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Learning Uncertainty Parameters for Assistance in Conflict Resolution

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***Abstract*—**
Helping Air Traffic Controllers (ATCOs) to solve conflicts is challenging because ATCOs only have a partial control on pilots reaction time and trajectory change, and cannot estimate very precisely the aircraft speed. A previous research [1] proposed a method to estimate ATCOs' uncertainty margins during their deconfliction task. It was shown that, given a predefined uncertainty model, it is possible to learn uncertainty parameters on two-aircraft exercises resolved by an automatic solver. In this article, we collect new data on a more realistic simulator showing a Singaporean En-Route sector and estimate individual and collective uncertainties. These uncertainties are then used in the automatic solver and the resolutions are compared to the actual maneuvers given by the ATCOs. Results on 6 ATCOs who performed several hours of control show that common uncertainties could be estimated with an error of the same range as individual uncertainties. When these uncertainties are used in the automatic solver the solutions are conform to the ATCOs decisions 77 per cent of the time which is 15 percent higher than without considering uncertainties.

Acknowledgement

We thank the ATCOs from ENAC who volunteered to participate in our experiments, giving several hours of their time. Their involvement is essential for collecting relevant data.

I. Introduction

Offering tools to help air traffic controllers (ATCOs) in their separation task is difficult for many reasons. Different ATCOs may have different behaviors depending on many factors such as habits, mental workload, uncertainty perceptions. The conflict resolution problem may also have many equivalent solutions and chosing between one or another can be very subjective. ATCOs have to face the lack of accuracy in their trajectory prediction. They neither control the pilots reaction time nor the precise trajectory change and therefore need to anticipate maneuvers with enough margins to maintain safe trajectories. A computed solution can be helpful to an ATCO if it chooses to maneuver the same aircraft than the ATCO's, if the maneuver starts at the same time, is of the same type, and offers extra margins that an ATCO is expecting. Learning uncertainties from observing ATCOs behavior is challenging and a method was introduced in [1] to address this issue.

In this article we go further by applying the method proposed in [1] to a more realistic dataset and then statistically compare the resolutions proposed by an automatic conflict resolution solver to the maneuvers decided by ATCOs. The dataset was built on a Singaporean airspace sector on which 6 French ATCOs performed simple conflict resolutions on hundreds of examples.

The current Air Traffic Control System has been historically organized into filters in order to ensure a tolerable level of complexity to ATCOs in their real time (5/10 minutes) tactical control tasks. The conflict detection and resolution en-route task ensured by ATCOs remains one of the least automated task in the whole system, even though a lot of research has been done to build automated solvers.

En-Route ATCOs use a 2D horizontal visualization to control the traffic. Aircraft are represented by plots and its past positions are materialized by a comet. The speed vector is represented by a line segment showing the future positions of the aircraft in 3, 6 or 9 minutes. On demand, ATCOs can also check distances between points but this information is not permanently displayed on their screen.

ATCOs can be assisted in the conflict detection task by tools. The Short Term Conflict Alert (STCA) tools are progressively introduced in En-Route displays in order to help the conflict detection. However they are not always reliable because the trajectory prediction used remains very simple. It has been shown that managing correctly uncertainties plays a key role in air traffic control.

In [2], Consiglio et al. measured the impact of pilot delay response on the safety of airbone separation. The range of delay studied was extended to 240 seconds showing that this parameter plays a great part in conflict resolution. In [3], Corver et al. explored sources of uncertainties and management strategies adopted by ATCOs. They show some uncertainties in trajectory prediction are constant, while others grow with time. Corver et al explains that ATCOs need to understand how alerts work, how prediction tools are designed and how the system can handle increasing uncertainties. Experiments on ATCO assistance tools for detection and resolution were first carried out in the 1990s. HIPS [4], [5] the Highly Interactive Problem Solver, issued from ARC2000 [6] introduced an interactive view of the conflict zones, called no-go-zones for a chosen aircraft. No-go-zones could take into account uncertainties. The concept was reintroduced in the Solution Space Based Diagram [7] to deal with 4D Trajectory Management. In [8], Bakker et al. compare different conflict prediction models using uncertainties. HIPS uses ellipses growing with time to model aircraft future positions and compares the distance between ellipses to the separation standard. Bakker and Blom compare the geometric conflict predictor and the probabilistic model used by [9] and later adopted by [10] in the American project URET (User Request Evaluation Tool). A third conflict predictor based on a collision risk approach is also introduced. The conflict predictor used by [10] in URET was introduced by [9] in the 90s. The model can display conflict probabilities in complex situations. A gaussian distribution, calibrated on observed data models the conflict probe. However very few details are given by Erzberger on how the uncertainties were adjusted. The conflict probe was also used by [11] to assist s in their detection task. [12] showed in 2008 to check how new displays of conflicts and an interactive conflict solver could help ATCOs deal with very dense traffic.

