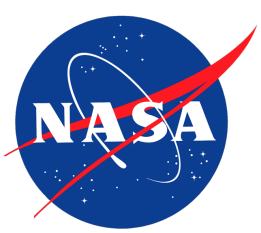

**An ODE-Fitting Approach to Estimate Critical Aircraft Performance
Parameters for Trajectory Prediction (Paper ID: 3208)**



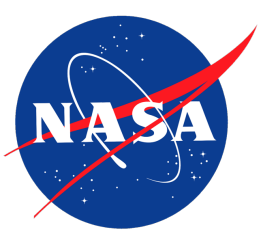
Tejas G. Puranik, Aida Sharif Rohani, Krishna M. Kalyanam
NASA Ames Research Center, Moffett Field, CA





Outline of the talk

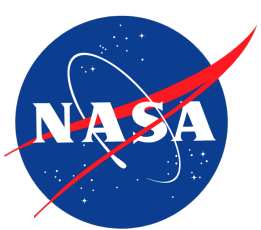
1. Introduction
2. Technical Approach
3. Implementation and Results
4. Conclusion



Trajectory Prediction and Aircraft Performance Models

- ❖ Transition towards trajectory-based operations (TBO) in NextGen.
- ❖ Accurate prediction of the aircraft's trajectory is essential because mismatch between the predicted and actual trajectory can lead to **scheduling errors** and **inefficiencies**.
- ❖ Ground-based decision support tools (DST) in air traffic management (ATM) typically perform trajectory prediction using **aircraft performance models** (APM).
 - Lack of knowledge of critical pieces of information can cause inaccuracies in APM predictions.
- ❖ In particular, the three critical APM parameters required for trajectory prediction using kinetic models are the **thrust setting**, **drag coefficients**, and **takeoff mass** of the aircraft.

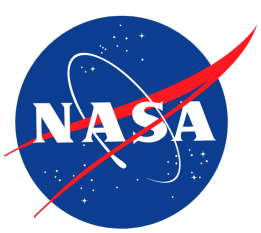
There is a potential to improve the accuracy of ground-based DST through incorporation of historical data in kinetic aircraft performance models used in trajectory prediction.



Literature Review – Observations

Literature typically divided into 3 main categories – mass, thrust, and drag estimation

- ❖ 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 to the data.



Research Objective and Contributions

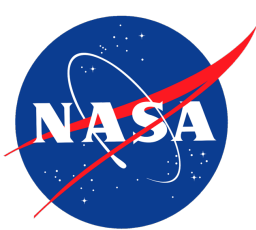
Research Objective

Overarching objective is **improving** the estimation of APM parameters—specifically thrust setting, drag coefficients, and takeoff weight—by using historical flight data in an offline ODE-fitting process.

Contributions

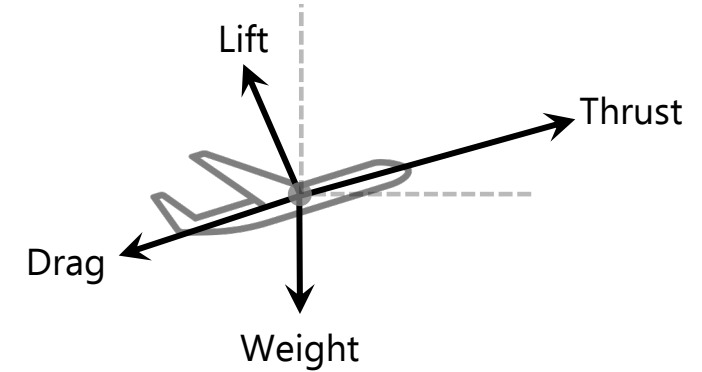
1. The approach **simultaneously** accounts for thrust, drag, and starting mass estimation in the optimization process.
2. The approach **fits aircraft altitude**, as opposed to directly fitting a noisy (and/or derived) rate of climb (ROC), via an ordinary differential equation (ODE) fitting approach, thereby directly incorporating physics.
3. The approach combines data from **all segments** of the flight that have non-zero ROC, as opposed to just the initial climb or final descent phase.

The APM parameters obtained from the developed approach are ultimately envisioned to be used in a Machine Learning (ML) model as labels to potentially improve current trajectory predictions.



