# [EN-A- 068] Online Trajectory Prediction through Updating Aircraft Position and Aircraft Intent

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**Abstract:** To facilitate decision support in the air traffic management domain, an online four dimensional trajectory prediction (4D-TP) method was proposed in this paper. First, this study outlined the processes of online 4D-TP, including preparation, computation and updating processes. Second, four major components of offline 4D-TP were discussed and presented, such as computation model, aircraft intent, environmental conditions and performance parameters. Third, this paper came up with an approach of current trajectory updating by using ADS-B Receiver and data processing algorithm. Furthermore, the strategy of aircraft intent updating was also put forward for online 4D-TP. And the aircraft intent should be updated while the deviation between the current and predicted trajectory exceeding the pre-defined threshold. Finally, a case study was carried out to demonstrate the performance and effectiveness of the proposed online 4D-TP method. The results indicated that the proposed online 4D-TP method is able to increase the prediction accuracy by triggering 4D-TP while the position or speed deviation is beyond the pre-defined threshold.

**Keywords:** air transportation; Trajectory Prediction; Air Traffic Management; Aircraft Intent; ADS-B

## 1. INTRODUCTION

Currently, the Air Traffic Management (ATM) relies on a set of operational measures for air traffic to fulfill the missions of separating, metering and sequencing. The ever continuous growth and still increasing demand of air transport are posing significant challenges to the civil aviation community as such current paradigms of ATM will not ensure the target levels of safety, capacity, efficiency and environmental sustainability in the future. As a consequence, several renovation initiatives have been launched, such as the Single European Sky ATM Research (SESAR), the Next Generation Air Transportation System (NextGen), and the Aviation System Block Upgrades (ASBU) framework. In the ATM domain, conflict detection and resolution, aircraft sequencing and scheduling, trajectory based operation are the most promising novel concepts and advanced technologies of the above renovation initiatives. And these concepts and technologies could not be implemented without the accurate Four Dimensional Trajectory Prediction (4D-TP).

4D Trajectory Prediction is the process that estimates a future 4D trajectory (in three spatial dimensions, i.e., latitude, longitude and altitude, plus time dimension) of individual aircraft through computation [1] on the basis of current aircraft state, estimated pilot's and/or controller's intent, expected environmental conditions and computer models of aircraft performance and procedures. The key issue of 4D-TP seems obvious that how to quickly and accurately predict the 4D trajectory and many researchers have devoted to addressing this issue.

Trajectory prediction is the process of estimating a future trajectory for an individual aircraft, thus the optimal estimation is a reliable method for 4D-TP. Additionally, the aircraft movement involves both continuous dynamics and discrete modes switching, then trajectory prediction can be viewed as a hybrid estimation problem which may be tackled with multiple-model methods. And the Interacting Multiple Model (IMM) algorithm is a case in point [2]. In order to produce better mode and state estimates, Hwang [3] proposed a modified version of the IMM algorithm, called the Residual-Mean Interacting Multiple Model (RMIMM) algorithm, based on a new likelihood function. Furthermore, in the ATM domain, an aircraft always flies over air routes, thereupon the transition probabilities of flight modes can be modeled as a state-dependent Markov process. As a result, Yepes and Hwang [4] proposed the State-Dependent Transition Hybrid Estimation (SDTHE) algorithm for trajectory tracking and predicting to infer aircraft intent and detect potential conflict. Zhang [5] presented the SDTHE algorithm with a new method for updating flight mode probabilities to improve the accuracy of mode estimation and trajectory prediction.

Kinematic and kinetic modeling is another important method to implement trajectory prediction on the basis of current aircraft state, estimated aircraft intent, expected environmental conditions and aircraft performance parameters. In other words, this method consists of four distinctive parts: computation model, aircraft intent, environmental conditions and performance parameters. As to computation model, Total Energy Model (TEM) [6] and Point-Mass Model (PMM) [7] are most extensively applied. PMM was utilized for trajectory optimization [8] by means of hybrid optimal control strategy. In terms of TEM, the energy sharing factor was a huge hurdle for trajectory prediction. As regards aircraft intent, the Aircraft Intent Description Language (AIDL) [9] was the most reliable way, which provided necessary elements to unambiguously formulate aircraft intent. As for environmental conditions, especially wind field, it can be obtained through observation and forecast, or local wind vector estimation. With regard to performance parameters, BADA [6] was widely used for the parameters of flight envelope, aerodynamics, engine thrust and fuel flow.