Research on automatic conflict resolution in the last 30 years [13], [14], [15], [16], [17], [18], [19], [20] shows that most of conflict situations can now be handled by automatic solvers. However hypotheses and uncertainties used to model the trajectories are generally not realistic enough to use such algorithms in practice, so that even in the most realistic models using simple maneuvers [13], [20], the solutions found by automatic solvers are never really compared to real ones. More recently, [21] has worked on a machine learning framework for predicting ATC Conflict Resolution Strategies. The idea was to learn ATCOs' preferences using machine learning methods. The idea was new but the amount of data necessary to reach a good result is huge and cannot be easily collected.

In a previous article, presented at ATM R&D Seminar in 2021 [1], we introduced a method to learn a simple uncertainty model from a real data set. The uncertainty model takes into account the aircraft speed, the pilot answer delay and the maneuver angle precision. In this article, we go further and try to check the conformance of the maneuvers obtained with an automatic solver using learned uncertainties.

In part II, we detail our modeling of the ATCOs prediction uncertainties. In part III, we summarize the uncertainties learning method introduced in [1] and detail the data used in part IV. In part V, we compare the maneuvers calculated by our automatic solver using these uncertainties with the actual maneuvers chosen by the ATCOs.

II. Maneuver and uncertainty model

We use a model similar to the previous research presented in [1] to model the maneuvers and represent uncertainties.

A. Maneuvers

We first consider that the aircraft is initially on a straight path between an origin point O and a destination point D. Maneuvers are heading changes of α degrees, starting at time t_0 and ending at time t_1. α is relative to the current heading. Figure 1 illustrates a maneuver example.

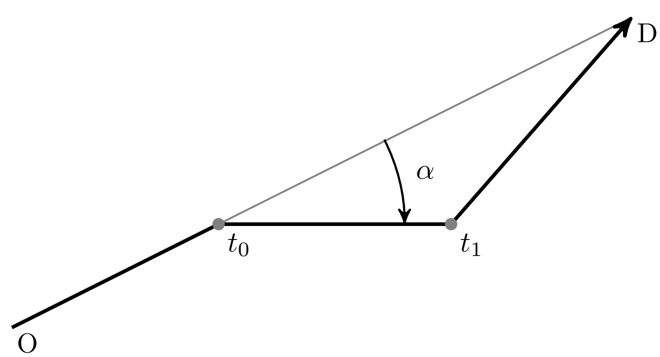

Fig. 1: Maneuver model.

B. Uncertainties

We use the uncertainty model presented in [1], with one simplification. In our previous article, the pilot reaction time could be different at the beginning and the end of the maneuver. We decided to define a unique reaction time ($\delta_{t_0} = \delta_{t_1}$) in the present model.

Thus, we model three different sources of uncertainties:

- When pilots get maneuver orders, they can react more or less quickly. An uncertainty $\delta_t \in [0, \Delta_t]$ representing the maximum reaction time for beginning a maneuver or resuming the initial route is associated with time t (see figure 2);
- An uncertainty $\varepsilon_\alpha \in [0, E_{\alpha_{Max}}]$ is associated with the heading change angle α (see figure 3);
- Aircraft speeds are also subject to an $\varepsilon_s \in [0, E_{s_{Max}}]$ error such that future positions of aircraft are spread over a range which grows with time (see figure 4);

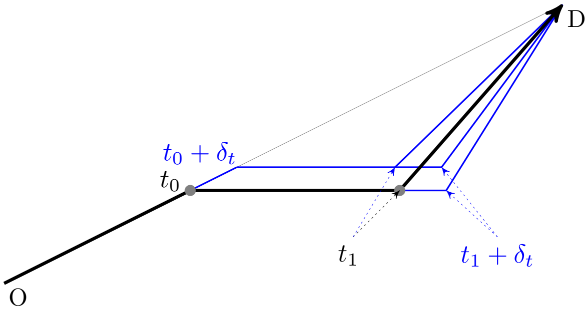

Fig. 2: Pilot execution time uncertainty: δ_t model.