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.



$$\underbrace{\frac{(T - D)V_t}{mg}}_{\text{Work done by forces acting on aircraft}} = \underbrace{\dot{h} + \frac{V_t}{g} \left[\dot{V}_t + \frac{d}{dt} (V_w \cos(\psi_a - \psi_w)) \right]}_{\text{Rate of change of total mechanical energy}}$$

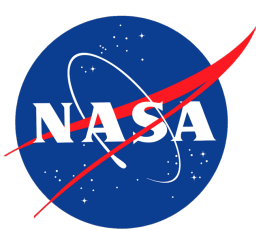
Operationalized based on available data and unknowns

Altitude Ordinary Differential Equation

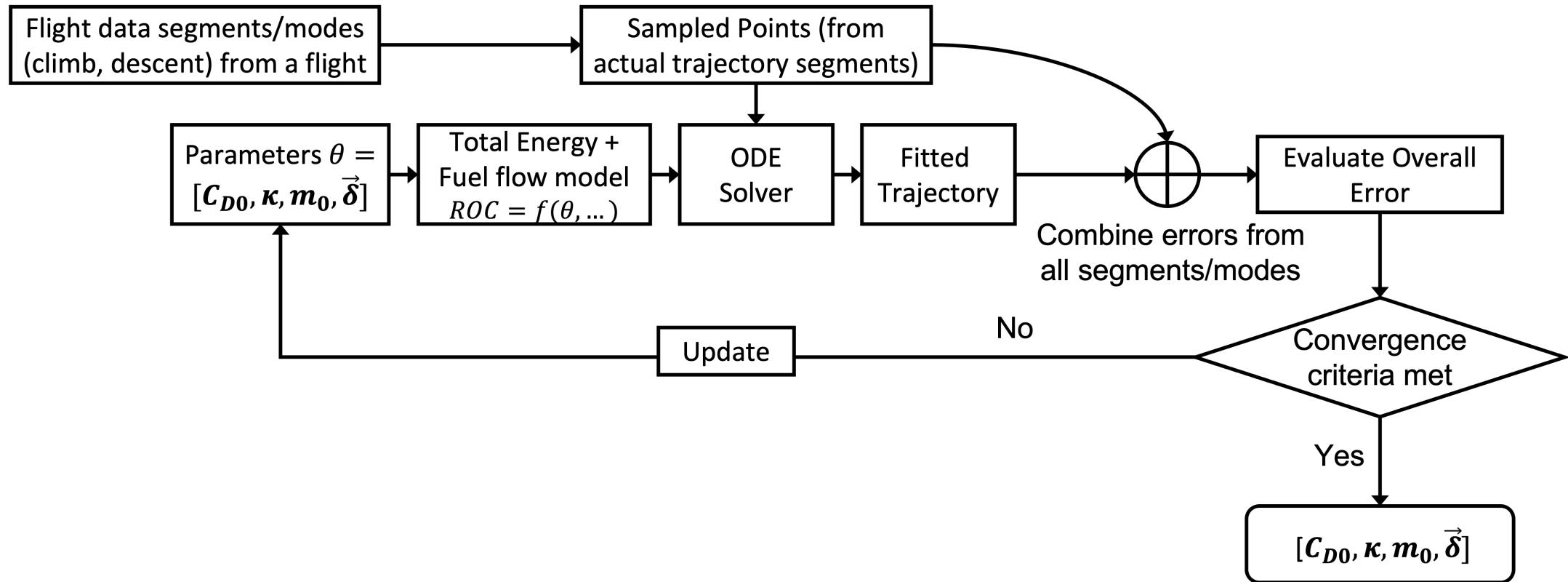
$$\dot{h} = \frac{\delta}{(m_0 - m_f)} \left[\frac{T_{max} V_t}{g \cdot AF} \right] - \frac{C_{D0}}{m_0 - m_f} \left[\frac{\rho V_t^2 S}{2gAF} \right] - \kappa (m_0 - m_f) \left[\frac{2g \cdot \cos^2 \gamma}{S \rho V_t \cdot AF} \right] \dots (1)$$

