

AIRCRAFT CLIMB PROFILE PREDICTION VIA MACHINE LEARNING-BASED FRAMEWORK

Hangyeol Seon[1], Keumjin Lee[1,2], Mark Brown[3], Hiroko Hirabayashi[3]

[1]Department of Advanced Air Transportation, Korea Aerospace University, Goyang 10540, Korea
[2]Department of Air Transportation and Logistics, Korea Aerospace University, Goyang 10540, Korea
[3]Air Traffic Management Department, Electronic Navigation Research Institute, Chofu, Tokyo 182-0012, Japan

Abstract

Accurate prediction of aircraft climb trajectories prior to departure is critical for effective air traffic management under trajectory-based operations. Current ground-based trajectory prediction systems relying on fixed performance tables frequently mispredict climb profiles by failing to account for environmental variations, leading to unexpected sector transitions and increased controller workload. In this study, we propose a two-step machine learning-based framework for pre-departure climb trajectory prediction. A Transformer-based regression model predicts the average rate of climb which is then combined with aircraft speed schedules and wind forecast data to construct the aircraft's vertical climb profile. The proposed framework is evaluated with a real-world flight trajectory dataset of departure flights from Korean international airports. The results demonstrate that the proposed model can capture flight-specific climb variability as opposed to the conventional method with fixed performance tables.

Keywords: Trajectory prediction, trajectory-based operations, machine learning, rate of climb, climb profile

1. Introduction

Trajectory-based operations (TBO), endorsed by the International Civil Aviation Organization (ICAO) through its Global Air Navigation Plan (GANP), provides a strategic framework for next-generation Air Traffic Management (ATM) [1]. Under TBO, the sharing of precise aircraft four-dimensional (4D) flight trajectory information between system actors increases predictability and allows more strategic, collaborative and proactive management of ATM resources, while reducing the need for tactical and reactive interventions by Air Traffic Controllers (ATCo). To this end, accurate trajectory prediction is becoming key to efficient ATM.

Japan's ATM system has been designed considering TBO principles. Every flight is associated with a predicted 4D trajectory generated from its flight plan before departure and updated during flight. Predicted trajectories are used for example to forecast ATCo workloads in en-route sectors to assist airspace management; for example, splitting or combining sectors to adjust capacity in response to demand, or introducing air traffic flow management (ATFM) measures to reduce excess demand and redistribute delay.

The airspace in Japan has undergone significant restructuring in recent years in response to increasing international and overflight traffic. A major change involves the horizontal division of en-route radar-controlled airspace into upper and lower sectors at Flight Level 335 (FL335), aimed at better aligning airspace structure with traffic characteristics: upper sectors primarily handle cruise

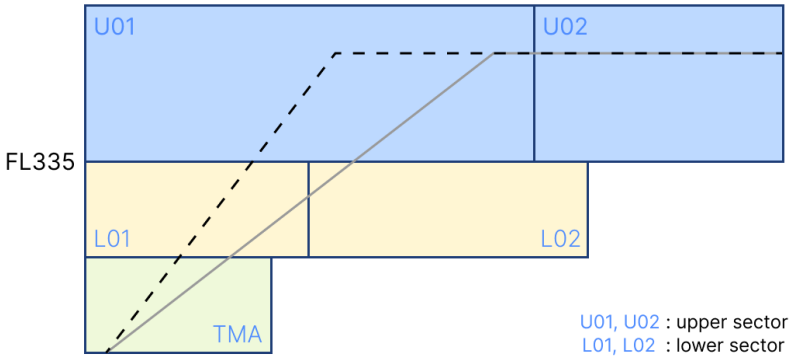


Figure 1 – Schematic diagram of the climb sector misprediction phenomenon (From [2])

traffic, whereas lower sectors handle climb, descent, and short-distance domestic cruise traffic [2]. However, this change has introduced new challenges regarding airspace management. Since the lower/upper division of airspace was introduced, there have been cases where the trajectories of departure traffic through en-route sectors from the Terminal Maneuvering Area (TMA) to the Top of Climb (TOC) are sometimes mispredicted by current ground-based trajectory prediction systems [2]. When an aircraft's actual Rate of Climb (ROC) is lower than the system's prediction, the flight may make an unpredicted entry into a downstream low-altitude sector before reaching upper airspace, thereby increasing coordination workload and complicating capacity management, as illustrated in Figure 1.

