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Machine Learning Approach for Aircraft Performance Model Parameter Estimation for Trajectory Prediction Applications

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Outline of the talk

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- Technical Approach
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  - Data Pipeline
  - ML Features and Labels
- Results
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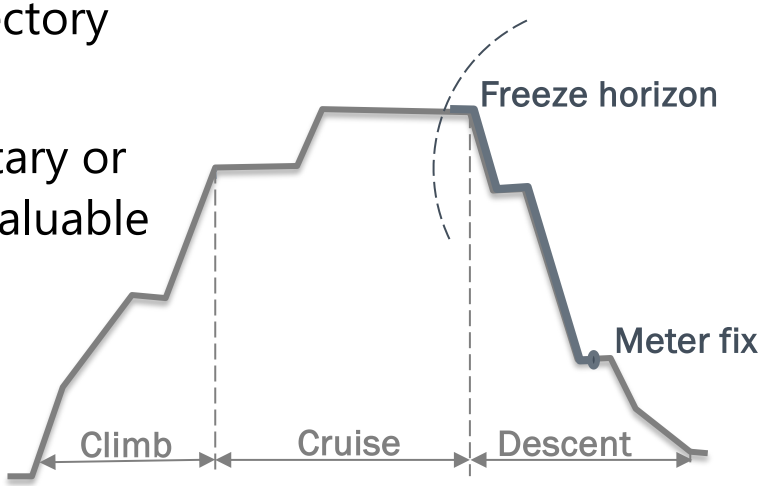
Background

- Aircraft trajectory prediction is a major concern in air traffic management (ATM).
- An accurate and efficient trajectory prediction is required to solve inefficiencies and **improve Estimated Time of Arrivals (ETAs) at meter fix**.
- Ground-based decision support tools (DST) in ATM typically perform trajectory prediction using **aircraft performance models** (APM).
- Some APM parameters may not be publicly available due to their proprietary or competitive nature. Thus, the **Base of Aircraft Data (BADA)** serves as a valuable substitute.
- Trajectory prediction accuracy can be improved by learning critical APM parameters such as **drag coefficients**, and **takeoff mass.**
- Standalone physical models are constrained by oversimplifications and assumptions, whereas Machine Learning (ML) algorithms excel in **capturing intricate dynamics** from **historical data** without the need for precise knowledge of every pertinent physical law and parameter.

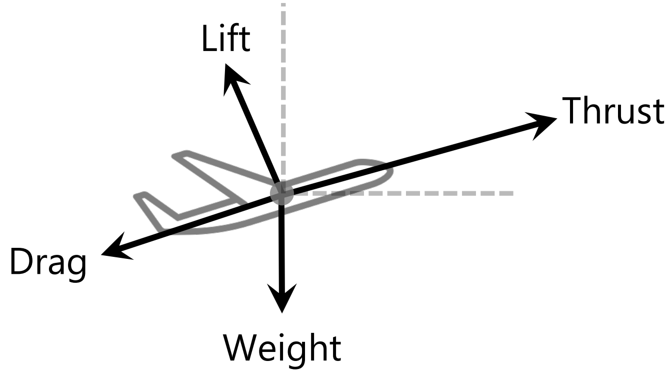


Literature Summary

- None of the methods simultaneously estimate **mass**, **thrust**, and **drag parameters**.
- Much of the work is conducted on **climb phase** data, with limited attention given to the descent phase. However, the descent phase is where there are lots of **challenges** and high **sensitivity** to APM parameters.
- In many of the approaches that use fitting, the **temporal aspect** of the data is not explicitly considered, and errors are minimized using trajectory points as data samples.
- Several past methods estimate the **initial mass/weight** but assume it to be **constant** during the sections that are being used to fit the data.

Theoretical Background

- ATM-related trajectory prediction applications use a simplified, point-mass model known as the **total energy model** (TEM).
- The model can then be used in conjunction with flight data, operating procedures, and other data sources to predict trajectories.