With the development of "Big Data" research in the ATM field, the machine learning is an essential supplement to trajectory prediction, especially for the flight time estimation. On the one hand, it is dependent on the similarity of trajectories. Hong and Lee [10] introduced a new framework for predicting arrival times for the identified trajectory patterns. Tastambekov et.al [11] put forward an innovative approach for trajectory prediction based on local linear functional regression. On the other hand, it is based on the reconstruction of input and output space. Leege [12] brought forward machine learning approach for trajectory prediction based on the historic aircraft trajectory and meteorological data.

As discussed above, there exist three main methods for trajectory prediction: optimal estimation, kinematic and kinetic modeling and machine learning. And these methods have been widely used to predict the future trajectory. So far, however, there has been little discussion about online trajectory prediction. With reference to this aspect of the research achievements, Alligier [13, 14] made the best of the past observations to estimate mass and thrust parameters so as to improve the prediction accuracy. Nevertheless, such studies only focused on the proper updating of several parameters. Consequently, in this paper, we propose an online 4D-TP method, which might enhance the function and improve the accuracy of trajectory prediction to facilitate decision support in the ATM domain.

This paper is organized as follows: First, an online 4D-TP problem is addressed in Section 2. Subsequently, section 3 details the model and method of online 4D trajectory prediction. The simulation and validation results are presented and discussed in Section 4, before the conclusion in Section 5.

## 2. PROBLEM FORMULATION

As trajectory prediction is the process of estimating a future trajectory for an individual aircraft, online 4D-TP needs to update the future trajectory estimation in response to several events such as availability of new constraint information or deviation between actual and predicted trajectory exceeding a predefined threshold. Thereupon, our proposed online 4D-TP method is composed of three processes: preparation, computation and updating. The process flow chart of online 4D-TP is shown in Figure 1.

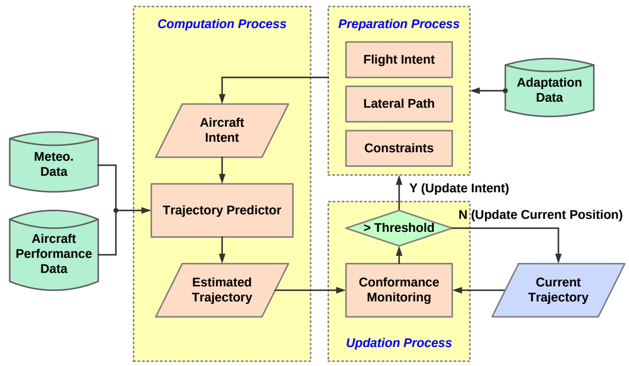



Figure 1 Process of online trajectory prediction

Meteorological data, aircraft performance data and adaption data provide support function for 4D-TP, in which adaption data consists of control airspace, control sectors, air routes, standard instrument departure (SID) and standard terminal arrival route (STAR).

Preparation process creates the initial version of flight intent based on flight plan and adaptation data. This process is activated at the beginning or when the trajectory prediction should be updated. Computation process constitutes the kernel function of 4D-TP, in which aircraft intent contains a description of the way the aircraft will be operated, trajectory predictor integrates aircraft intent information into 4D trajectory using the atmospheric conditions and the aircraft performance parameters, and estimated trajectory serves as the output of 4D-TP. For online 4D-TP, updating process plays an important role, which may result in the generation of a new aircraft intent by triggering preparation process. Conformance monitoring in the updating process aims at determining whether the re-estimation is required or not, which depends on the deviation between predicted trajectory and current trajectory whether exceeds the pre-defined threshold or not.