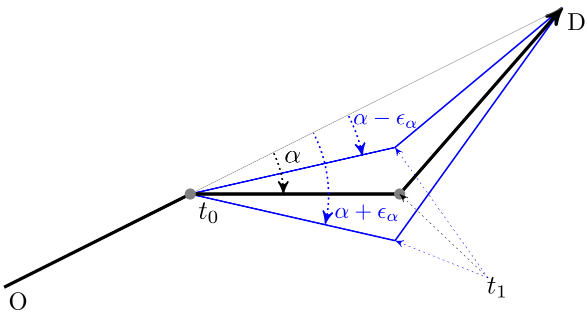

Fig. 3: Maneuver angle uncertainty: ε_α model.

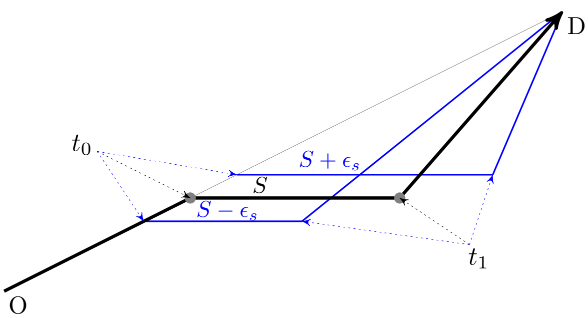

Fig. 4: Speed uncertainty: ε_s

III. Uncertainty Learning method

In this section, we briefly summarize the learning method used in [1] to determine the uncertainties from solved conflicts.

In order to calibrate the uncertainty model presented in part II, we adjust the various uncertainty parameters until the trajectories' envelopes between aircraft are separated by an average distance n_d. Indeed, we suppose that ATCOs try to keep a distance between aircraft which can be bigger than 5 nautical miles. This is why this targeted distance n_d is an additional parameter to measure.

Thus, we defined a function $d_\omega(\varepsilon_s, \delta_t, \varepsilon_\alpha)$ that calculates the minimum distance between trajectories, given the uncertainty parameters $(\varepsilon_s, \delta_t, \varepsilon_\alpha)$, on the scenario ω. Function d_ω can be applied to a benchmark Ω of deconflicted aircraft scenarios and our objective is to minimize:

$$D_\Omega(\varepsilon_s, \delta_t, \varepsilon_\alpha, n_d) = \sum_{\omega \in \Omega} [d_\omega(\varepsilon_s, \delta_t, \varepsilon_\alpha) - n_d]^2 \qquad (1)$$

For the benchmark Ω, the minimum of D_Ω returns the uncertainty parameters for which resolutions comply *the most* with n_d when these uncertainties are applied and thus calibrates the values of these uncertainties on the benchmark.

We use the same simple evolutionary algorithm (EA) to find the four parameters ε_s, δ_t, ε_α and n_d that minimize D_Ω on a benchmark of solved scenarios Ω.

The elements in our EA population are coded by four variables:

- The velocity uncertainty (between 0 and 40 %) $\varepsilon_s \in [0; 0.4]$;
- The pilot answer uncertainty at the beginning and at the end of the maneuver $\delta_t \in [0; 120]$;
- The heading uncertainty during the maneuver $\varepsilon_\alpha \in [0; 10]$;
- The separation standard targeted $n_d \in [5; n_{dsup}]$.

In section V, we first perform experiments with $n_d = n_{dsup} = 5$ NM, (we suppose that the controllers target the separation standard of 5 nautical miles). We then perform experiments with $n_{dsup} = 10$ where the n_d can vary between 5 and 10 nautical miles.

Because the EA searches for a maximum, we used the following fitness function to minimize the difference between d_ω and n_d for each $\omega \in \Omega$:

$$f(\varepsilon_s, \delta_t, \varepsilon_\alpha, n_d) = \frac{|\Omega|}{|\Omega| + D_\Omega(\varepsilon_s, \delta_t, \varepsilon_\alpha, n_d)} \qquad (2)$$

IV. Data

A. Experiments and exercise selection

Data were collected from six French ATCOs from ENAC. Four of them performed twice a two hour session, and two of them only one session of two hours. Figure 5 gives an example of conflict solved by the six ATCOs.