Work done by forces acting on aircraft equated to change in total mechanical energy →

$$\frac{(T-D)V_t}{mg} = \dot{h} + \frac{V_t}{g}\left[\dot{V}_t + \frac{d}{dt}\left(V_w\cos(\psi_a - \psi_w)\right)\right]$$

T – thrust
D – drag
$\dot{h}$ – rate of climb
V_w – wind speed
V_t – true airspeed
ψ_w – wind direction
ψ_a – heading
$\dot{h}$ – rate of climb
g – gravity acceleration

ODE Equations

- By substituting the D and T (using their standard models), and assuming a clean drag configuration and neglecting wind-related components, the ODE equations are:

Altitude ODE (rate of climb)

$$\dot{h} = \frac{\delta}{(m_0 - m_f)}\left[\frac{T_{max}V_t}{g \cdot AF}\right] - \frac{C_{D0}}{m_0 - m_f}\left[\frac{\rho V_t^2 S\psi_w}{2gAF}\right] - \kappa(m_0 - m_f)\left[\frac{2g.\cos^2\gamma}{S\rho V_t \cdot AF}\right]$$

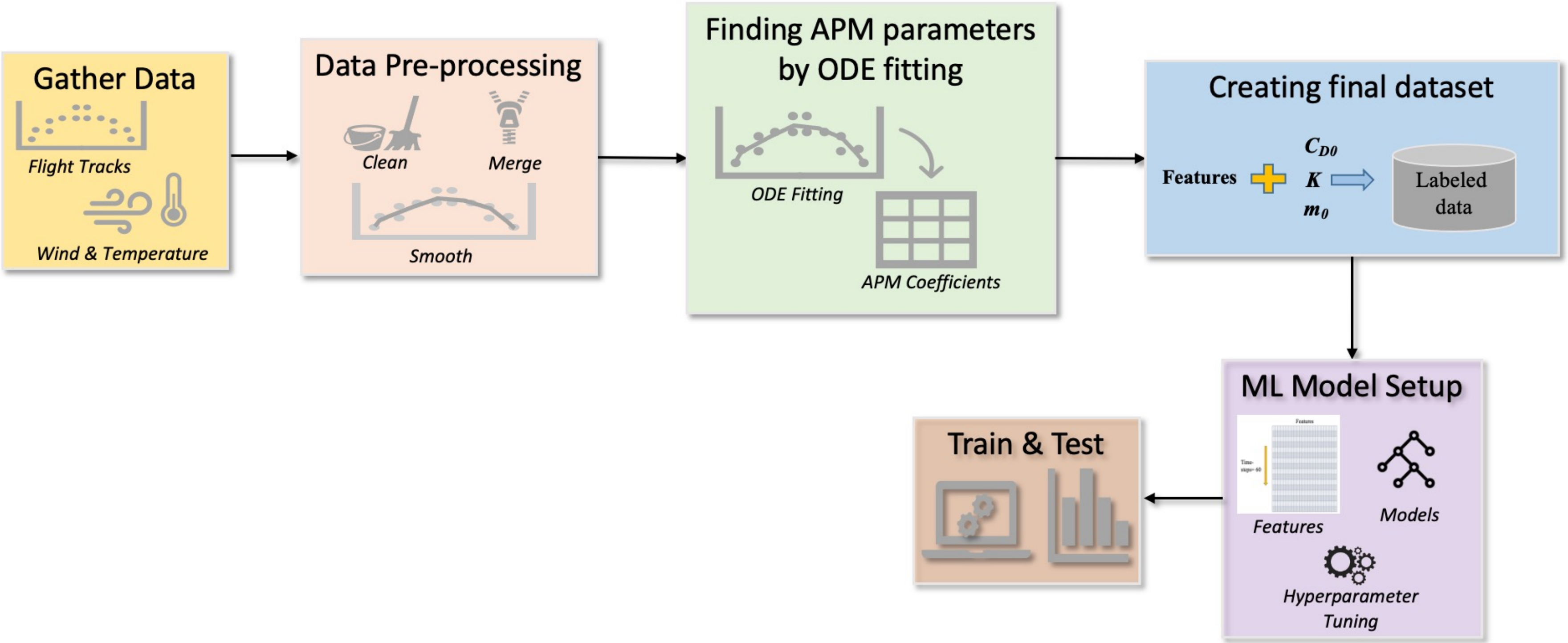
Mass ODE (fuel burn)

$$\dot{m} = -f$$

- The APM parameters are calculated by fitting the ODEs to reconstruct the altitude profile of a historical flight with minimal error.
- The estimated APM parameters (drag coefficients and initial aircraft mass) are our labels or ground truth data in the ML solution.