Mass Ordinary Differential Equation

$$\dot{m} = -f \dots (2)$$



Problem Setup

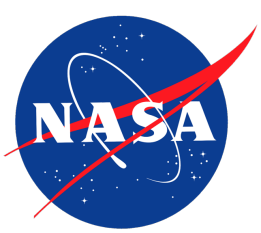


Data Sources →

NASA's Sherlock Data Warehouse

Rapid Refresh (RAP) data from NOAA

FAA Aircraft Registry



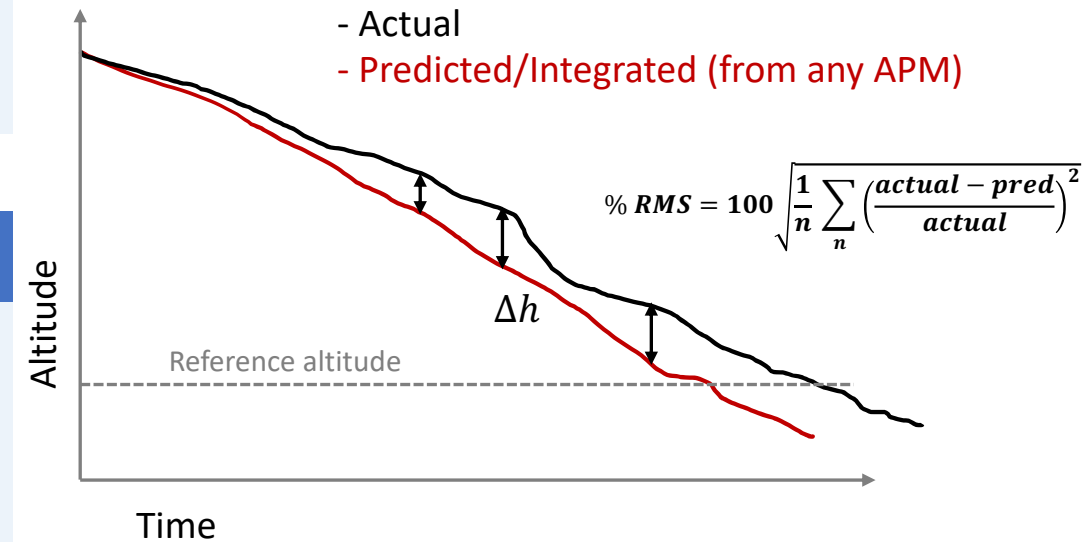
Implementation

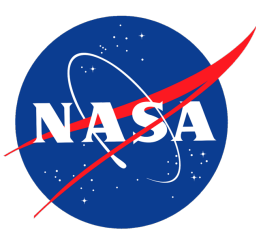
Results overview

- ODE-fitting process applied to several historical flights and optimal APM coefficients are obtained.
- The output for each flight is a set of **five APM parameters** as well as an RMS error value that indicates how well the altitude is fit.

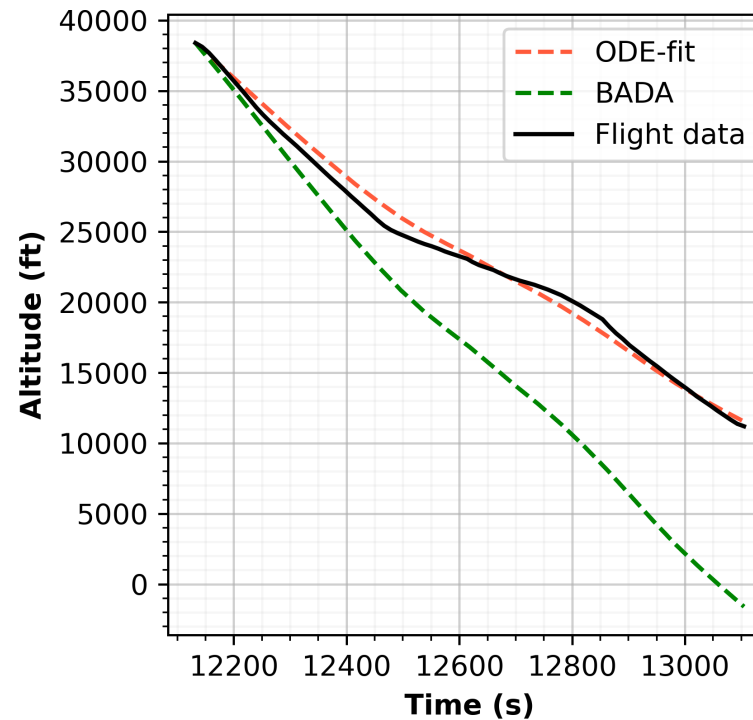
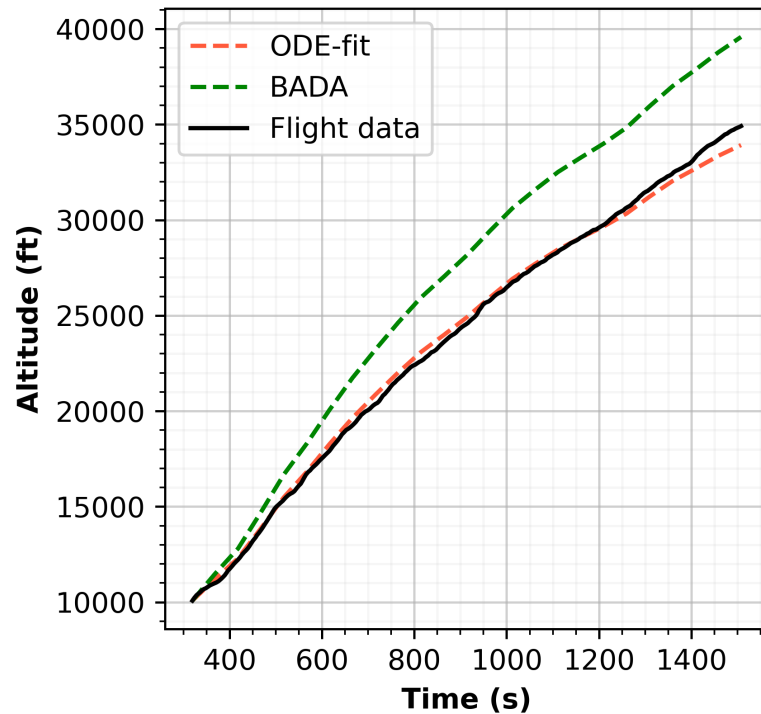
Constraints/Assumptions