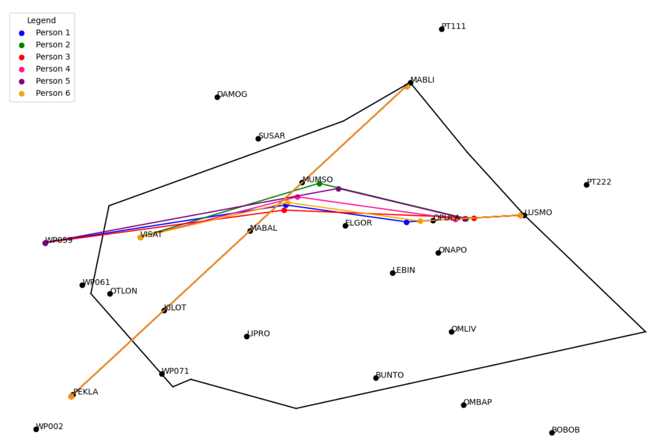

Fig. 5: Example of an exercise resolved by all ATCOs

In order to collect data, experiments done by Guleria et al. [21] were extended at ENAC with 6 French ATCOs. The traffic simulation performed by Guleria's software introduces an en-route Singaporean sector. Guleria's software uses two windows: a radar view on which ATCOs can observe the traffic sector (see Figure 6) and a maneuver selection window in which users can give maneuvers (see Figure 7). The exercises proposed are simple two-aircraft conflicts for which aircraft speeds and altitudes are constant.

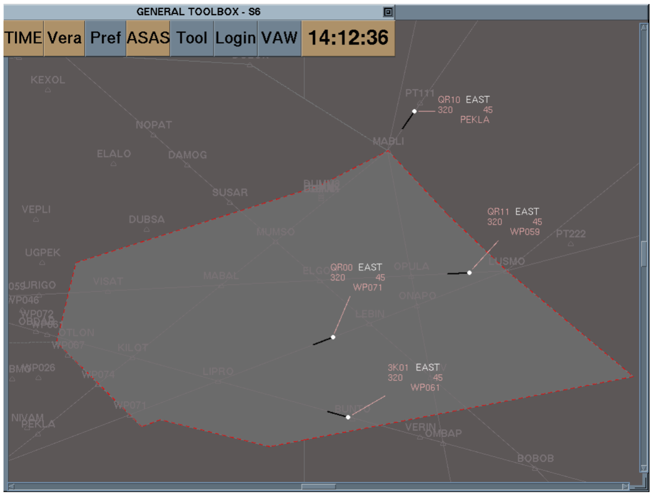

Fig. 6: Radar view

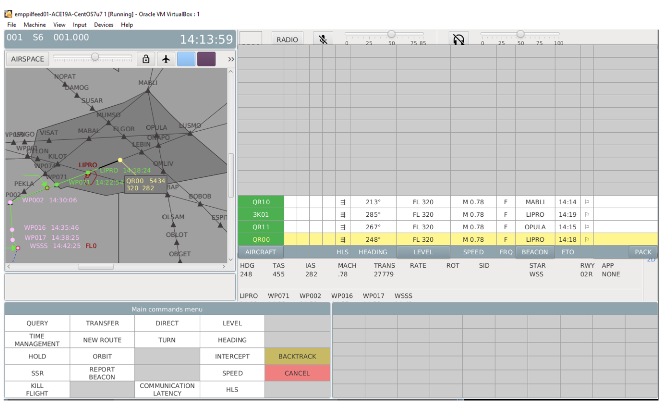

Fig. 7: Maneuver selection window

In our maneuver model, we consider that aircraft fly from an origin point O to a destination point D directly. However, the routes proposed by the simulations are not always direct: there are portions of trajectories, at the entrance and exit of the sector, where the heading of the aircraft may vary to follow a beacon. In order to deal with this pattern, we filtered exercises for which aircraft are maneuvered on a direct section of the route, and keep these sections of trajectories only. We also filtered exercises for which controllers maneuvered only one aircraft and only once which is the most common situation. In table I, the second column shows the number of filtered exercises for each ATCO, and the third column shows the number of filtered exercises for which no conflict remained. These exercises were used for the uncertainty learning phase. We can notice that 7 exercises remained unsolved by some ATCOs.

