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Experiments on Geospatial Data Modelling for Long-Term Trajectory Prediction of Aircrafts

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Abstract. While predicting human and vehicle trajectories is a deeply investigated field of research, predicting aircraft trajectories remains a less explored frontier. Still, the long-term prediction of aircraft movements is a fundamental challenge in aviation, influencing Air Traffic Management (ATM), operational efficiency, and flight safety. Traditional trajectory prediction models are often primarily focused on a 2D prediction. With this work, we evaluate different data representation methods in the field of long-term aircraft trajectory prediction using a state-of-the-art mobility prediction method, namely a CVAE-LSTM. We show that the H3 grid presents advantages for this task. With that, we explore a fascinating field of future mobility research, as the used data allows for various technical analyses without implying threats to personal privacy-relevant information.

Submission Type. model, analysis, case study

BoK Concepts. [TA14-3] Predictive modelling products, [DM5-3] Modelling 3D, [TA14-2] Descriptive analytics products

Keywords. Trajectory Data Representation, Aircraft Trajectories, Long-Term Trajectory Prediction, H3

1 Introduction

Predicting 4D aircraft trajectories is a fundamental challenge in aviation, influencing Air Traffic Management (ATM), operational efficiency, and flight safety. We generally differentiate between short-term predictions (up to 10 minutes) for safety purposes and long-term predictions (greater than 10 min) for strategic aircraft management (Shafienya and Regan, 2022). Long-term planning is essential as airspace congestion continues to increase: Precise strategic trajectory forecasting is then essential for optimizing airspace and airport utilization, minimizing delays, and ensuring safe separation between aircraft.

This poses a significant challenge for the traditional trajectory prediction methods deployed in general mobility research (Mokbel et al., 2024) or 2D path planning and collision control for cars and ships (Karle et al., 2022; Fu et al., 2024; Elayam et al., 2022; Drapier et al., 2024; Liu et al., 2024). These trajectory prediction models often primarily focus on model optimization in 2D and lack integration of state-of-the-art geospatial data representations for more dimensions. Examples range from Long Short-Term Memory (LSTM) based methods to more complex architectures using Conditional Variational Autoencoders (CVAEs), Transformers, and Diffusion models (Fu et al., 2024; Bharilya and Kumar, 2024; Teeti et al., 2022; Schuetz and Flohr, 2023).

With this work, we present our research on long-term aircraft trajectory prediction with a special focus on different trajectory representation approaches. Specifically, we explore the effectiveness of hierarchical hexagonal spatial index (H3) as an alternative to conventional vector-based representations, which rely on latitude, longitude pairs, or Cartesian projections. With that, we contribute to the growing body of research on data-driven trajectory prediction in the aviation domain. Experimental results with a CVAE-LSTM model indicate that using H3 indexing enables a more structured and sparse representation of aircraft trajectories.

2 Background on Aircraft Trajectory Prediction

In aviation, a trajectory T^i is normally represented as a sequence of N equally spaced state vectors v_t^i over time, capturing an aircraft's flight path (Ayala et al., 2023):

$$T^i_{1\_N} = \{v^i_1, v^i_2, \ldots, v^i_N\}. \quad (1)$$

Each state vector v includes at least the aircraft's position, i.e., latitude, longitude, and altitude, along with time, forming a discrete-time state transition model (Georgiou et al., 2018). For an aircraft i at time t, its state vector is defined as

$$v_t^i = (lat_t^i, lon_t^i, alt_t^i, ..., t). \quad (2)$$

The time interval between consecutive state vectors, known as the sample interval, determines the sequence's length and resolution.

To consider that a predicted trajectory is accurate to the true trajectory of an aircraft, position errors along the horizontal (latitude and longitude) and the vertical (altitude) axes are measured. ATM and air traffic control systems have different safety requirements depending on the flight phase. Still, they consider deviations greater than 9.26 km horizontally and ≈ 500 m vertically (Federal Aviation Administration, 2025; Gong and McNally, 2004).