The current trajectory offers a baseline for conformance monitoring to trigger online 4D-TP whether or not. In this paper, the current trajectory was obtained through the Automatic Dependent Surveillance - Broadcast (ADS-B) receiver (BAR6216 ADS-B 1090MHZ Receiver).

## 3. MODEL AND METHOD

### 3.1 4D Trajectory Prediction

We use the following symbols and parameters to construct the integrated arrival and departure sequencing mode.

Even though Point-Mass Model (PMM) does not reflect all the intricacies of an aircraft movement, it is reasonably accurate and very commonly used in the ATM research field. Figure 2 summarizes major variables of a PMM for an aircraft movement: The horizontal position ($x$ and $y$) and altitude ($h$) of the aircraft, the True Airspeed ($V_{TAS}$), the flight path angle ($\gamma$), heading angle ($\psi$) and bank angle ($\phi$). The forces applied to the aircraft are its weight ($mg$), the engine thrust ($T$), and the aerodynamic forces of lift ($L$) and drag ($D$). The aerodynamic forces depend on the angle of attack ($\alpha$) and the side slip angle ($\beta$).

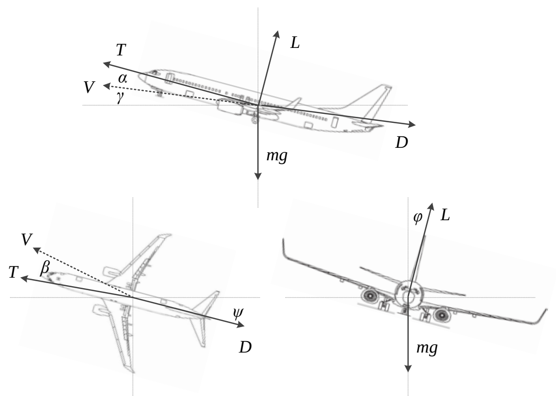



Figure 2 Diagram of forces acting on an aircraft

From the point of view of the ATM field, we can assume trimmed flight conditions, $\alpha = \beta = 0$, ignore fast dynamics, and treat $\gamma$, $T$ and $\phi$ as inputs. Thus, the PMM of an aircraft movement becomes:

$$\begin{aligned}
\dot{x} &= V_{\mathrm{TAS}} \sin(\psi)\cos(\gamma) + w_1 \\
\dot{y} &= V_{\mathrm{TAS}} \cos(\psi)\cos(\gamma) + w_2 \\
\dot{h} &= V_{\mathrm{TAS}} \sin(\gamma) \\
\dot{V}_{\mathrm{TAS}} &= (T - D)/m - g\sin(\gamma) \\
\dot{\psi} &= g\tan\phi / V_{\mathrm{TAS}} \\
\dot{m} &= -\eta T
\end{aligned}$$

where $w_1$ and $w_2$ are the east-trending and north-trending wind velocity components respectively, and $\eta$ is a thrust-specific fuel consumption parameter.

### 3.2 Current Trajectory Updating

For online 4D-TP, updating plays an important role, which comprises the tasks of current trajectory updating and aircraft intent updating. In our research, the provision of available current trajectory consists of: receiving, decomposing and decoding, as shown in Figure 3.

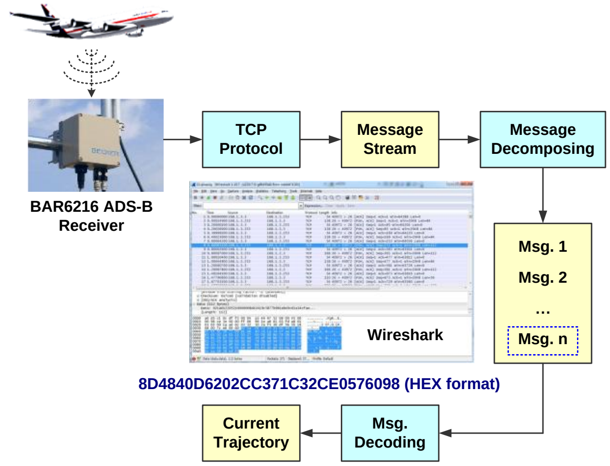



Figure 3 Processing steps for current trajectory updating

Firstly, an ADS-B Receiver is employed to receive the message streams which are broadcasted from aircrafts in TCP Protocol at every second. Such message streams contain the information sent by all aircrafts within the coverage of ADS-B Receiver.