B. Trajectory Prediction Start Time

Figure 8 illustrates the trajectory envelopes for a maneuvered aircraft when maneuver starts at time t = 0 sec. (a.) and

TABLE I: Numbers of exercises kept

Candidate	Filtered Exercises	Ex with no remaining conflict
1	53	52
2	124	119
3	124	123
4	33	33
5	31	31
6	44	44
Total	409	402

at time t = 60 sec. (b.). The envelopes including uncertainties are drawn in white and the conflict zones are in red. Even if the same uncertainties are considered in both cases, envelopes are not identical. Indeed, the more we move forward in time, the more precise the future positions of the aircraft become.

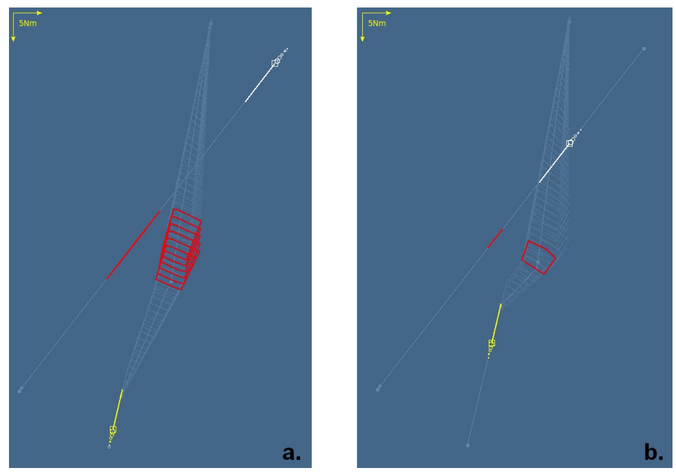

Fig. 8: Trajectories envelopes size

Consequently, we must determine for each exercise an appropriate starting time from which we will consider uncertainties. Two steps need to be considered: first, the time used by the ATCO to take a decision. Second, the duration of the ATCO's action to apply this decision.

For the first step, we do not have a lot of indicators to approximate the numbers of seconds required by the ATCO to take a decision. As the ATCO is estimating a dynamic evolution of a sector, we can suppose that between 10 and 20 seconds of reflection (t_r) are required to choose the aircraft to be maneuvered and a maneuver for this aircraft.

Then, the ATCO needs to put this order in the simulator using the maneuver window presented in figure 7.

In order to calculate the time of the maneuver order action, we use the Keystroke-level model which predicts the required time for the user to complete a task without error using an interactive computer system. With this method, we use 3 action types:

- H : Homing the hand on the mouse ($0.4s$);
- P : Pointing ($1.1s$);
- B : Press button ($0.1s$);

The successive steps executed by the ATCO to order a maneuver are the following:

TABLE II: Comparison between ATCOs on same exercises

Number of ATCOs (n_c)	2	3	4	5	6
Number of exercises	57	38	7	7	10
SASD (%)	79	87	43	57	60

- Take the mouse (H);
- Select the maneuvered aircraft (P + B);
- Select the deviation amplitude (P + B);
- Confirm (P + B).

The action of mental activity is included in the decision time of the ATCO stated earlier. Finally, we estimate that the sum of time to decide the maneuver and enter it in the simulator could vary between 14 and 24 seconds. We fixed this lag to 20 seconds in the experiments.

C. Data analysis

A first analysis of the collected data illustrates ATCOs behavior.

In this article, we decided to simply compare the resolutions of the different ATCOs according to the direction of the maneuvered aircraft.

If we consider all the exercises solved by at least two different ATCOs, we can distinguish maneuvers with the following criteria:

- $aircraft_1$ is turned to the left;
- $aircraft_1$ is turned to the right;
- $aircraft_2$ is turned to the left;
- $aircraft_2$ is turned to the right.

On average, 1.17 different solutions out of 4 options were proposed by ATCOs for each exercise.

Table II shows the number of exercises solved by 2 to 6 ATCOs and the percentage of these exercises for which all ATCOs maneuvered the same aircraft in the same direction ($SASD$). In a majority of cases, ATCOs make the same decisions. However, when we focus on exercises solved by more ATCOs ($n_c \geq 4$), the percentage of agreement statistically decreases.

When we consider all the exercises solved by at least two ATCOs, we count 433 pairs of ATCOs who solved 119 different exercises and 84% of the time ATCOs took the same decision. In the following, we denote by Ω_{all} the set of exercises solved by at least 2 ATCOs.