3 Related Work

The related work is separated into two parts: the methods for trajectory prediction and the corresponding data representations that serve as a basis for these prediction approaches.

3.1 Methods for Trajectory Prediction

Different methodological approaches have been developed for trajectory prediction in aviation (Zeng et al., 2022). As illustrated in Figure 1, the methods found in the literature of this domain can be classified into kinetics-based, state estimation, data-driven, and hybrid approaches. Classical methods, such as kinetic models and state estimation techniques, e.g., differential equations and Markov Decision Processes, offer robustness but often require simplifications that limit their effectiveness in complex real-world scenarios (Hong et al., 2023; Zhang et al., 2018; Lee et al., 2009). Data-driven approaches, leveraging machine learning, are gaining popularity for their ability to capture intricate dependencies (Ayala et al., 2023; Schuster and Paliwal, 1997; Graves, 2012). Hybrid methods, which integrate classical models with probabilistic techniques, are also being explored to improve long-term prediction accuracy while maintaining computational efficiency (Wang et al., 2024). Recent research has focused on refining data-driven or hybrid approaches, specially focusing on sequence modeling models, to enhance prediction reliability and applicability in commercial aviation (Zeng et al., 2022).

3.2 Typical Data Representations for Trajectories

Various geospatial data representation methods have been proposed for trajectory prediction in general and aircraft trajectory prediction in specific. They differ primarily in their spatial dimensions, which are primarily 2D, 3D, or 4D. Most aircraft-related studies employ vector-based representations, encoding GPS trajectory positions using geodetic coordinates (Shafienya and Regan, 2022; Zhang et al., 2022; Wu et al., 2022b; Yang et al., 2023; Zhang and Liu, 2024), sometimes mapped to Cartesian coordinates for better distance calculations (Wu et al., 2022a; Pang and Liu, 2020; Shi et al., 2020). Some researchers have used grid-based methods, such as cubic grids, to incorporate additional data like wind patterns (Ayhan and Samet, 2016; Schimpf et al., 2023; Zhai et al., 2019; Torres and Dehn, 2017), while others have explored alternative approaches, such as Uber's hierarchical hexagonal spatial index (H3)[1], for improving resolution and computational efficiency on collision detection and trajectory modeling (Sahadevan Neelakandan and Al Ali, 2023; Ostroumov, 2024). A visualization of the H3 hierarchical hexagonal spatial index is given in Figure 2.

Beyond aviation, trajectory prediction for autonomous vehicles has also evolved with the introduction of multi-resolution hexagonal grids and hierarchical square grid systems, such as Geohash, to improve storage efficiency and model performance (Hu et al., 2022). Especially, Uber's H3 framework, which employs hexagonal raster grids, has gained traction for motion modeling, offering reduced distortions compared to traditional map projections. These grids vary in sizes per resolution, ranging from approximately 1200 km for the coarsest, lowest-resolution, to 60 cm for the finest, highest-resolution, as depicted in Table 1. Its hierarchical nature allows for selective resolution adjustments, making it particularly effective for processing large-scale geospatial data. Recent studies confirm that H3 outperforms traditional indexing methods in terms of runtime, memory efficiency, and scalability, making it a promising tool for trajectory prediction across various domains in 2D (Al-Lawati et al., 2024; Shiri et al., 2024; Oje et al., 2024; Kmoch et al., 2022; Wen et al., 2021; Yan et al., 2023; Elayam et al., 2022).

Table 1. Descriptive information about each H3 resolution (Res.) available in Uber's framework.