Subsequently, decomposition step is implemented to obtain the message of every aircraft. As can be seen from Figure 3, through Wireshark, every line represents an message, which indicates the one kind of particular flight information (in HEX format) of a particular aircraft.

Finally, decoding should be carried out to determine the identification, position and velocity of every aircraft within the coverage of ADS-B Receiver. Prior to this, HEX format of each message needs to be converted to Binary format so that each message is composed of 112 bits.

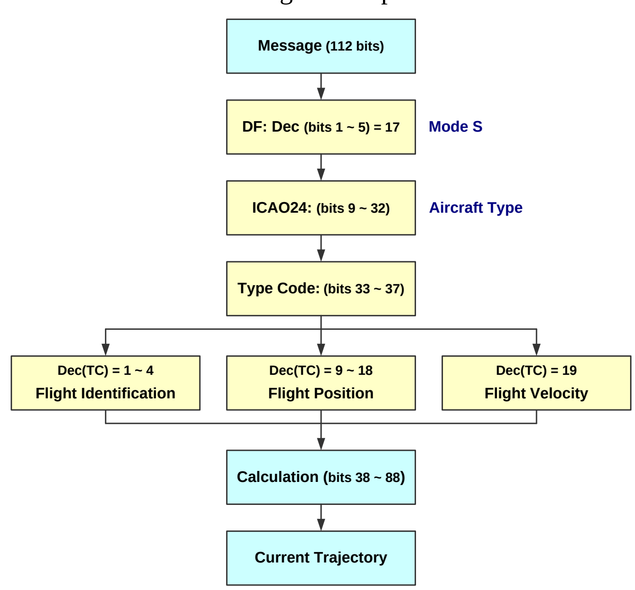



Figure 4 Message decoding for current trajectory updating

The above cases detail how to determine the flight identification, position and velocity of every aircraft based on the 112 bits data packets, as shown in Figure 4.

### 3.3 Aircraft Intent Updating

For online 4D-TP, current trajectory is employed to implement trajectory conformance monitoring. In turn, conformance monitoring acts as a trigger to generate a new aircraft intent. If the deviation between current trajectory and predicted trajectory exceeds the pre-defined threshold, trajectory re-prediction is required. If not, keep on updating the current trajectory. Figure 5 illustrates the whole process.

As far as aircraft intent updating is concerned, this paper takes advantage of the distances and angles between current position and the waypoints along Air Route or Standard Instrument Departure Route (SID) or Standard Terminal Arrival Route (STAR). Figure 6 provides aircraft intent updating strategy within arrival context, where STAR is defined as a series of waypoints (WP) from WP1 to WP5.

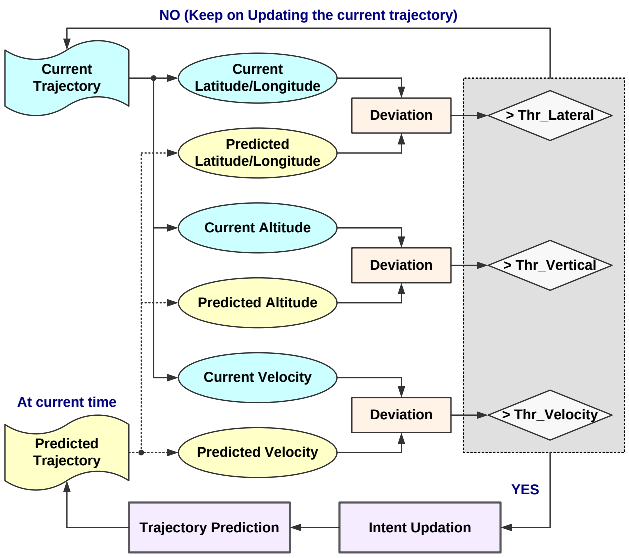



Figure 5 Process of online trajectory prediction

As shown in Figure 6, aircraft intent updating strategy is composed of the following steps:

Firstly, calculate the distances ($d_i$,) and angles ($\varphi_i$) between aircraft current position and the waypoints along STAR.