As an illustrative example, the dashed line in Figure 1 denotes the predicted trajectory, whereas the solid line denotes the actual flown trajectory. Although the ground-based system predicts that the aircraft will enter the upper airspace (U01 and U02) after L01, the actual trajectory continues through L02 before reaching the upper sector. Consequently, the controller in L02 needs to handle unplanned traffic, resulting in increased workload and less accurate sector occupancy estimates. The misprediction was found to be due to the use of fixed climb rate values in simple table-based climb performance calculations that did not take into account the effect of temperature, resulting in overestimating ROC during the summer, when the lower air density due to elevated temperatures reduces performance.

It is important to accurately predict the climb trajectory to reduce such unexpected workload and coordination issues. Using fixed performance tables to calculate nominal climb profiles for each aircraft type is rapid and adequate for some applications but is not robust against environmental variations. One way of improving climb prediction accuracy at the expense of increased computation time and complexity is to use a simplified physics-based flight model parameterized by aircraft performance, a widely-used example being the EUROCONTROL Base of Aircraft Data (BADA). However, the accurate prediction of climb trajectory by ground-based ATM systems remains challenging due to uncertainties inherent in the climb phase of flight. These uncertainties arise from factors such as aircraft mass, thrust setting, speed profile, and environmental conditions, which are not fully observable by ground-based systems at prediction time [3, 4]. As a result, physics-based models such as BADA often rely on nominal aircraft mass and reference speed-profile values, leading to systematic climb prediction errors [5].

One way to reduce such errors is to use powerful statistically-based and data-driven techniques such as have been developed in the fields of optimization and artificial intelligence. This can even allow consideration of stochastic factors that are difficult to incorporate into physical models. Such techniques have been applied in applications aimed at providing a short-term "lookahead" climb profile estimation, for example ATCo support tools to help better predict vertical separations of climbing traffic and reduce inefficient level-off instructions. Data obtained in real-time during the earlier stages of climb, either inferred from time histories of position and altitude or obtained directly

via downlink of flight parameters, may be applied to refine the climb estimate. Prior studies include supervised machine learning to estimate hidden operational factors such as aircraft mass and speed intent for BADA-based climb prediction [6, 7, 8], generative models that augment BADA thrust parameters with data-driven corrections [9], and clustering-based analysis of historical climb profiles to characterize vertical trajectory variability [10]. However, these approaches are not applicable to pre-departure estimation.

The present study is aimed at improving the prediction of climb profiles using only information available before flight. As an initial step, we attempted to apply regression (machine learning) from historical climb profile samples to estimate the relationship between ROC and factors that can be obtained from the flight plan [2]. In this study, we propose a two-step machine learning-based framework for aircraft climb profile prediction. Figure 2 provides an overview of the proposed framework. In Step 1, a Transformer-based model predicts the average ROC from 10,000ft to the top of climb using various input features, while attention scores are analyzed to examine the relevance of each feature. In Step 2, the predicted ROC is combined with the aircraft speed schedule and forecast wind data to sequentially construct the vertical climb profile between 10,000ft and the TOC. This two-step design combines the flexibility of data-driven ROC prediction with the physics-informed consistency of vertical profile construction. The proposed framework is evaluated using Automatic Dependent Surveillance-Broadcast (ADS-B) data collected from flights departing Korean international airports.