Res.	# Cells	Avg. Area (km^2)	Avg. Edge Length (km)
0	122	$2,562,182.16$	1281.26
	⋮		
5	$2,016,842$	252.90	9.85
6	$14,117,882$	36.13	3.72
7	$98,825,162$	5.16	1.41
8	$691,776,122$	0.74	0.53
9	$4,842,432,842$	0.11	0.20
10	$33,897,029,882$	0.015	0.076
11	$237,279,209,162$	0.0021	0.029
	⋮		
15	$569,707,381,193,162$	0.00000090	0.0006

[1] https://github.com/uber/h3, last accessed 11.02.2025

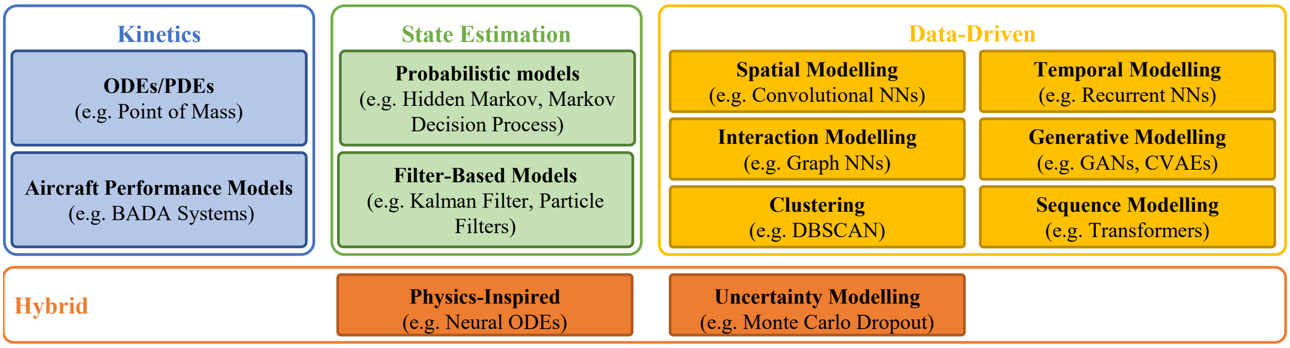


Figure 1. Taxonomy of methods for trajectory prediction in aviation.

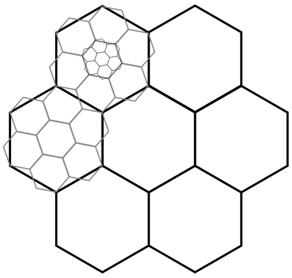


Figure 2. Example of a H3 grid in three different resolutions.

4 Methods

The paper's primary goal is to explore state-of-the-art trajectory representations in the aviation domain. To this end, we evaluate different data representations on long-term aircraft trajectory prediction using a well-established model. The method consists of a) the data preparation and adaptation into discrete spatial representation, b) the proposition of a CVAE-LSTM model for the long-term prediction of aircraft movements, and c) the proposition and discussion of error measures.

Given clean aircraft trajectories (sufficiently smooth, no outliers, equally sampled), the question remains how to best prepare this data for data-driven prediction approaches. As discussed in the related works Section 3.2, various representations for trajectory data were proposed. As state-of-the-art sequence prediction techniques often originally stem from natural language processing tasks, many of them require categorical, respectively discrete inputs. Therefore, for further study, the location data of trajectories is once taken in traditional latitude, longitude, and altitude pairs and additionally mapped onto the discrete hierarchical hexagonal spatial grid (H3) with an additional altitude component. Both representations are then tokenized into discrete tokens for consecutive learning approaches. The time dimension was converted into a differential feature relative to the flight's start time, a technique proven effective in other studies (Ayala et al., 2023; Guo et al., 2024).