Secondly, find the nearest waypoint, where $WP_2$ is the case in Figure 6. And compare the angle of such nearest waypoint with 90 degree. If the angle is higher than 90 (Case A), it means that the aircraft should fly to such waypoint. Otherwise (Case B), it means that the aircraft has passed such waypoint.

Thirdly, trigger the preparation process and update the altitude and speed constraints at every waypoint to be passed subsequently based on the current altitude/speed, in which the conversion of Ground Speed (GS) to True Air Speed (TAS) and Calibrated Air Speed (CAS) are needed.

Finally, re-generate the aircraft intent and re-predict the 4D trajectory based on subsection 3.1.

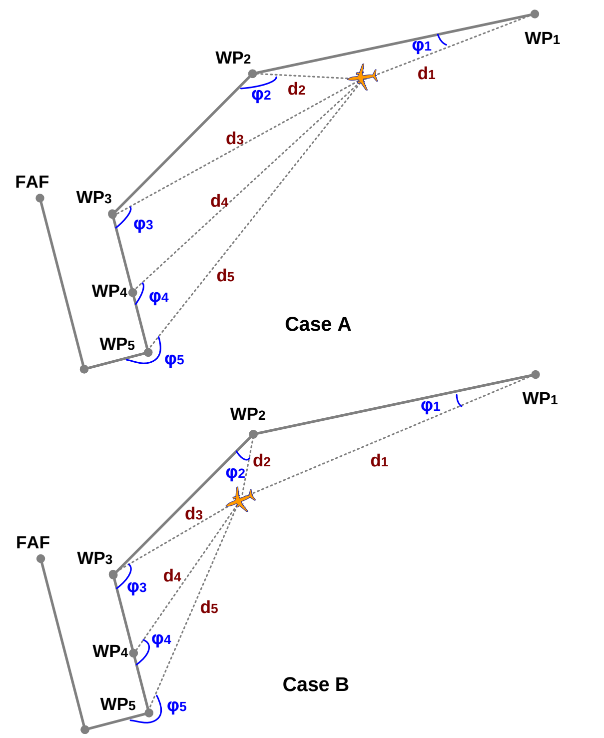



Figure 6 Diagram of the aircraft intent updating

## 4. SIMULATION AND DISCUSSION

In this section, we took Nanjing Lukou airport (ZSNJ) into consideration. And the operational scenario is shown in Figure 7. It provided the SIDs, STARs and sectorization around ZSNJ airport, in which the grey lines represented the sectorizaiton of terminal area, the blue and red dotted lines represented SIDs and STARs, respectively.