- Segments of flight below 10,000 ft MSL are ignored because we are focusing on **clean drag** configuration.
- Flights that do not converge during the ODE-fitting, either due to the bounds on the parameters or other reasons, are excluded.
- Starting mass range is chosen based on the minimum and maximum values recommended by BADA.
- **Fuel flow** law and **max thrust** values based on BADA.
- **Wind gradient** terms in ODE ignored in the current formulation.

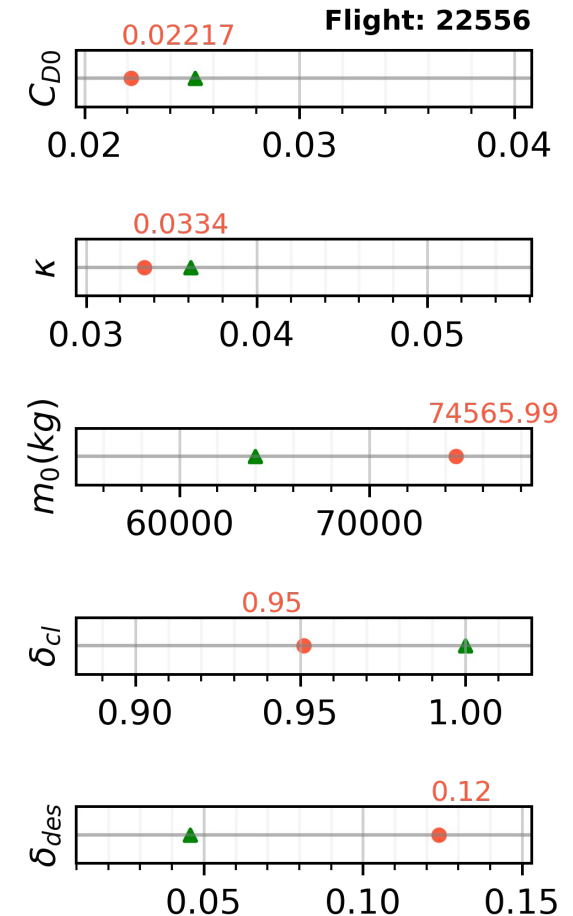


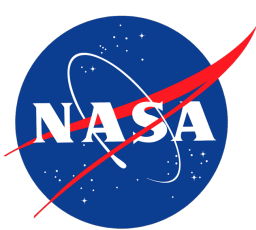


Individual Flight Results (A320: LAX - CVG)