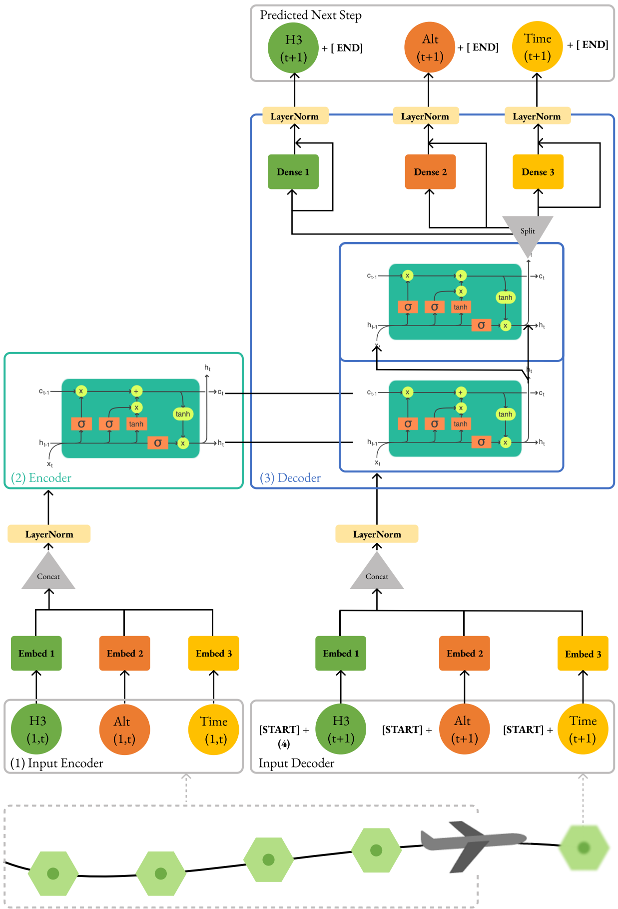


Figure 3. Model architecture of the proposed CVAE-LSTM model. During training, we employed a teaching forcing method (1,2,3) and shifted the target sequences by adding a `[START]` token at the beginning (4).

For the actual prediction, this work employs a CVAE *architecture*, with LSTM layers to predict the next trajectory positions, which is schematically presented in Figure 3. This model was inspired by the work of (Ayala et al., 2023). Still, we replaced the Convolutional Neural Network (CNN) encoder with LSTMs for simplicity, given that our dataset was not large enough to successfully train convolutional layers from the ground.

The model begins with the embedding layers for each input feature (1), essentially linear layers designed to map token indices into better representations in the latent space. We used an embed size of 128. Next, all the embedded features are concatenated, normalized, and passed through an LSTM encoder (2), with 1024 as hidden size, extracting the spatial-temporal features from input sequences. Following the encoder, we added a two-layer LSTM decoder (3), also with a hidden size of 1024. It takes the previous predictions as input and the hidden state from the encoder.

As illustrated in the diagram in Figure 3, the historical data is fed into the model on the encoder part, providing context for the prediction processes occurring on the decoder side. During training, true previous targets are input for the decoder instead of the previously predicted values. This is known as a *teacher forcing training method* and helps the model to converge faster. To achieve this, we shifted the target sequence by one position by adding a `[START]` token at the beginning (4). During inference, the previous predictions are fed into the decoder, as the true values are not available at this stage. We employ a Negative Log Likelihood Loss per predicted feature. This loss is particularly effective for training models in classification tasks with multiple classes, as it measures how well the predicted probability distribution aligns with the true class labels. In our case, each token corresponds to a discrete value of one dimension of the trajectory's state vector.

4.1 Implementation Details

During training, we employed the Adam optimizer with an initial learning rate lr of $1\mathrm{e}{-4}$. The model was trained for 100 epochs with a batch size of 64. An early stopping technique was used to prevent overfitting halting training when the validation loss start increasing over a tolerance for three epochs. The complete list of training hyperparameters is presented in Table 2. The dataset was randomly partitioned into training (70%), validation (20%), and testing (10%) sets, ensuring no overlap between the different sets.

Table 2. Hyperparameters used during training and evaluation processes.

Parameter	Value
Batch size	64
Optimizer	Adam
Optimizer params	$lr = 1\mathrm{e}{-4}, \beta_1 = 0.9, \beta_2 = 0.999$, weight_decay=1e−5
Dropout rate	0.2
Activation	LogSoftmax
# Epochs	100

4.2 Evalution Metrics

The prediction accuracy is systematically evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), well-known performance metrics in the trajectory prediction domain. It is clear to the authors, that this might sound counterintuitive given the categorical nature of predictions into distinct tokenized locations, still for the application domain it is rather unimportant whether the right distinct values are predicted but instead a continuous spatial distance to the actual trajectory is beneficial. Therefore, we propose to transform the aircraft's coordinates into a unified Earth-Centered Earth-Fixed (ECEF) coordinate system before computing the prediction errors. This approach ensures that all positional data is represented relative to a single, well-defined origin.