2. Methodology

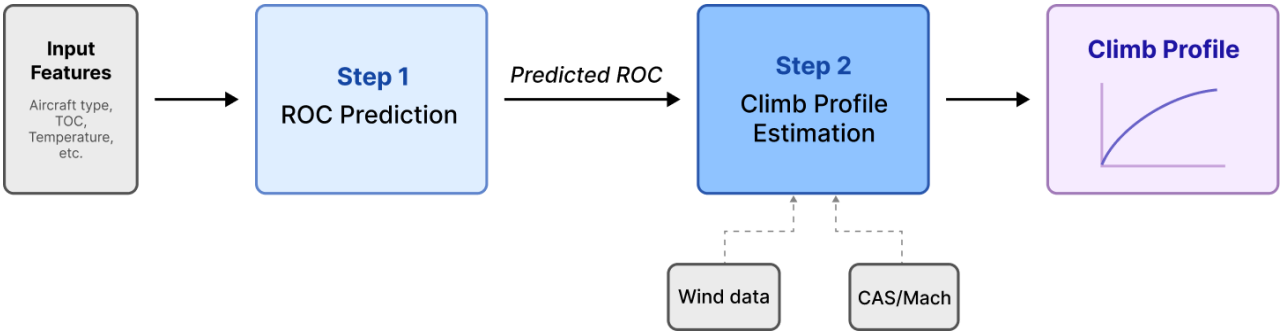


Figure 2 – Overview of the proposed ROC-based climb profile prediction framework

2.1 Step 1: ROC Prediction

Step 1 predicts the average ROC for each flight using a Transformer-based regression model. The model receives input features that are available prior to departure and outputs a predicted ROC value. At the current stage of this research, the model only provides a single ROC value representing the average climb performance of a flight between 10,000 ft and the TOC.

2.1.1 Transformer

The Transformer is a deep learning architecture originally introduced for sequence-to-sequence tasks in natural language processing [11]. It relies entirely on self-attention mechanisms to model dependencies among input elements, without using recurrent or convolutional structures. The core component is the multi-head self-attention layer, which computes how much attention each input element should receive relative to the others. Each attention layer is followed by a feed-forward network, with residual connections around both sub-layers.

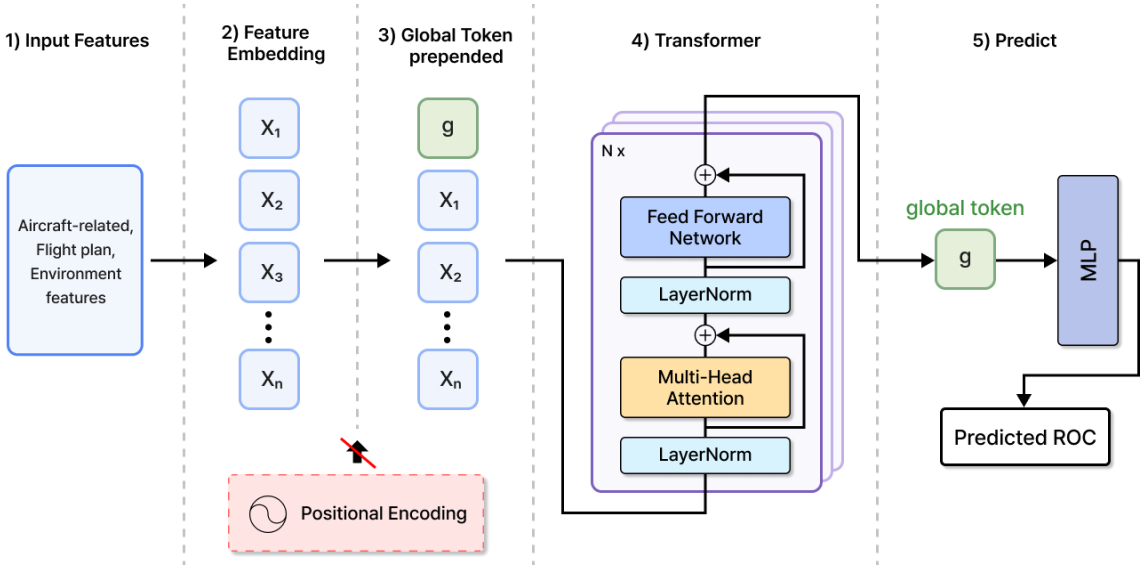


Figure 3 – Overall architecture of Transformer-based ROC estimation

Figure 3 shows the Transformer-based ROC estimation architecture. In the proposed architecture, a global token is appended to the input sequence to aggregate information across all input features and serve as the prediction representation for ROC estimation. Positional encoding is excluded because the input features represent independent attributes related to ROC with no inherent sequential ordering.