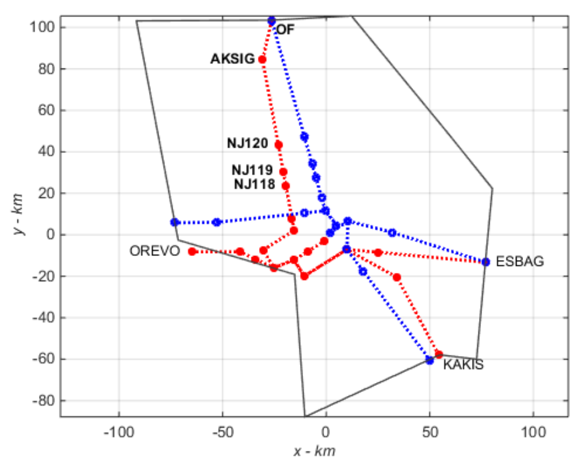



Figure 7 Diagram of the simulation scenario at ZSNJ

In this case, the most attention was paid to the validation of online 4D-TP for arrival aircrafts through OF-71F. From Figure 7, we could find that OF-71F was composed of the following waypoints: OF, AKSIG, NJ120, NJ119, NJ118 and so on. The subsequent waypoints after NJ118 in OF-71F were out of the range of ADS-B receiver as it was located at our lab. Therefore, in this case, we focused on the comparison between ETAs (obtained from online 4D-TP) and ATAs (obtained from ADS-B receiver) at the following waypoints NJ120, NJ119, NJ118.

For this validation, an online 4D-TP tool was developed using C++ programming language in the VS2005 and Qt4.5 development environment under Windows 7 operating system. Figure 8 presented the interface of the online 4D-TP tool, in which the dotted grey and blue lines denoted STARs and SIDs of ZSNJ airport respectively, the grey lines represented the tracks of departure and overfly aircrafts, the turquoise line indicated the tracks of arrival aircrafts, and the yellow line signified the preview of the online 4D-TP results. In this case, the pre-defined thresholds in Figure 5 were set as follows: Thr_Lateral = 6 km, Thr_Vertical = 300 m. If the deviation between the current trajectory and predicted trajectory exceeds these pre-defined thresholds, trajectory re-prediction was triggered. And these pre-defined thresholds were variable system parameters, which could be changed according to the users' requirements.

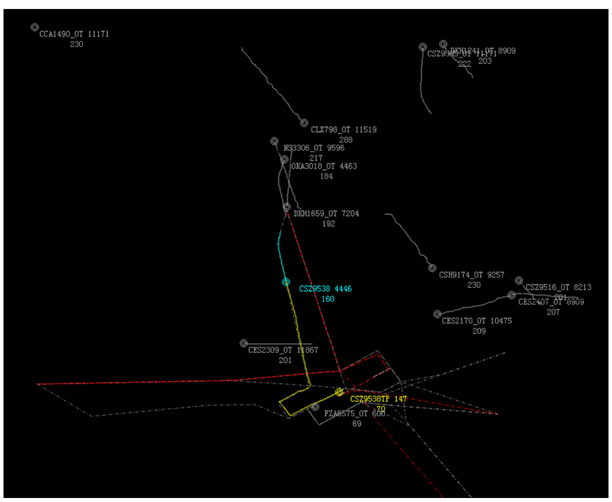
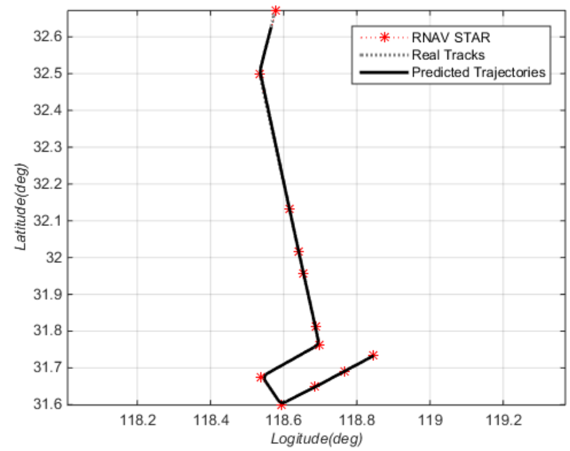


Figure 8 Diagram of interface of the online 4D-TP tool

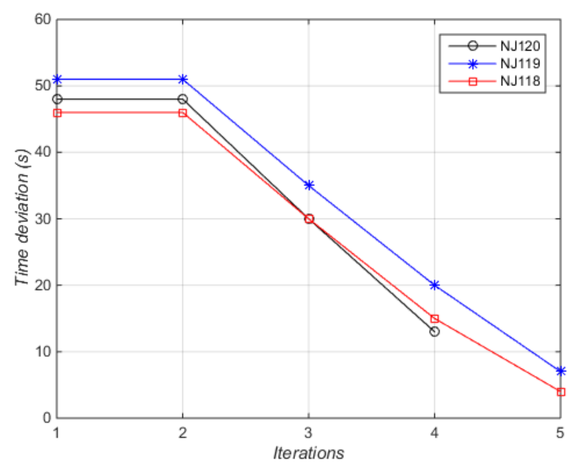
### 4.1 Results

CCA1817, Boeing 737-800 from ZBAA (Capital International Airport) to ZSNJ operated in Oct. 16th, 2016, was chosen as the validation candidate. And the results of online 4D-TP were shown in Figure 9.