Data and Software Availability

Research code and computational workflows supporting this publication are available in 2025-AGILE-AircraftTrajectoryPrediction (https://github.com/tum-bgd/2025-AGILE-AircraftTrajectoryPrediction). Research data supporting this publication was downloaded from the OpenSky Network (https://opensky-network.org/) with scripts provided in the repository as described in Section 5.

5 Dataset

The dataset comprises historical ADS-B trajectory data sourced from the OpenSky Network (Schäfer et al., 2014) and processed using version `2.11.1` of the `Traffic` toolbox (Olive, 2019). It includes $2{,}334$ flights landing at Toulouse-Blagnac Airport (LFBO) between October 1 and November 5, 2024, with an average flight distance of approximately 797.54 km and a duration of 76.08 minutes. Due to the irregular time spacing of ADS-B recordings, missing data points were interpolated using cubic spline interpolation to create a smoother dataset. To balance data volume with computational efficiency, trajectories were resampled at intervals of 5, 10, 20, and 30 seconds, as well as 1 minute, allowing the model to be tested across various configurations. Anomalous values were removed using threshold-based filtering and median smoothing, including implausibly high speeds, vertical rates, and altitudes. Additionally, complex flight operations such as go-arounds and holding patterns were excluded to prevent confusion in the model. As ground segments are not well covered in the ADS-B data, points within 5 km of the origin and destination airports were also removed.

6 Experiments and Results

To show the applicabilty of our approach we conduct two experiments: First we evaluate the distinct spatial grid system H3 in different resolutions against the standard latitude, longitude and altitude representation. Then we evaluate the long-term prediction performance of the propsed approach.

6.1 Different H3 Resolutions

An experiment comparing different grid resolutions against a geodetic baseline data representation was conducted to identify the best grid resolutions for predicting aircraft trajectories. The tested H3 resolutions, ranging from 5 to 11, respect aviation's distance safety standards (approximately 9.26 km horizontally and 500 m vertically (Federal Aviation Administration, 2025)) while ensuring good computational performance. All the trajectories were re-sampled to 60 second intervals between positions, and the input and output sequence lengths were kept fixed at 5 and 60 points, respectively. The results, shown in Table 3, indicate that the lowest prediction errors occur at the resolution 5. This behavior is not expected since a high-resolution number means smaller grid areas, which should lead to smaller distance errors. However, by analyzing the RMSE, we can notice the presence of large values in the distance calculations, indicating that true values were outside, and spatially far, from the predicted H3 cell. This happens because flights often follow similar paths, and some departure airports are underrepresented. Due to that, the data had some high-probability concentration cells in specific geographic areas, such as the Paris-Toulouse route. Hence, less frequent cells were often misclassified into cells inside these zones instead of spatially close ones. This pattern significantly increases the horizontal errors when more cells are added with fine-grained resolutions.

Table 3. Results of global spatial MAE and RMSE per spatial feature and chosen data representation (Baseline Latitude and Longitude and different H3 grid resolutions). The best results for each error metric are highlighted in bold.

		MAE		RMSE	
		X (km)	Y (km)	X (km)	Y (km)
Basel. Lat.,Lon.		347.941	505.121	608.317	947.573
H3 Resolution	5	**32.428**	**42.566**	**92.035**	**115.732**
	6	50.225	62.577	132.781	164.336
	7	88.262	124.694	195.682	293.530
	8	194.095	273.405	441.892	677.890
	9	215.824	332.284	383.219	604.977
	10	240.655	363.235	337.013	510.632
	11	375.999	550.849	693.119	979.535