Table 1 – Description of input features for ROC prediction

Category	Feature	Description
Aircraft-related features	Aircraft operator	Airline call sign associated with each flight
	Aircraft type	Aircraft model or type designation
	Flight category	Domestic or international
Flight plan features	Departure aerodrome	Departure airport, either Incheon (RKSI) or Gimpo (RKSS)
	GD	Great-circle distance between the departure and destination aerodromes
	TOC	Top of Climb, the altitude at which the cruise phase begins
Environmental features	Season	Summer (Jun~Aug), winter (Nov~Jan), and other
	Tsurf	Temperature at surface
	T100-T350	Temperature at every 5,000ft altitude interval 10,000~35,000ft

As shown in Table 1, the input features selected in this study include both categorical and numerical factors that potentially affect the ROC of aircraft during the climb phase. These features include: (i)

Aircraft-related features, such as aircraft operator, aircraft type, and flight category (domestic/international); (ii) Flight plan features, such as departure aerodrome, great circle distance (GD), and TOC; and (iii) Environmental features, such as season and temperatures at the airport reference point at the surface and at every 5,000 ft altitude interval from 10,000 to 35,000 ft.

Take-off weight is known to be a key influential factor affecting climb performance but is not available to ATM systems at present (although this may change if operators see a benefit from allowing better ATM trajectory predictions). In [2], we had access to flight plan information and used estimated elapsed time (EET) as a surrogate for weight, since this is correlated with planned fuel burn. For the present study, detailed flight plan information was not available, so the GD between departure and destination were used instead, since this is also correlated with trip fuel albeit less strongly than EET.

Aircraft operator (OPR) was selected as a feature because the performances of a given aircraft type may vary between operators due to factors such as operating policy (e.g., cost index selection and use of thrust derating), engine type (not reflected in the ICAO aircraft type code), aircraft subtypes (different gross weight variants), and empty weights differing between due to cabin configuration etc. Similarly, International/Domestic was selected as a factor since for a given aircraft type and operator, equipage and configuration, therefore weights, may vary between domestic and international fleets.

The dataset is constructed by filtering for trajectories that exhibited a continuous climb profile from 10,000 ft to the TOC, explicitly excluding trajectories containing intermediate level-offs or cruise segments during the climb. Aircraft types with insufficient sample sizes are omitted, resulting in a dataset of 104,514 flights. For model development and evaluation, the dataset is divided into a training set, validation set, and test set, with an 8:1:1 ratio.

2.2 Step 2: Climb Profile Estimation

Step 2 constructs the vertical climb profile of the target aircraft by combining the predicted ROC from Step 1 with the aircraft speed schedule and meteorological wind forecast data.

2.2.1 Aircraft Performance Data

The climb profile construction methodology proposed in this study uses the speed data obtained from the EUROCONTROL Aircraft Performance Database (EAPD) [12], a publicly available source providing indicative performance data for a wide range of aircraft types. The EAPD specifies, for the climb phase, a calibrated airspeed (CAS) below the transition altitude and a Mach number above it. In this study, the CAS/Mach speed schedule is used to determine the aircraft's TAS at each segment along the climb profile, which is then converted to ground speed (GS) using wind forecast data.

2.2.2 Climb Profile Estimation Model

The climb profile is constructed by sequentially integrating aircraft's altitude along the lateral climb profile obtained from the filed flight plan. The lateral climb profile is divided into consecutive segments, and the altitude at each segment's endpoint is computed using the predicted ROC, the speed schedule obtained from the EAPD, and local meteorological wind forecast data. The overall process of climb profile construction is illustrated in Figure 4. In the steps below, the formulae are mostly obtained from the BADA report [13].

Step 1. At each segment, the local atmospheric state is first retrieved from the meteorological forecast data. The required atmospheric state includes temperature, pressure, and wind components.