C_{D0} – parasite drag coefficient
κ – induced drag coefficient
m_0 – starting mass
δ – thrust settings

Data Processing and ML Pipeline



- Historical flight data from one year at **four airports** (DEN, DFW, LAX, MSP) and **three airframe types** (A320, B737, B738)
- ODE-fitting is required to obtain 'labels' for the flight trajectory and train the ML model
- ML model will capture relationship between the flight features and APM coefficients

ML Solutions: Feature Sets

1. Aircraft type
2. Month
3. Day of week
4. Destination
5. Start hour
6. Current temperature/pressure
7. Airline
8. Total distance traveled
9. Avg. Mach in cruise
10. Avg. altitude in cruise
11. Engine

Solution 1 ← (features 1–11)

Potentially known prior to flight departure

1. Avg. Rate in climb/descent
2. Avg. CAS in climb/descent
3. Avg. Mach in climb/descent

Solution 2 ← (all features)

Features and Labels

Feature and label space are one-dimensional.

Features / **Labels**

Sample	Aircraf	Airline	Month	Distance	...	C_{D0} , K , m_0
1	B738	AAL	01	252		0.023, 0.031, 71
2	A320	ASA	10	665		0.022, 0.041, 68
3	B737	DAL	09	393		0.020, 0.032, 77
⋮						
n	A320	UAL0	12	243		0.025, 0.043, 69

Performance Metrics

- **MSE** (mean squared error): It is the sum of the square of the difference between the predicted and actual target variables, divided by the number of data points.

$$\frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2$$

- **MAPE** (mean absolute percent error): It is the average of the absolute value of the difference between the predicted and actual target variables, divided by actual target values.

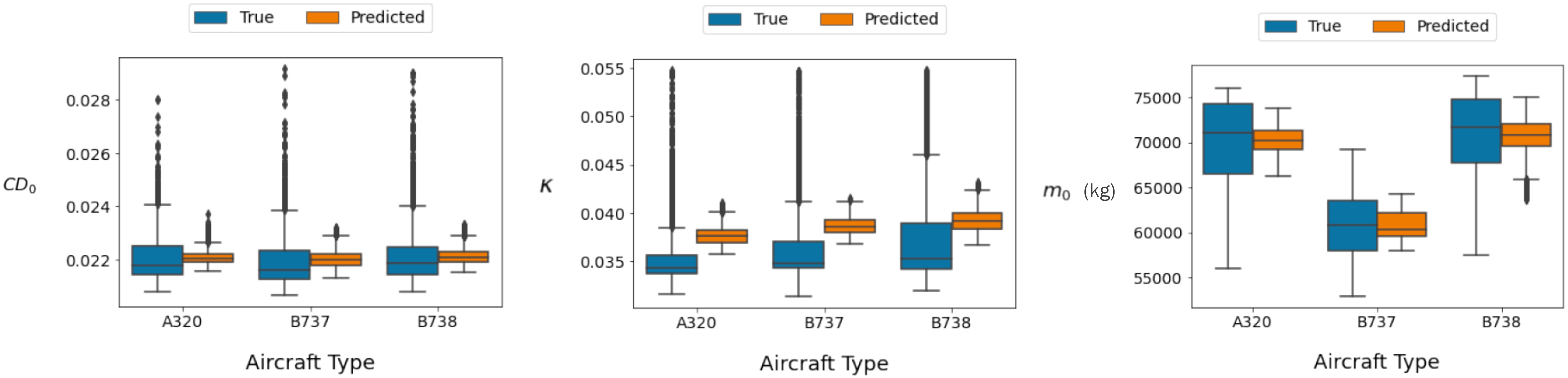
$$\frac{100}{n}\sum_{i}^{n}\frac{y_i - \hat{y}_i}{y_i}$$

ML Performance Scores

	ML model	MSE	MAPE (C_{D0})	MAPE (K)	MAPE (m_0)
Solution 1	Linear regression	0.025	3.03%	8.37%	5.3%
	Random forest regression	0.024	3.19 %	6.21%	5.77%
	XGBoost	0.031	3.22%	6.04%	7.0%
Solution 2	Linear regression	0.025	3.03%	6.93%	4.67%
	Random forest regression	0.021	3.01%	6.07%	3.89%
	XGBoost	0.026	2.95%	6.13%	45.61%