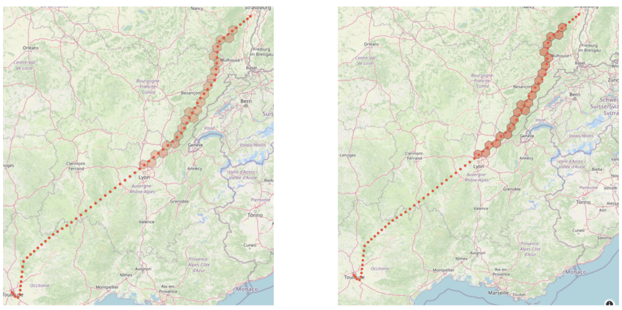
6.2 Different Long-term Prediction Ranges

Further, we analyzed the proposed data representation under different long-term prediction ranges, specifically look-ahead times (LATs) of 30 and 60 minutes. This experiment aimed to determine whether the error bounds of such a data representation remained within aviation specifications. To explore the impact of different sampling rates, we tested multiple sampling intervals to assess whether more frequent trajectory sampling led to improved performance. For consistency, we only used the fifth resolution grid of H3, as previous experiments indicated it generally yielded better results. The input sequence was fixed at two minutes, resulting in 24, 12, 4, and 2 trajectory points for the 5-, 10-, 20-, 30-, and 60-second sampling times, respectively. Table 4 presents the spatial errors for these sampling times and look-ahead predictions. The results indicate that for longer-range predictions, less frequent trajectory sampling generally leads to lower errors. The best overall spatial error was approximately 32 km in both look-ahead times, which shows consistency instead of an increasing pattern with the increase in the prediction range. However, none of the configurations produced results approaching the 9.26 km horizontal safety margins required in aviation.

Table 4. Results of global spatial MAE and RMSE per feature and sampling time (ST) for each look-ahead time (LAT). The best results per feature and prediction length are highlighted in bold. As data representation, an H3 grid of resolution 5 is chosen.

LAT (min)	ST (s)	MAE		RMSE	
		X (km)	Y (km)	X (km)	Y (km)
30	5	261.242	286.252	408.017	544.501
	10	303.056	346.598	457.504	588.518
	20	228.064	286.933	393.055	547.494
	30	34.945	59.469	125.844	196.429
	60	**31.694**	**35.807**	**117.308**	**112.321**
60	5	358.490	472.021	467.870	687.508
	10	298.051	333.066	415.271	567.649
	20	248.198	444.592	475.836	822.712
	30	**31.435**	**33.809**	**82.885**	**88.986**
	60	32.428	42.566	92.035	115.732

Nevertheless, Figure 4 illustrates that the model can accurately identify the next H3 cells in the 30-minute prediction scenario for some trajectories. This shows promising results despite the necessary adjustments required to make the predictions compliant with aviation safety standards.



(a) (b)

Figure 4. An example of a flight prediction of the model trained with a 60 s sampling time with H3 at resolution 5 using 2 minutes input and 30 minutes look-ahead time. In (a), the ground truth (red dots) is plotted together with the ground truth H3 cells. In (b), the predicted cells overlay the previous plot, showing a true prediction.

7 Conclusion

In this work, we showed that predicting aircraft trajectories poses a relevant application field for mobility research. We conducted initial experiments on applying state-of-the-art trajectory representation methods on aircraft flight paths. Specifically, we proposed to use H3 as a distinct spatial grid and showed that this data representation results in superior prediction performance compared to the standard geodetic representation in spatial coordinates. While H3 indexing presents a viable alternative to traditional coordinate systems, further refinements are necessary to achieve the high accuracy required for practical implementation in air traffic control and flight management systems as they pose high safety standards, such as using 3D grids with weather data, and more advance model architectures.

Apart from improving the pure model prediction performance, future work might investigate further postprocessing steps to extrapolate the sequence of predicted trajectory cells to actual continuous trajectories. This might include cleaning the trajectory data based on the physical limitations of aircraft travel and introducing methods to smooth out potential discontinuities. In general, the authors propose that the field of trajectory prediction in mobility science takes aircraft trajectories more into account, as they offer big data volumes without huge privacy risks involved.

Declaration of Generative AI in writing

The authors declare that they have used Generative AI tools in the preparation of this manuscript. Specifically, the AI tools were utilized for language editing and improving grammar and sentence structure but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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