Step 2. The local temperature T is, then, used to compute the speed of sound a:

$$a = \sqrt{\kappa R T} \tag{1}$$

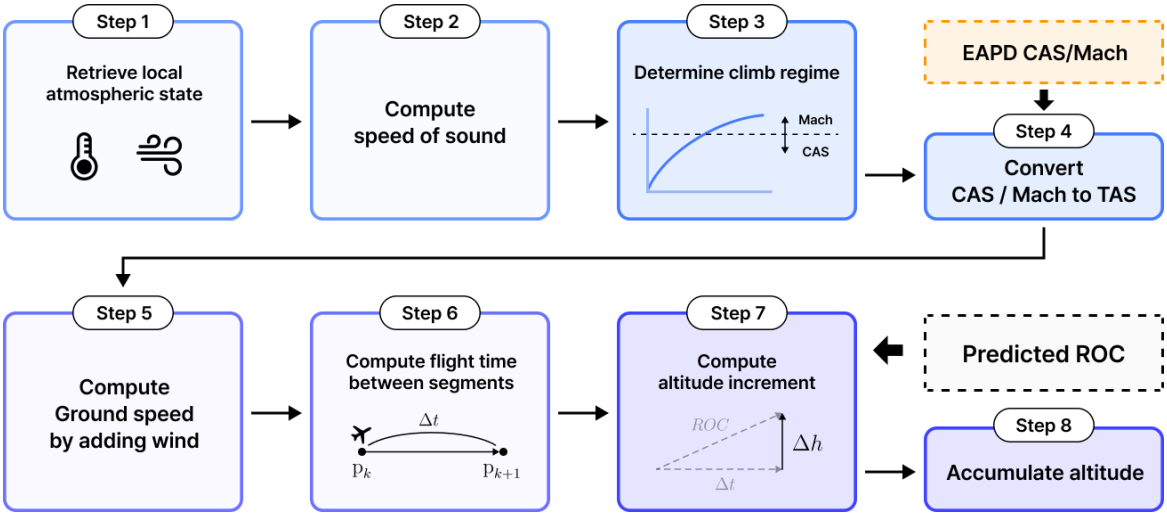


Figure 4 – Overall process of climb profile construction

where κ is the adiabatic index of air and R is the real gas constant for air.

Step 3. The CAS/Mach transition altitude is computed from the scheduled CAS and Mach number obtained from the EAPD. This altitude, also referred to as the crossover altitude, represents the geopotential pressure altitude at which the scheduled CAS and Mach number correspond to the same TAS. The pressure at the transition altitude, p_{trans}, is calculated as:

$$p_{\text{trans}} = p_0 \frac{\left[1+\left(\frac{\kappa-1}{2}\right)\left(\frac{V_{CAS}}{a_0}\right)^2\right]^{\frac{\kappa}{\kappa-1}}-1}{\left[1+\frac{\kappa-1}{2}M^2\right]^{\frac{\kappa}{\kappa-1}}-1} \tag{2}$$

where p_0 is the mean sea-level reference pressure, a_0 is the speed of sound under standard mean sea-level conditions, V_{CAS} is the scheduled calibrated airspeed, and M is the scheduled Mach number. The corresponding transition altitude $H_{p,\text{trans}}$ is then obtained from the standard atmosphere pressure-altitude relation as:

$$H_{p,\text{trans}} = \frac{T_0}{\beta_T}\left[\left(\frac{p_{\text{trans}}}{p_0}\right)^{\frac{-\beta_T R}{g_0}} - 1\right] \tag{3}$$

where T_0 is the mean sea-level reference temperature, β_T is the International Standard Atmosphere (ISA) temperature gradient below the tropopause, and g_0 is the gravitational acceleration.

The flight speed regime is determined by comparing the current segment altitude with $H_{p,\text{trans}}$. Below the transition altitude, the aircraft is assumed to follow the scheduled CAS, whereas above it, the aircraft follows the scheduled Mach number.

Step 4. In the constant-CAS phase, the scheduled CAS is converted into TAS using the compressible-flow relation:

$$V_{TAS} = \left[\frac{2}{\mu}\frac{p}{\rho}\left\{\left(1+\frac{p_0}{p}\left[\left(1+\frac{\mu}{2}\frac{\rho_0}{p_0}{V_{CAS}}^2\right)^{\frac{1}{\mu}}-1\right]\right)^{\mu}-1\right\}\right]^{\frac{1}{2}} \tag{4}$$

where $\mu = (\kappa-1)/\kappa$, and p_0 and ρ_0 are the mean sea-level reference pressure and density, respectively. In the constant-Mach phase, TAS is calculated as:

$$V_{TAS} = M \cdot a \tag{5}$$

where M is the scheduled Mach number.