V. Experimental Results

A. Learned Uncertainties

With the Evolutionary Algorithm (EA) presented in part III, we determined uncertainties for all participants with $n_{dsup} = 5$ NM, (second table III), and with $n_{dsup} = 10$ NM (third table).

We also tried to evaluate ATCOs all together (last column). Indeed, it would be simpler for an operational use to determine common uncertainties for all ATCOs. But in [1], we found a large model error in the evaluation of ATCOs all together and decided to learn uncertainties on individuals and on the whole group in order to compare the results.

TABLE III: Uncertainties found and errors obtained after learning

ATCO (n)	1	2	3	4	5	6	All
nbs_n	52	119	123	33	31	44	402
ν_{init}	3.39	2.71	3.81	3.62	4.4	3.59	3.44
σ_{init}	1.6	1.33	1.57	1.94	1.8	1.88	1.68
n_{dsup} = 5 NM							
ϵ_s	0.014	0.02	0.022	0.01	0.0	0.02	0.018
δ_t	51	47	69	85	72	114	85
ϵ_α	4.5	0.3	1.3	3.9	8.2	0.	0.85
ν	1.07	0.88	0.94	1.35	1.33	1.1	1.12
σ	0.82	0.7	0.89	1.12	0.71	0.87	0.91
n_{dsup} = 10 NM							
ϵ_s	0.015	0.021	0.023	0.01	0.0	0.021	0.018
δ_t	56	52	65	96	62	115	87
ϵ_α	4	0.	1.4	3.4	4.7	0	0.87
n_d^2	25	25	25	25	39	25	25
ν	1.06	0.88	0.94	1.37	1.32	1.1	1.11
σ	0.82	0.70	0.88	1.11	0.72	0.88	0.91

The first three lines indicate the number of exercises (Ω_n cardinal, nbs_n), the mean value of $|d_\omega - 5|$ and the standard deviation of $|d_\omega - 5|$ (σ_{init}) without considering any uncertainty. The following lines of each table give the different uncertainties found : ε_s, δ_t and ε_α for the second table, and $\varepsilon_s, \delta_t, \varepsilon_\alpha$, and n_d for the third table. The last two lines in each table give the mean and standard deviation of $|d_\omega - n_d|$, which represent the model errors.

In general, the speed uncertainties determined are very small (2% on average). The heading uncertainties vary between 0 and 8.2 degrees depending on ATCOs with a mean value around 3 degrees when the separation distance targeted is 5 nautical miles and 2.25 degrees when the separation distance targeted is 5.27. However, the uncertainty regarding the pilot reaction time δ_t is quite large, and varies a lot between participants, ranging from 47 to 115 seconds with a mean of 87 seconds when the whole group is considered. When considering ATCOs all together, the error of the model is similar to the errors observed on each ATCO (last two lines of the tables).

B. Model errors and distributions

For all ATCOs, the standard deviation of $|d_\omega - n_d|$ is lower when uncertainties are applied than without uncertainties (σ_{init}), whether $n_{dsup} = 5$ or $n_{dsup} = 10$, which was expected.

Figure 9 represents, for ATCOs separately, the distributions of the minimum separation distances between trajectory envelopes without considering uncertainties (in red) and considering individual uncertainties determined with the learning method (in green) when $n_{dsup} = 10$ nautical miles.

Figure 10 represents, for ATCOs all together, the distributions of the minimum separation distances between trajectory envelopes without considering uncertainties (in red) and considering the common uncertainties determined with the learning method (in green) when $n_{dsup} = 10$ nautical miles.

The distributions are mostly less spread out with the uncertainties found, which is consistent with the decrease in the standard deviation of the model error.