True vs ML Predicted Labels

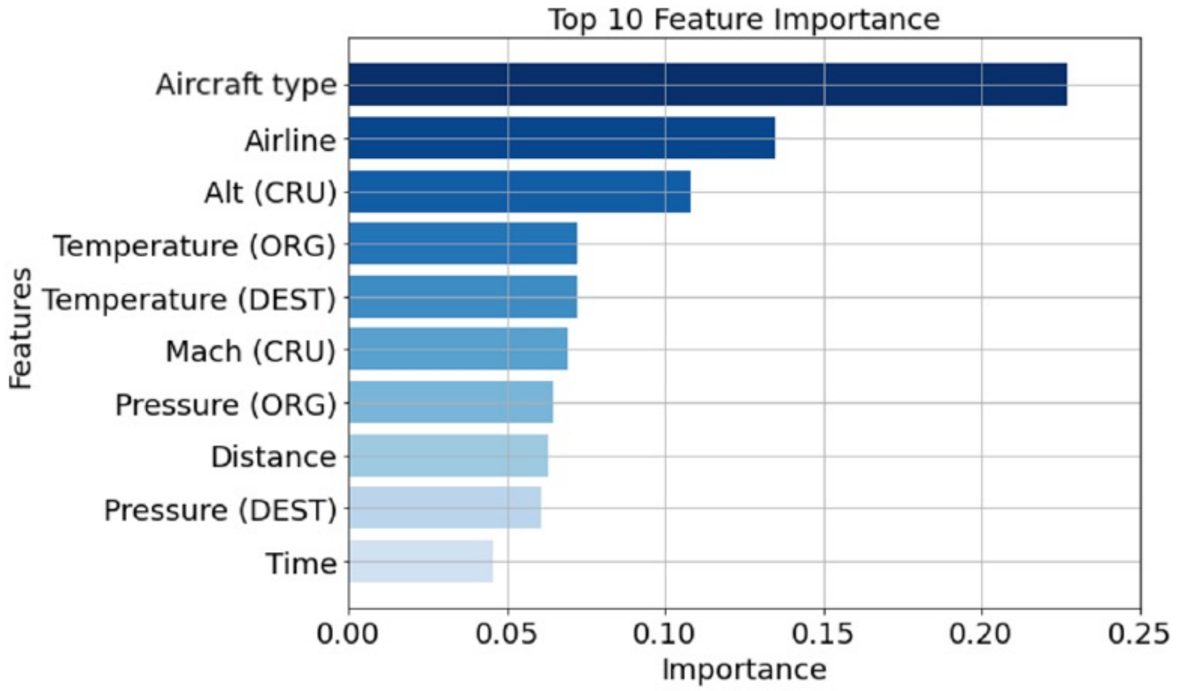
- It predicts the central tendency of C_{D0} and κ values but may not fully capture their variability.
- The model accurately predicts m_0 with clear distinctions between different aircraft types.



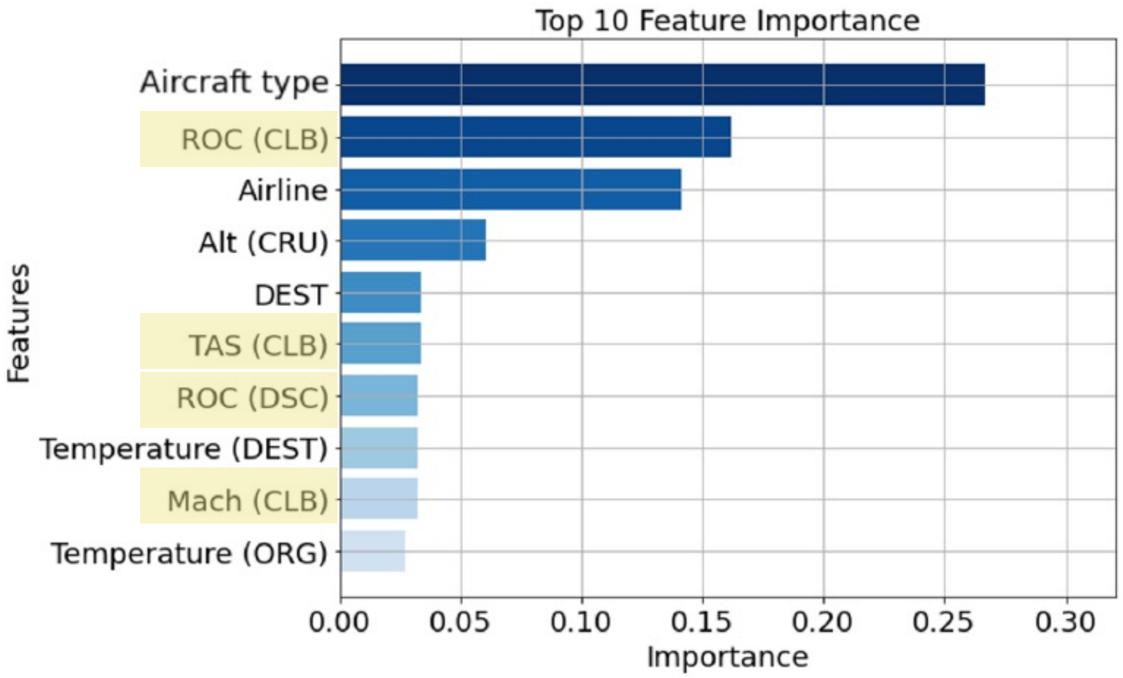
Important Features

In both Solutions, **"Aircraft Type"** emerged as the most influential feature, underscoring its significant impact on the predicted outcomes.