Step 5. The ground speed GS is obtained by adding the along-track wind component v to the TAS:

$$GS = V_{TAS} \pm v \tag{6}$$

Step 6. For a segment with along-track distance d, the traversal time is computed as:

$$\Delta t = d/GS \tag{7}$$

Step 7. The altitude increment over the segment is then estimated using the predicted ROC:

$$\Delta h = ROC \cdot \Delta t \tag{8}$$

Step 8. Finally, the altitude at the next segment's endpoint is updated as:

$$h_{k+1} = h_k + \Delta h \tag{9}$$

where k denotes the segment index along the lateral climb profile, while h_k and h_{k+1} are the aircraft altitudes at the current and next segment endpoints, respectively. This process is repeated along the lateral climb profile until the altitude reaches the TOC.

3. Numerical results

3.1 Target Airspace

The numerical experiments are conducted using ADS-B trajectory data in South Korea for departures from Incheon International Airport (RKSI) and Gimpo International Airport (RKSS) between 1st January and 31st December 2024. The dataset includes both domestic and international departures. After the preprocessing process described in Section 2.2.2, 104,514 departure flights are used for this numerical analysis.

3.2 Results and Discussion

3.2.1 ROC Prediction

The ROC prediction performance was evaluated using the coefficient of determination (R^2), root mean squared error (RMSE) and mean absolute error (MAE), which are defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{11}$$

where n denotes the number of samples, y_i and $\hat{y}_i$ denote the actual and predicted ROC values, respectively.

The model was trained using a mean squared error (MSE) loss and compared with the histogram gradient-boosting regression (HGB) model used in previous work [2]. The HGB baseline achieved R^2, RMSE, and MAE values of 0.8583, 186.67 ft/min, and 137.00 ft/min, respectively, whereas the proposed Transformer model achieved R^2, RMSE, and MAE values of 0.8624, 158.00 ft/min, and 114.37 ft/min. Compared with the HGB baseline, the proposed Transformer-based prediction model reduced RMSE and MAE by approximately 15.4% and 16.5%, respectively. These performance gains likely reflect the ability of the proposed ROC prediction model to capture complex cross-feature interactions, particularly among aircraft characteristics, flight-plan variables, and environmental conditions.

Table 2 – Results of feature ablation analysis

	Input feature	R^2	RMSE (ft/min)	MAE (ft/min)
	All	0.8624	158.00	114.37
	Feature exclusion			
Categorical	OPR (aircraft operator)	0.8369	173.09	126.40
	ACTYPE (aircraft type)	0.7566	211.43	155.50
	ADEP (departure aerodrome)	0.8533	164.13	117.69
	INTDOM (international or domestic)	0.8554	162.95	117.93
	Season	0.8548	163.30	119.01
Numerical	GD	0.8082	187.68	136.81
	TOC	0.6933	237.30	157.48
	Tsurf (surface temperature)	0.8559	162.62	118.00
	T100–T350 (temperature at FL100–FL350)	0.8475	167.36	123.20