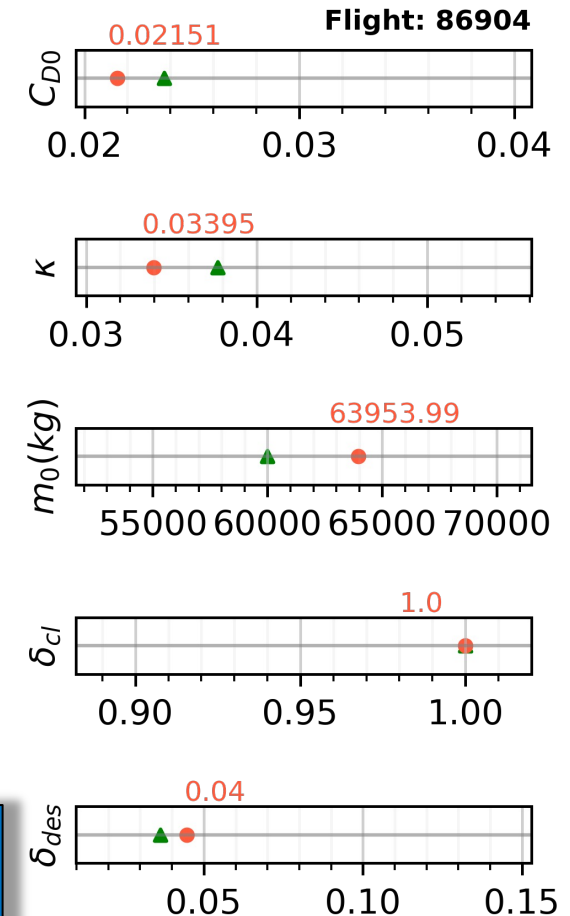
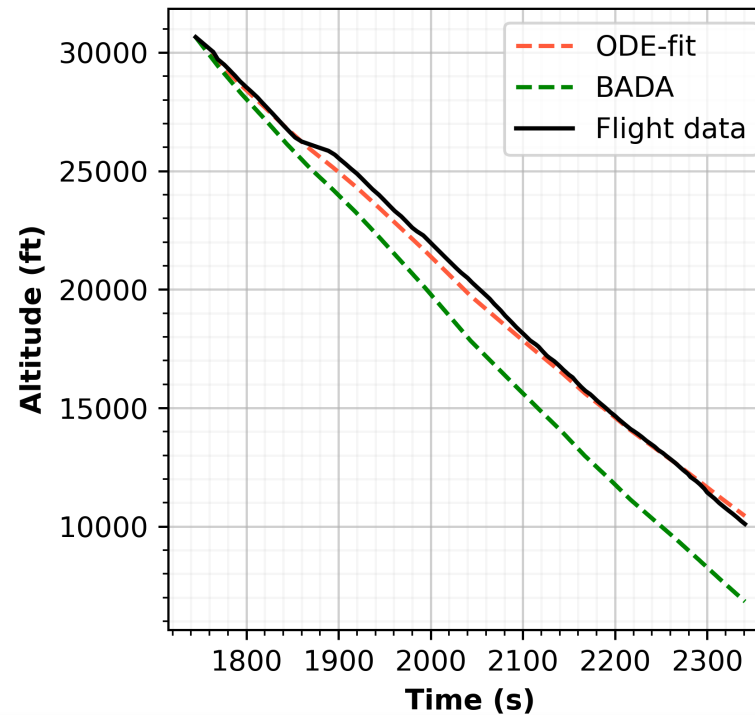
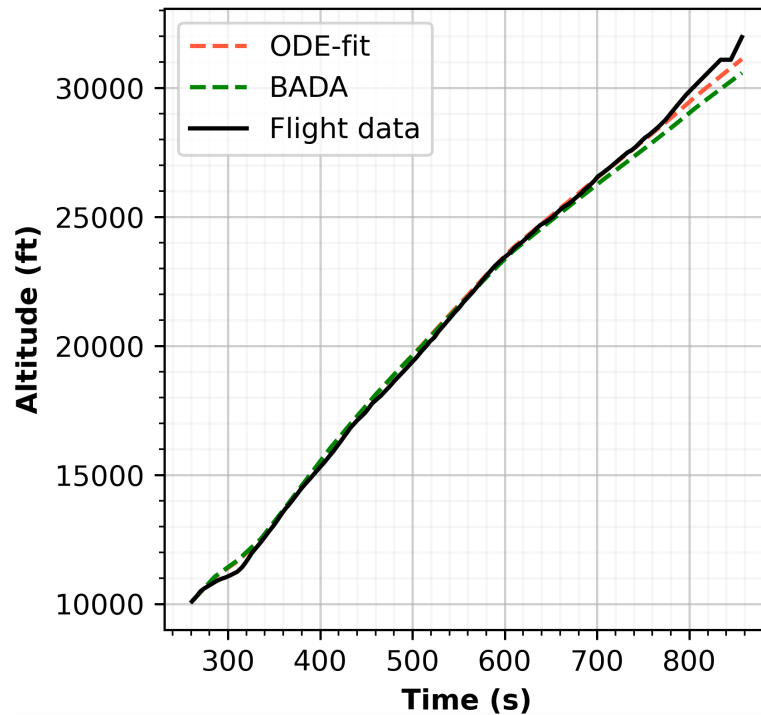


- The optimized solution shows better fit with the flight data compared to the baseline APM parameters.
- Optimal solution differs from baseline for all parameters.