Solution 1

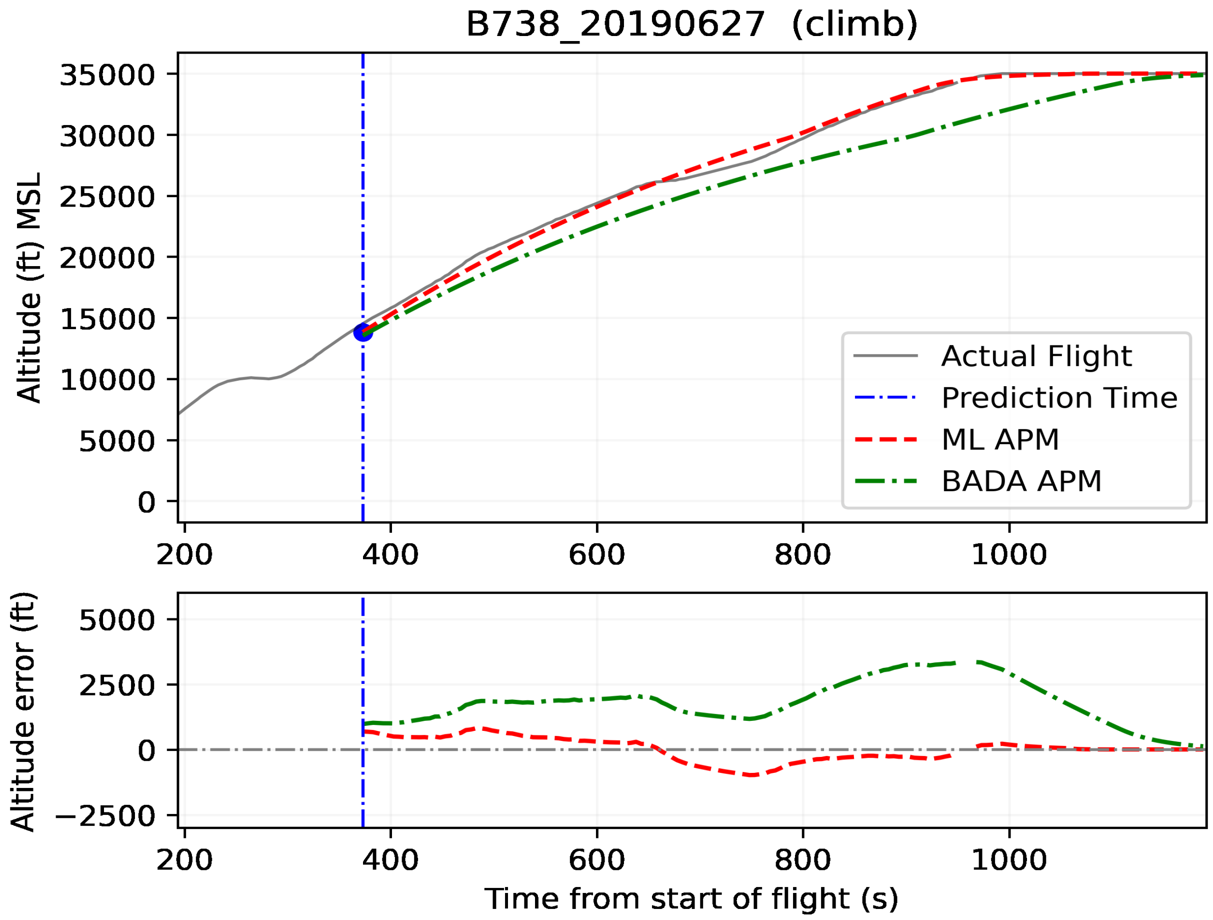


Solution 2



ADK Simulation

- After the ML portion of the work is complete, the ML-derived models are evaluated using **NASA's Airspace Autonomy Development Kit** (ADK) simulation software.
- ADK includes models of airspace, airports, aircraft performance, wind, weather, and atmospheric conditions.
- We performed two sets of predictions for each flight, one using the **baseline BADA APM parameters** (fixed) and a second one using the **ML-derived APM parameters** (customized based on a specific flight).