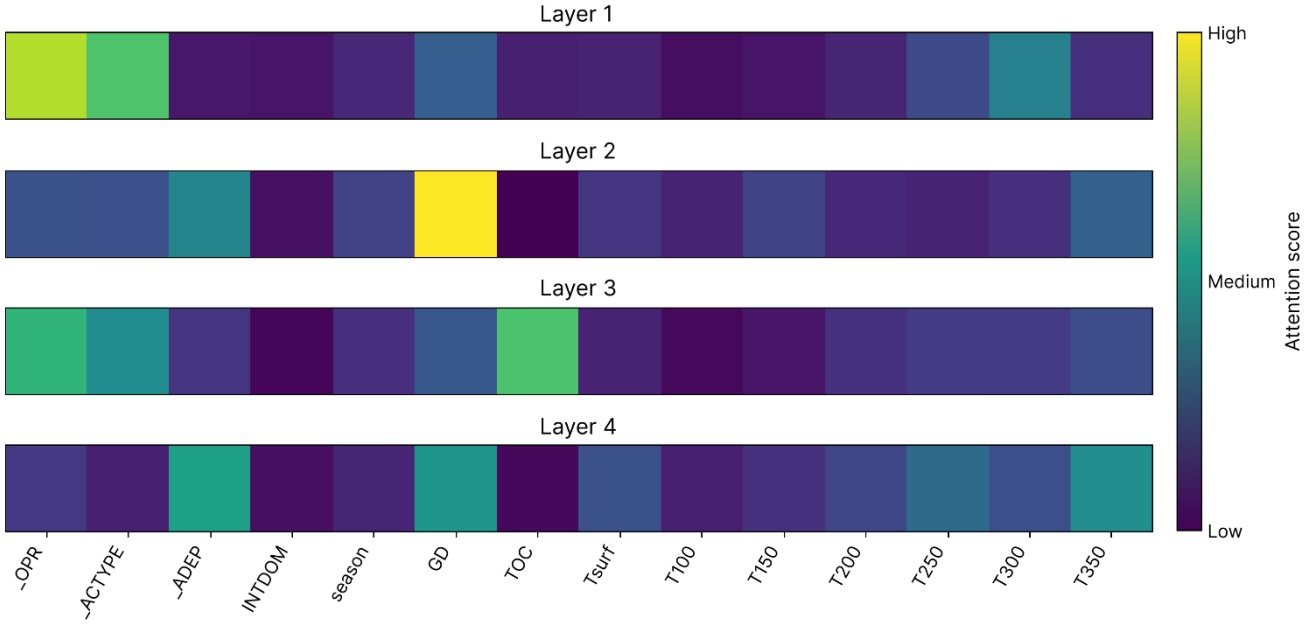


Figure 5 – Attention score heatmap by layer

A feature ablation study was conducted to assess the relative contribution of each feature to ROC prediction accuracy. As shown in Table 2, the TOC feature has the strongest influence on ROC prediction (i.e., the greatest reduction in prediction accuracy when removed), followed by ACTYPE and GD.

Figure 5 shows the layer-wise attention scores of the Transformer model, where the x-axis represents the input features. The attention patterns indicate that the model attends different feature groups across layers rather than concentrating on a single variable. In the early layer, relatively high attention scores are assigned to aircraft-related features such as aircraft operator and aircraft type, while

subsequent layers show stronger attention to flight-plan variables such as GD and TOC, as well as selected altitude-dependent temperature features. These patterns are consistent with the feature ablation results: removing aircraft type and TOC caused the largest performance degradation, confirming that these features carry the most predictive information for ROC estimation.

3.2.2 Climb Profile Estimation

The climb profile estimation method described in Section 2.3.2 was applied to several representative departure flights. For each flight, the vertical profile was constructed along the lateral climb route using the predicted ROC, the CAS/Mach speed schedule obtained from the EAPD, and along-track wind components. The results were compared with the actual climb profiles obtained from ADS-B data.