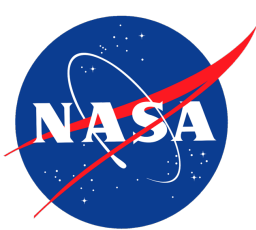




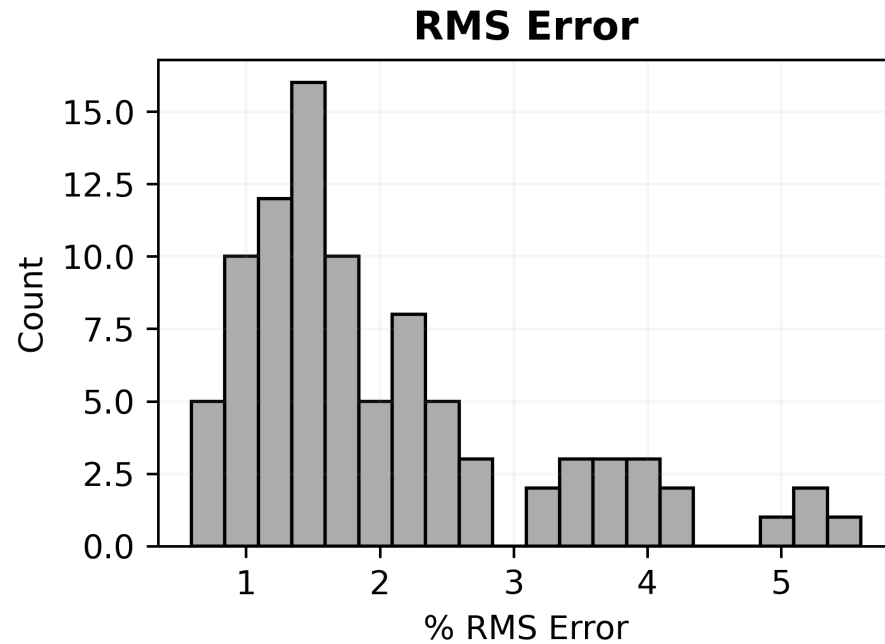
Individual Flight Results (B737: PHX-SAN)



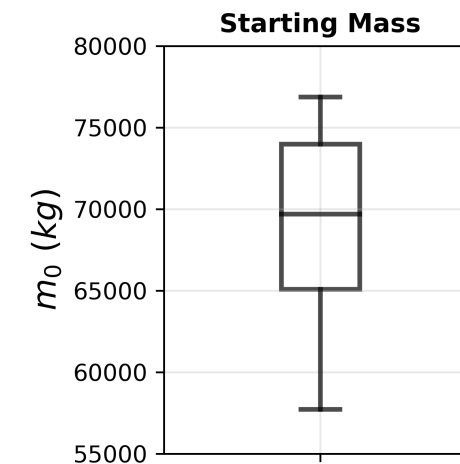
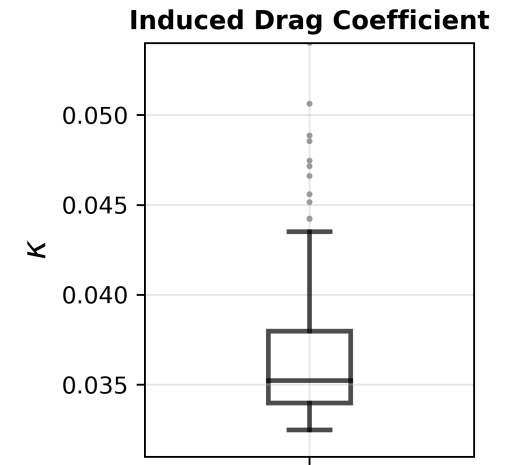
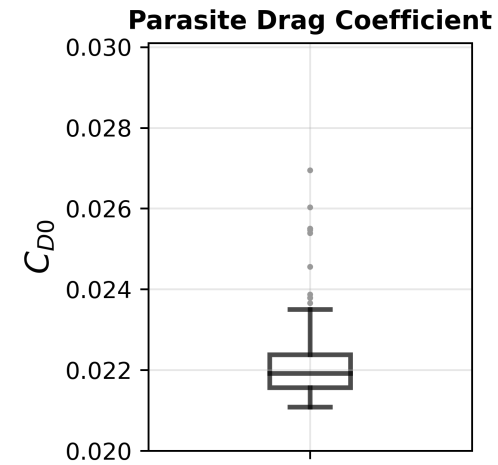
- The optimized solution shows better fit with the flight data compared to the baseline APM parameters.
- Few differences in climb phase, but significant differences in descent phase between baseline and optimal solution.

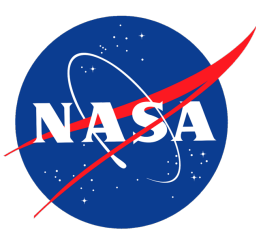


Collective Results



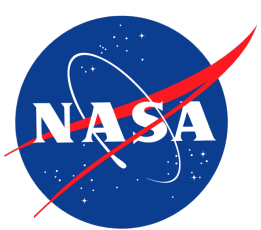
- Applied the approach on 90 different flights of the B738 airframe arriving at LAX airport.
- RMS error for most flights is within 5%.