Conclusion and Contributions

Contributions:

- Developed a novel ODE-fitting approach that estimates **all four APM parameters simultaneously.**
- Engineered two ML solutions to map APM parameters to flight data. One leveraged **preflight information**, while the other used features derived from **in-flight data**.
- Built a pipeline consisting of data processing, **ODE-fitting**, and **ML modeling** to obtain updated APM coefficients using historical flight data from one year at **four airports** and **three airframe types.**
- Simulated several flights in ADK and compared predicted trajectories using **BADA parameters** and **ML ones.**

Conclusions:

- The inclusion of in-flight summary values enhanced the accuracy of our ML predictions.
- Aircraft type was shown to have the highest importance among all features which signifies its strong correlation with the initial mass of the aircraft (one of ML labels).
- ML parameters showed better trajectory prediction compared to baseline/fixed parameters in the ADK simulation.

Questions?

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References

1. Anon, “Doc 9854 – Global Air Traffic Management operational concept,”2005, Publisher: International Aviation Civil Organization (ICAO) Montreal, QC, Canada.
2. S. Mondoloni and N. Rozen, “Aircraft trajectory prediction and synchronization for air traffic management applications,” Progress in aerospace sciences, vol. 119, no. 100640, 2020.
3. R. M. Sgorcea and L. A. Weitz, “Role of aircraft descent speed schedule prediction in achieving trajectory-based operations,” in AIAA Aviation 2021 Forum, no. 2021-2374, 2021.
4. R. Slattery and Y. Zhao, “Trajectory synthesis for air traffic automation,” Journal of Guidance, Control, and Dynamics, vol. 20, no. 2, pp. 232– 238, 1997.
5. M. R. Jackson, Y. J. Zhao, and R. A. Slattery, “Sensitivity of trajectory prediction in air traffic management,” Journal of Guidance, Control, and Dynamics, vol. 22, no. 2, pp. 219–228, 1999.
6. A. Nuic, D. Poles, and V. Mouillet, “BADA: An advanced aircraft performance model for present and future ATM systems,” International journal of adaptive control and signal processing, vol. 24, no. 10, pp. 850–866, 2010.
7. J. Sun, J. Ellerbroek, and J. M. Hoekstra, “Aircraft initial mass estimation using Bayesian inference method,” Transportation Research Part C: Emerging Technologies, vol. 90, pp. 59–73, 2018.
8. H.-T. Lee and G. Chatterji, “Closed-form takeoff weight estimation model for air transportation simulation,” in 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, no. 2010-9156, 2010.
9. J. Sun, H. Blom, J. Ellerbroek, and J. M. Hoekstra, “Aircraft mass and thrust estimation using recursive Bayesian method,” in 8th International Conference on Research in Air Transportation, Barcelona, Spain, 2018.
10. C. Schultz, D. Thipphavong, and H. Erzberger, “Adaptive trajectory prediction algorithm for climbing flights,” in AIAA Guidance, Navigation, and Control Conference, no. 2012-4931, 2012.
11. R. Dalmau, X. Prats, A. Ramonjoan, and S. Soley, “Estimating fuel consumption from radar tracks: a validation exercise using FDR and radar tracks from descent trajectories,” CEAS Aeronautical Journal, vol. 11, no. 2, pp. 355–365, 2020.
12. R. Alligier, D. Gianazza, and N. Durand, “Energy rate prediction using an equivalent thrust setting profile,” in ICRAT 2012, 5th International Conference on Research in Air Transportation, 2012.
13. R. Alligier, D. Gianazza, and N. Durand, “Learning the aircraft mass and thrust to improve the ground-based trajectory prediction of climbing flights,” Transportation Research Part C: Emerging Technologies, vol. 36, pp. 45–60, 2013.
14. J. Sun, J. M. Hoekstra, and J. Ellerbroek, “Estimating aircraft drag polar using open flight surveillance data and a stochastic total energy model,” Transportation Research Part C: Emerging Technologies, vol. 114, pp. 391–404, 2020.
15. T. Jeeves and R. Hooke, “Direct search solution of numerical and statistical problems,” Journal of the ACM, vol. 8, no. 2, pp. 212–229, 1961.
16. J. Sun, J. Ellerbroek, and J. M. Hoekstra, “WRAP: An open-source kinematic aircraft performance model,” Transportation Research Part C: Emerging Technologies, vol. 98, pp. 118–138, 2019