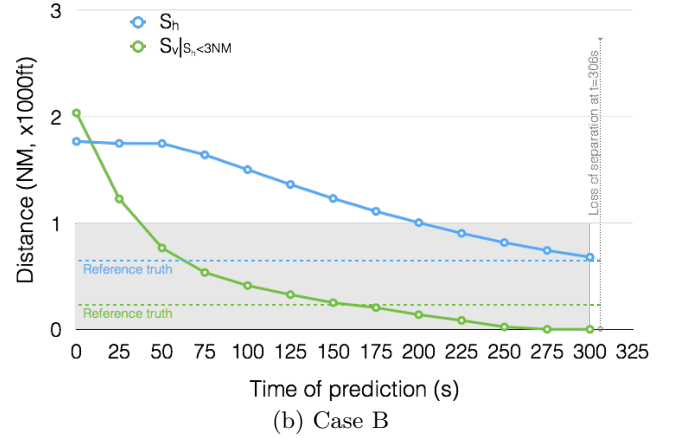
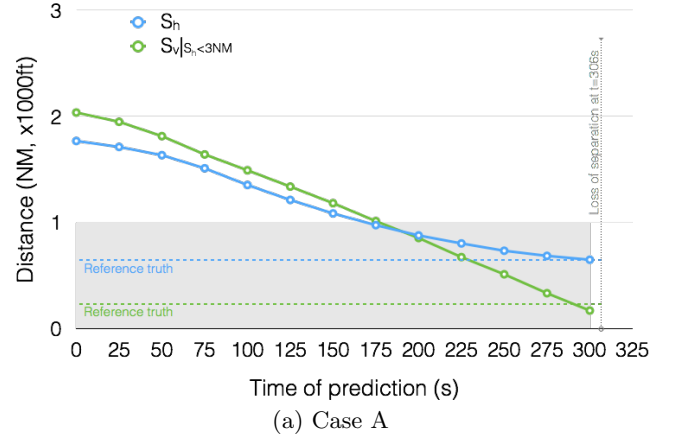


Figure 6: Predicted minimum horizontal and vertical distances between the ownship (BCN) and the intruder (RES) at different predictions and the real situation.

and without parameter estimation (cases A and B).

Case C: Flight Plan with ETA

The shared flight intents contain estimated time of arrival (ETA) at each fix.

Case D: Flight Plan with velocity estimates

The shared flight intents contain estimated velocities at each fix.

Figure 8 shows the along track deviation error for cases C_A and C_B (vertical errors are similar in magnitude than those for cases A and B respectively, so these are omitted from the paper). These plots demonstrate that knowing the ETA at fixes reduces the uncertainty highly. Furthermore, with mass estimation, these are even smaller, and in the example, always lower than 0.1 NM.

Finally, figure 9 shows the along track deviation error for cases D_A and D_B . As for cases C_A and C_B , vertical error plots are omitted from the paper. In these cases, the along track error is higher when compared to cases C_A and C_B . Again, estimating the mass iteratively helps reducing the error to more than a half.

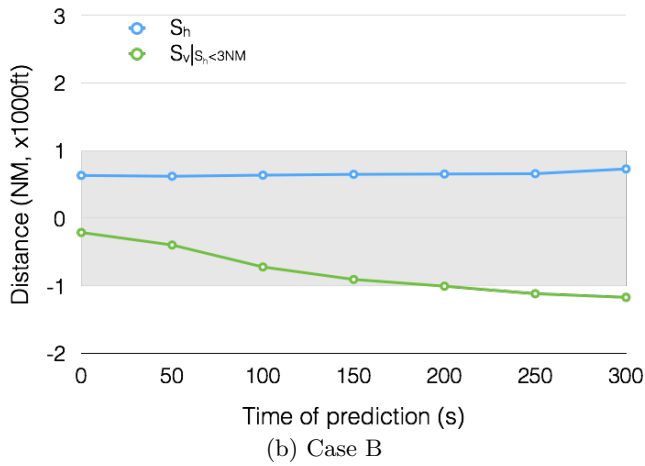
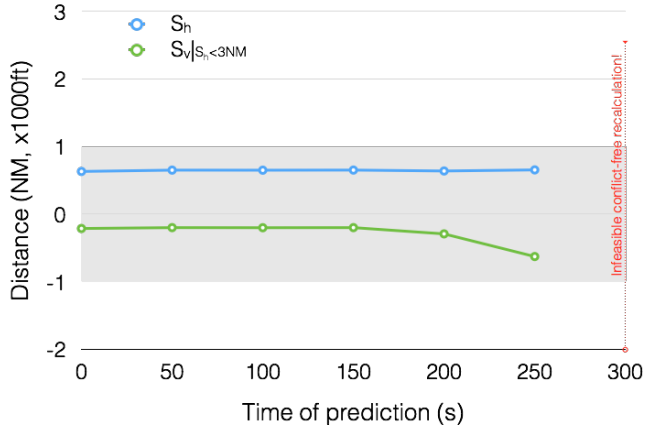
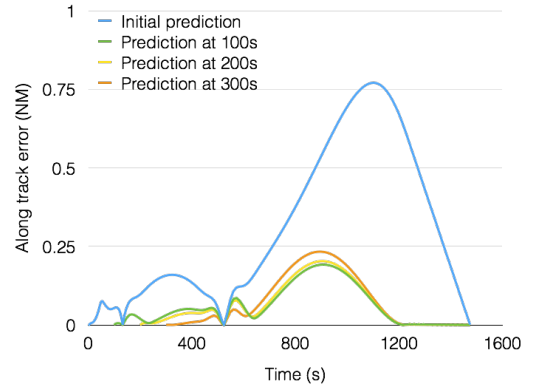


Figure 7: Minimum horizontal and vertical distances between the ownship (BCN) and the intruder (RES) at different recalculation times.