Figure 9(a) presented the lateral tracks of CCA1817, including the RNAV STAR, real tracks from ADS-B receiver and predicted trajectories from online 4D-TP tool. Figure 9(b) provided the deviation between the ETAs and ATAs at different waypoints (NJ120, NJ119 and NJ 118) during different iterations of 4D-TP. When CCA1817 entered the approach control area, the 4D-TP was triggered, and the deviations between the ETAs and ATAs at different waypoints were around 50 seconds. At the last iteration of 4D-TP, the deviation could be constrained within 10 seconds at waypoints NJ119 and NJ118.




(a) Comparison of lateral tracks




(b) Deviation between ETAs and ATAs

Figure 9 Results of Online 4D-TP for CCA 1817

### 4.2 Discussion

As shown in Figure 9, the developed online 4D-TP tool was able to increase prediction accuracy by triggering 4D-TP while the position or speed error was beyond the pre-defined threshold. In this case, only position error was taken into consideration as the speed error could be reflected by the lateral position error. Meanwhile, the value of pre-defined threshold had an influence on the iterations of online 4D-TP. If a small threshold was defined, then the online 4D-TP might be activated frequently. Otherwise, the online 4D-TP might not be triggered in time. Furthermore, future work is required to design an appropriate index by considering those mentioned threshold simultaneously.

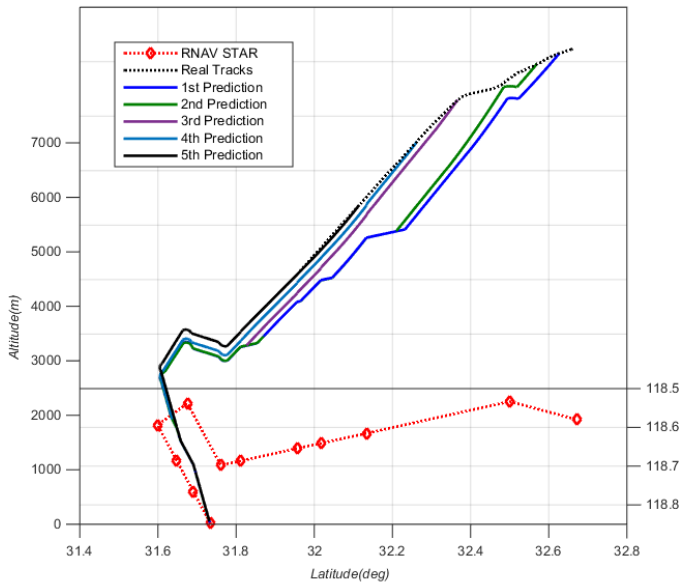



Figure 10 Results of CCA1817 in 3D perspective

Additionally, we made a depth analysis about this case. And the results of online 4D-TP for CCA1817 was presented in 3D perspective, as shown in Figure 10. From it we could find that the altitude deviation was the major course to activate online 4D-TP. In other words, the aircraft intent played a key role in 4D-TP for arrivals. As it could be seen from Figure 10, after the 3rd prediction the predicted trajectory coincided with the real track. This is critical issue for future research. And a feasible approach might be using guidance targets downlinked from the FMS in real time to construct the aircraft intent model [15] for arrival aircrafts.