Discussion: From ODE-fitting to Trajectory Prediction

- ❖ Proposed method faithfully reproduces altitude trajectory. Providing a way of using **flight-specific data** to update/improve **kinetic** APMs.
- ❖ **Under-constrained** and **highly-coupled** problem results in multiple solutions that are close to each other in vertical trajectory but far apart in APM parameter space.
- ❖ APM parameter set that works well for one phase may not work as well in another phase.
- ❖ Due to the nature of the problem, there is a likelihood that the ODE-fitting will try to **compensate** for errors or differences in trajectory due to one or more of the other causes.
- ❖ Can be integrated into existing trajectory prediction or ATM application by fixing parameters that cannot be varied in that system and optimizing for the remaining ones.



Conclusion

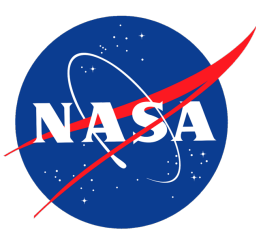
- ❖ Implemented a novel approach for **simultaneously** estimating APM parameters using historical data for kinetic APM.
- ❖ Demonstrated better goodness-of-fit for **three aircraft** types with optimized parameters than the baseline.
- ❖ Reduced the number of assumptions made and allowed the search for the best set of APM parameters.

Ongoing Work

- ❖ Ongoing work identifying the **sensitivity** of the obtained ODE-fit solution at the optimal point to assess its robustness.
- ❖ The implementation of this approach on **thousands of historical flights** is being conducted for more detailed statistical analysis.
- ❖ Machine Learning (ML) models will be trained to learn the **mapping** between APM coefficients and predictors of interest.
- ❖ Testing will be conducted using the fitted APM coefficients in a trajectory prediction tool for **independent validation**.

Questions?

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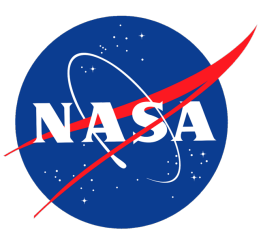
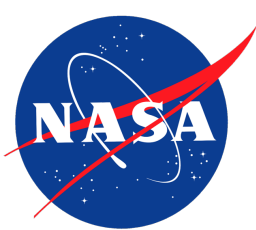


Image Credits

❖ Slide 1:

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Literature Review

- ❖ Limitations in available **data** for ATM applications and the **inherent coupling** between the variables of interest leads to several variations of APM coefficient estimation using historical data.
- ❖ Eurocontrol's Base of Aircraft Data (**BADA**) is a kinetic APM that is among the most **widely used** for ATM applications.
- ❖ Literature typically divided into 3 main categories:

1. Mass Estimation

- Estimation of starting weight or mass of aircraft.
- Generally, trajectory data from climbing segment used in conjunction with various algorithms.
- Fuel consumption can also be the target variable.
- *BADA coefficients used for other APM parameters that are not being estimated.*

Sun et al. (2018)
Lee and Chatterji (2010)
Sun et al. (2018)
Schultz et al. (2012)
Dalmau et al. (2020)

2. Thrust / Thrust Law Estimation

- BADA thrust model modified to obtain equivalent thrust setting (or multiplier).
- Energy rate may used to obtain equivalent thrust setting.
- *BADA coefficients used for other APM parameters that are not being estimated.*

Sun et al. (2018)
Alligier et al. (2012)
Alligier et al. (2013)

3. Drag Estimation

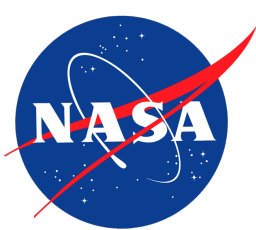
- Drag coefficients used in kinetic APM estimated using trajectory data, assumptions about the configuration (clean or not), etc.
- *BADA coefficients used for other APM parameters that are not being estimated.*

Sun et al. (2020)

Other

- Some studies combine the estimation of one or more APM parameters.
- *BADA coefficients used for other APM parameters that are not being estimated.*

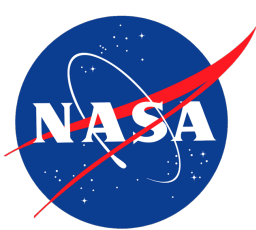
Sun et al. (2018)
Sun et al. (2020)