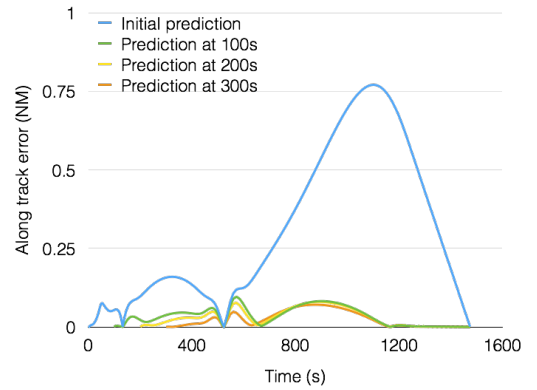
Conclusively, even if nowadays such information sharing is still far from operational implementation, we present results on the degree that these could help in improving air traffic predictability, more so in combination with the mass estimation model. Besides, similar degrees of information sharing are already contemplated in concepts such as Trajectory Based Operations (TBO) and System Wide Information Management (SWIM) and alike, fostered within SESAR and NextGen programmes.

5. CONCLUSION AND FURTHER WORK

In a very secretive air traffic system, the application of efficient collaborative operations such as TBO and self separation remain a big challenge. For such concepts to be effective, an accurate awareness of surrounding traffic's future states is required. But such accuracy is impeded when basic aircraft parameters such as aircraft weight, performance data or airline strategies are not available at the time of prediction. In this paper the authors have described a framework to compensate this hindrance by continuously integrating the state of the surrounding traffic to improve the ownship knowledge of other aircraft's dynamics. We use



(a) Case C_A



(b) Case C_B

Figure 8: Along track deviation between the intruder predicted trajectory and the reference truth after each recalculation for cases C_A and C_B.

direct collocation methods to convert the complex problem into a continuous multiphase optimal control problem that is solved with NLP techniques. This same framework is used for conflict-free trajectory optimisation, prediction and parameter estimation.

The effectivity of the whole framework is demonstrated with a semi-cooperative scenario where aircraft current state and future intents are shared between airspace users (ADS-B). In it, two aircraft depart from close-by airports in the Catalonia region, in a configuration that soon leads to a loss of separation. It is shown how the prediction of the potential conflict is enhanced (i.e. is realised earlier by the affected aircraft) when a parameter estimation process is used in combination with the trajectory prediction. Specifically, the estimation of the other aircraft mass, which was previously unknown, is inferred, reaching estimation errors below 2% soon after take-off.

Furthermore, once the ownship has generated a more accurate prediction of the intruder (thanks to a better estimate of the take-off mass) it directly regenerates a cost-optimal conflict-free trajectory of its own, in a continuous iterative process. In [19, 20] we monitor the conformance of the intruder's current state with respect to the predicted trajectory and relaunch the process when the residuals go over certain threshold, although for simplification, the current

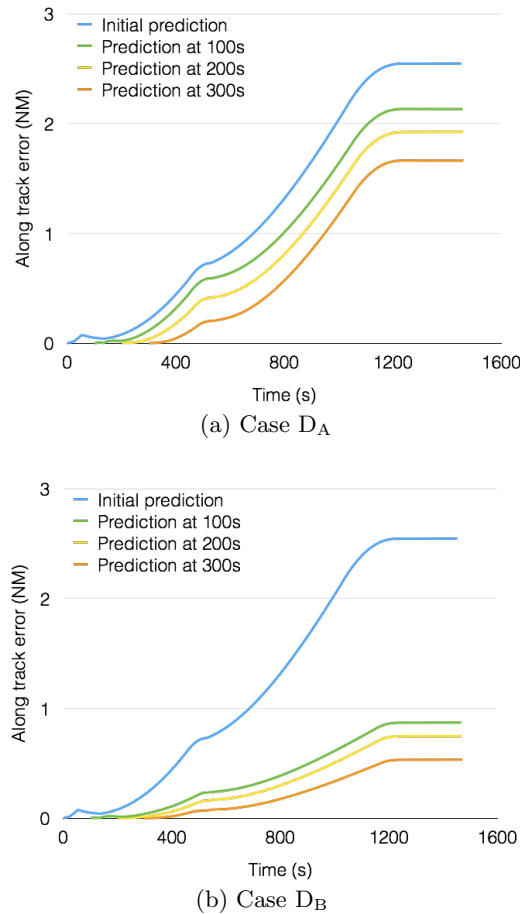


Figure 9: Along track deviation between the intruder predicted trajectory and the reference truth after each recalculation for cases D_A and D_B .

paper has set this iterations to happen on a timely basis. This will be integrated in the future.

Despite the higher vertical predictability, big lateral deviations still occur due to the inaccuracies of the performance model used in the trajectory prediction process. We show an example of how more informed flight intents in combination with the parameter estimation method reduces inaccuracies greatly. However, without the will of cooperation and information sharing, this is probably very utopic. Therefore, future research should focus on adding the estimation of other performance parameters (i.e. drag and thrust corrections) and airline strategies (i.e. cost index). Besides, external factors such as meteorological events and ATCo advisories should also be taken into account, along with integrating state sensor errors.

In a highly automated air traffic system the framework described in this paper enhances the situational awareness of the airspace user by enhancing its knowledge of surrounding traffic and potential loss of separation in account of cost-optimal trajectory generation.

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