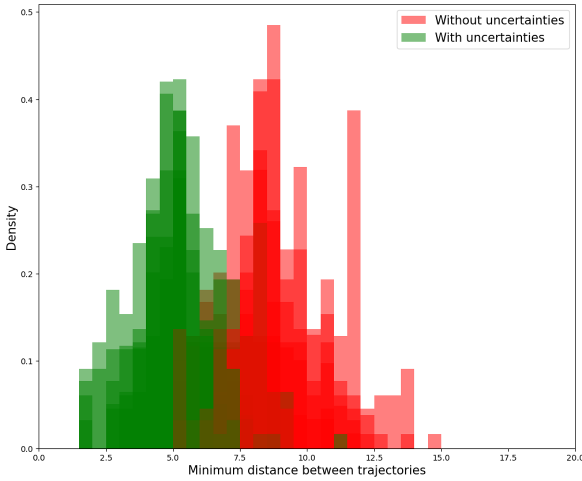

Fig. 9: Minimum distance distributions with individual uncertainties

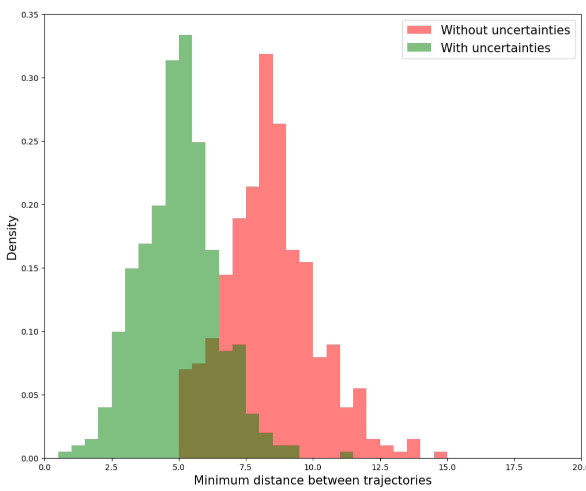

Fig. 10: Minimum distance distribution with the common uncertainties

C. *Resolutions found with the automatic solver*

1) Automatic solver conformance: In order to check if our automatic solver is able to find the maneuvers chosen by the ATCOs, we use the uncertainties learned and run the automatic solver with these uncertainties. The automatic solver used in our experiments is an Evolutionary Algorithm described in [13] and [22] but uses the uncertainty model presented in this article. It finds optimal maneuvers (t_0, t_1, α) for each aircraft of a scenario with the uncertainty parameters chosen. The EA creates a population of 50 random solutions. It first tries to find conflict free-solutions without trying to optimize maneuvers and then spends an extra 20 generations minimizing the number of maneuvers and finally minimizing the generated delays. In order to compare the results on the same dataset as in part IV-C, we only take into account exercises in Ω_{all}

TABLE IV: Comparison between ATCOs and solver resolutions on common exercises

ATCO (n)	1	2	3	4	5	6	Total
$\lvert\Omega_n\rvert$	22	107	114	33	31	44	351
Without uncertainties							
SASD (%)	68	62	65	67	61	50	62
With individual uncertainties							
SASD (%)	91	83	80	64	65	61	76
With common uncertainties							
SASD (%)	77	84	74	82	77	61	77

(exercises solved by two or more ATCOs). In table IV, Ω_n is the exercise set of the n^{th} ATCO where $\forall\omega \in \Omega_n, \omega \in \Omega_{all}$. $SASD$ gives the percentage of maneuvers complying to the ATCO's choices. On average, with the common uncertainties the automatic solver agrees with the ATCOs 77 per cent of the time, which can seem low considering that ATCOs agree with each other 84 per cent of the time. However, the automatic solver used without uncertainties agreed with ATCOs only 62 per cent of the time, showing that considering uncertainties improves the automatic solver compliance.

Several reasons could explain the fact that the automatic solver does not reach a higher rate of compliance:

- Some constraints (such as the maneuver must start inside the sector) are not taken into account in our automatic solver (an example in the next section illustrates this phenomenon); However, this may not explain the difference in every case, because we noticed that ATCOs did not always respect the border constraint as well.
- ATCOs may have extra habits besides the simple delay minimization criteria used by the solver.
- Sometimes, choosing a maneuver or another does not make a big difference in terms of delay. Humans tend to reproduce habits whereas the automatic solver only chooses the delay criteria.

In theory, for the same solved exercise, 4 different maneuvers are possible depending on which aircraft is chosen to turn right or left. Consequently *SASD* could be as low as 25 percent. In practice, the automatic solver often shows that it is possible to maneuver one aircraft or the other, but only on one side, with little difference in delay, which would still keep *SASD* around 50 percent. Consequently, a percentage of 77 per cent is quite significant.

2) Example analysis: The automatic solver synchronizes its resolution with the ATCO's maneuver start time on each exercise. Two different ATCOs may not start a maneuver at the same time. Consequently, the automatic solver resolutions can be different for the same exercise solved by two different ATCOs even if we consider the same uncertainties.