## 5. CONCLUSION

This paper has developed an online 4D-TP method, which is composed of preparation process, computation process and updating process. For online 4D-TP, the last process plays the most important role, including current trajectory updating and aircraft intent updating. By using the ADS-B Receiver, we could receive several messages every second. After message receiving, decomposing and decoding, the flight identification, position and velocity of every aircraft could be determined. Meanwhile, as to the updating of aircraft intent, it is mainly dependent on the deviation between the current and predicted trajectory exceeding the pre-defined threshold whether or not.

The following conclusions can be drawn from the present study: 1) computation model, performance parameters, aircraft intent and environmental condition are all the key factors for 4D-TP; 2) the proposed online 4D-TP method is able to increase the prediction accuracy by triggering 4D-TP while the position or speed deviation is beyond the pre-defined threshold. Overall, this study serves as a basis and can also be applied to conflict detection, conflict resolution, aircraft sequencing and scheduling, etc. However, further research should be undertaken in the following areas, like an appropriate index to trigger the re-prediction, and an applicable aircraft intent downlinked from the air.

## 6. ACKNOWLEDGMENTS

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## 7. REFERENCES

[1]. FAA/EUROCONTROL COOPERATIVE R&D, Common TP structure and terminology in support of SESAR & NextGen. FAA/EUROCONTROL Action Plan 16, 2010.

[2]. L. Xie, J. F. Zhang, D. Sui, Aircraft track prediction based on interacting multiple model filtering algorithm, Aeronautical Computing Technique 5 (2012) 68-71.

[3]. I. Hwang, J. Hwang, C. Tomlin, Flight-mode-based aircraft conflict detection using a residual-mean IMM algorithm, in: AIAA Guidance, Navigation, and Control Conference and Exhibit, 2003, pp.1-11.

[4]. J. L. Yepes, I. Hwang, M. Rotea, New algorithms for aircraft intent inference and trajectory prediction, J. Guid. Control Dyn. 2 (2007) 370-382.

[5]. J. F. Zhang, D. Sui, X. M. Tang, Aircraft trajectory prediction based on SDTHE, System Engineering - Theory & Practice. 11 (2014) 2955-2964.

[6]. EUROCONTROL EXPERIMENTAL CENTER, User manual for the Base of Aircraft Data (BADA), revision 3.12, EEC Technical Report No.12/04, 2014.

[7]. L. A. Weitz, Derivation of a point-mass aircraft model used for fast-time simulation, MITRE Technical Report, MTR150184, 2015.

[8]. A. Franco, D. Rivas. Optimization of multiphase aircraft trajectories using hybrid optimal control, J. Guid. Control Dyn. 3 (2015) 452-467.

[9]. J. A. Besada, G. Frontera, J. Crespo, et al, Automated aircraft trajectory prediction based on formal intent-related language processing, IEEE Trans. Intell.

Transp. Syst. 3 (2013) 1067-1082.

[10]. S. K. Hong, K. J. Lee, Trajectory prediction for vectored area navigation arrivals, J. Aerosp. Inf. Syst. 7 (2015) 1-13.

[11]. K. Tastambekov, S. Puechmorel, D. Delahaye, C. Rabut. Aircraft trajectory forecasting using local functional regression in Sobolev space, Transp. Res., Part C, Emerg. Technol. 39 (2014) 1-22.

[12]. A. Leege, M. Paassen, M. Mulder. A machine learning approach to trajectory prediction, in: AIAA Guidance, Navigation, and Control Conference, 2013, pp.1-14.

[13]. R. Alligier, D. Gianazza, N. Durand, Learning the aircraft mass and thrust to improve the ground-based trajectory prediction of climbing finglights, Transp. Res., Part C, Emerg. Technol. 36 (2013) 45-60.

[14]. R. Alligier, D. Gianazza, N. Durand, Machine learning and mass estimation methods for ground-based aircraft climb prediction, IEEE Trans. Intell. Transp. Syst. 6 (2015): 3138-3149.

[15]. J. Bronsvoort, G. McDonald, M. Vilaplana, J. A. Besada, Two-stage approach to integrated air/ground trajectory prediction, J. Guid. Control Dyn. 6 (2014) 2035-2039.

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