Data Sources

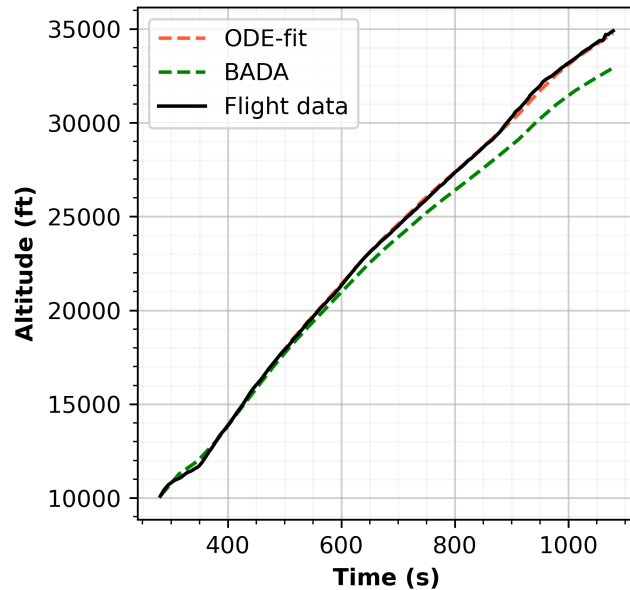
1. Trajectory Data from NASA's Sherlock Data Warehouse (called integrated flight format or IFF). Parameters available include:
 - Aircraft type, airline, flight plan information, latitude, longitude, altitude, ground speed, etc.
 - Raw track data has position report every 6 to 12 seconds.
2. Rapid Refresh Meteorological Data (RAP) from National Oceanic and Atmospheric Administration (NOAA)
 - Wind speed, temperature, air pressure, etc.
3. Engine information obtained from FAA aircraft registry database

Preprocessing merges the RAP, IFF, and other data sets. Derived quantities such as Mach number, true airspeed, etc. obtained using merged data.

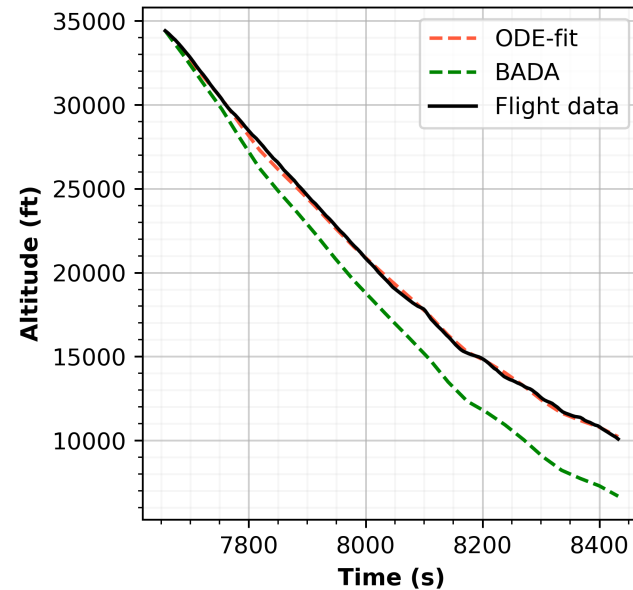


Individual Flight Results

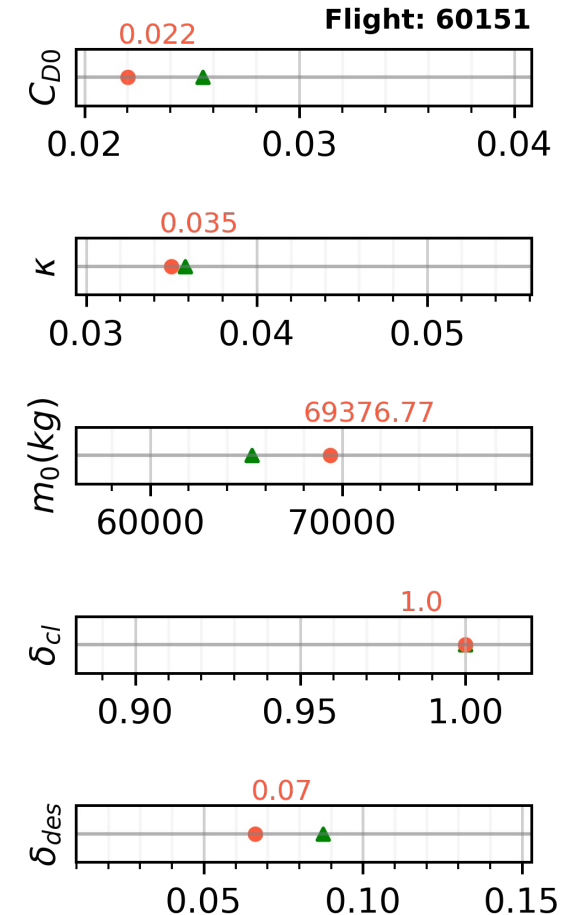
60151 - Altitude (B738: SNA-DFW)

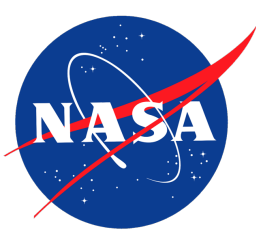


60151 - Altitude (B738: SNA-DFW)



The optimized solution shows better fit with the flight data compared to the baseline APM parameters





Appendix: Sensitivity Analysis