Figure 11 illustrates a unique exercise solved by ATCOs (green trajectories) and the automatic solver (red trajectories) considering common uncertainties found. We can notice that the maneuver start times (decided by ATCOs) vary, which impacts the automatic resolutions. In this case, 5 ATCOs made the same decision, but one moved another aircraft. The automatic solver takes the same decision as the majority here.

Figure 12 illustrates an exercise for which the aircraft moved by the automatic solver generally differs from the one moved by the ATCOs. One reason could be that with the automatic solver, the maneuver sometimes starts before the aircraft enters the sector. When the automatic solver agrees with the ATCO, it starts the maneuver inside the sector. We did not add this constraint in the automatic solver because on some exercises, ATCOs did not respect the border constraints as well.

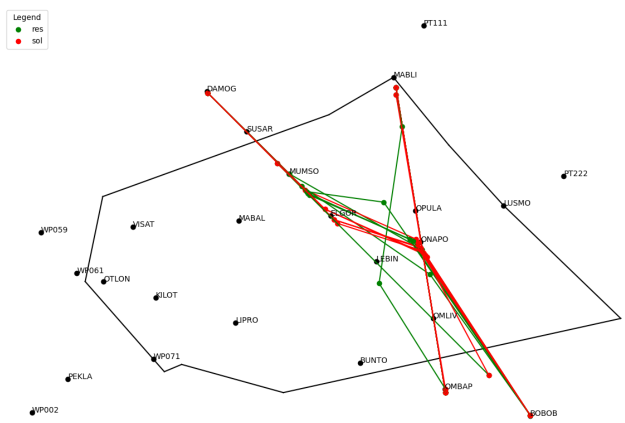

Fig. 11: Exercise example where automatic resolutions are similar to ATCOs resolutions

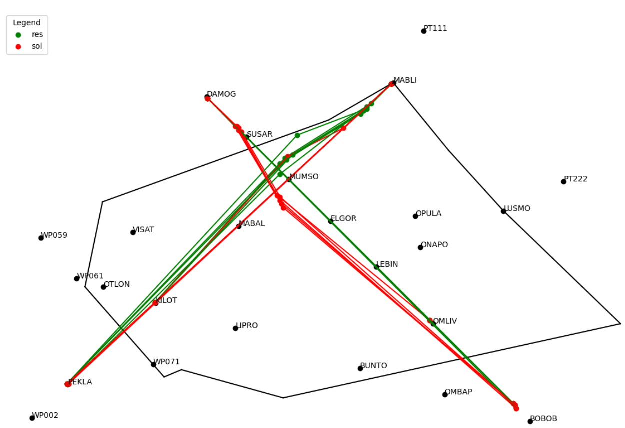

Fig. 12: Exercise example where automatic resolutions are not similar to ATCOs resolutions

VI. Conclusion and Further Work

In this article we test an uncertainty learning model on experimental data based on simulation sets that are closer to ATCOs practice.

While results obtained in [1] tended to show that it was necessary to determine the uncertainties of the ATCOs individually, the results of these experiments show that it is possible to determine common uncertainties for ATCOs without degrading the quality of our results. Using a real sector representation and a more realistic simulator can probably explain this result. ATCOs certainly had a more common estimation of the standard separation and aircraft speeds than in the previous experiments. They also had more chances to be in agreement with each other dealing with only two aircraft. In [1], a more random traffic involving up to 5 aircraft conflicts showed more differences in ATCOs choices.

Using these uncertainties to tune an automatic solver allowed us to compare automatic resolutions to ATCOs maneuvers. Results show that 77 per cent of the time the automatic solver decided to move the same aircraft in the same direction, which is higher with adding uncertainties to the solver than without (the figure falls to 62 percent only). However this result can appear disappointing considering that 84 per cent of the time, ATCOs chose to move the same aircraft in the same direction on the same exercise. Looking at examples helps finding explanations. Unfortunately we did not constrain the automatic solver to keep maneuvers inside the sector, because the ATCOs did not always respect this constraint neither. Other explanations may have an impact on these results. ATCOs may have habits that are not taken into account by our solver.

In future work, we will improve our solver to comply with the sectors constraints and only consider maneuvers solved by ATCOs inside the sector. Our team also currently works on collecting big radar datasets and ”demaneuver” trajectories (remove ATCOs maneuvers) in order to compare automatic resolutions and actual resolutions on more realistic and much bigger datasets. We could imagine, in the long term future, to collect ATCOs resolutions directly in operational centers in order to learn transparently their behavior.

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