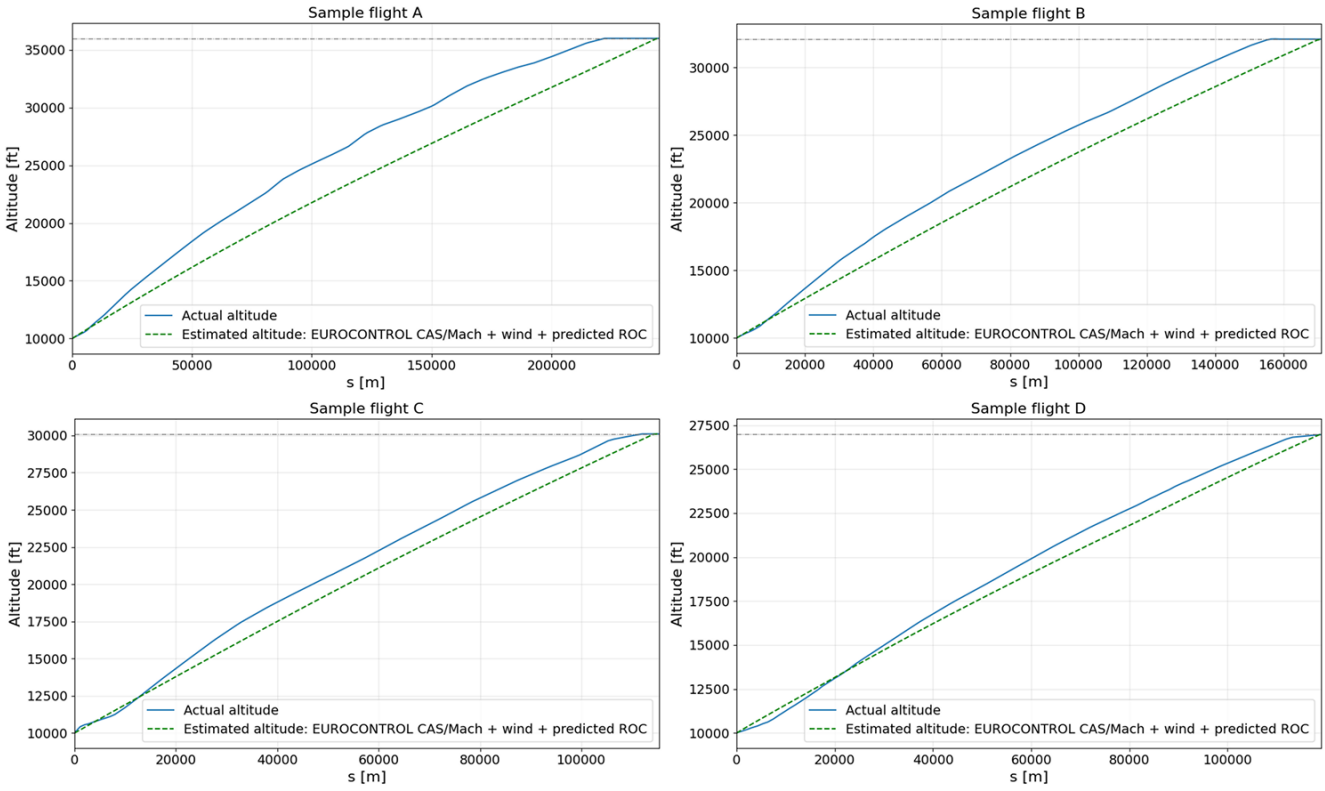


Figure 6 – Climb profile estimation results for representative sample trajectories

Figure 6 compares the climb profiles of four sample flights with the same aircraft type (B38M). The blue solid line denotes the actual ADS-B altitude profile, and the green dashed line denotes the estimated profile by the proposed method. The proposed method incorporates flight-specific speed scheduling and environmental effects, allowing it to capture the variability in climb behavior across individual flights. Although the estimated profile appears nearly linear at first glance, it shows a slightly curved altitude-distance relationship due to variations in ground speed along the route, arising from speed scheduling and wind effects.

The ADS-B data reveals considerable variability in climb trajectories even among flights of the same aircraft type, driven by flight-specific factors such as aircraft weight, thrust setting, and atmospheric conditions. By combining the predicted ROC with the CAS/Mach speed schedule from the EAPD and forecast wind data, the proposed method produces climb profiles that capture this flight-specific variability more effectively. It is worth noting that the proposed method uses a single average ROC rather than altitude-dependent rates, yet the estimated profiles show reasonable agreement with the actual ADS-B trajectories when combined with appropriate speed and wind inputs.

4. Conclusion and Future works

We proposed a two-step machine learning-based framework for climb profile prediction. In the first step, a Transformer model predicts the average ROC from aircraft-related, flight-plan, and environmental features. In the second step, the predicted ROC is combined with the CAS/Mach speed schedule from the EAPD and forecast wind data to construct the vertical climb profile along the lateral flight path. Numerical experiments using Korean ADS-B data showed that the proposed Transformer-based model achieves improved ROC prediction accuracy compared with the HGB baseline. Furthermore, the climb profile estimated by the proposed framework demonstrates its ability to capture flight-specific variability in climb behavior.

Future work will extend the current average-ROC formulation toward segment-wise or altitude-dependent ROC prediction to better capture local climb-rate variations. More detailed speed estimation will also be investigated to reflect flight-specific speed profiles across altitude. In addition, the proposed framework will be evaluated in terms of sector transition timing and sector occupancy prediction, which are directly related to workload and capacity management in horizontally-divided airspace.

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6. Contact Author Email Address

shg990607@gmail.com

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