Machine Learning based Aircraft Performance Model Estimation for Trajectory Prediction

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The accurate prediction of aircraft trajectory by ground-based decision support tools is a critical component of air traffic management in the US National Airspace System (NAS). Accurate predictions of where the aircraft will be in the future or when they will arrive at specific locations (e.g., fixes) is a key enabler for sequencing and efficient arrival management of flights. Traditional physics based aircraft trajectory prediction relies on a simplified point-mass total energy model whose parameters are referred to as Aircraft Performance Model (APM) parameters. Even though the performance coefficients and weight of an aircraft are a vital part of the aircraft performance model's predictions and accuracy, these coefficients are proprietary in nature and therefore, unavailable to decision-support tools. Current approaches freeze some coefficients to default base of aircraft data (BADA) values and optimize others. However, the APM parameters are highly coupled by the flight dynamics and prioritizing one parameter over others leads to bias and skewed predictions. To alleviate this problem, we provide a combined optimization framework to predict all the critical (thrust, drag and weight) APM parameters.

This paper is focused on training Machine Learning (ML) models that map historical flights to optimized APM parameters that provide the best fit (in terms of prediction error). Our dataset obtained from NASA's Sherlock data warehouse is comprised of thousands of historical flights and includes weather and track data collected from 2019. Using different subsets of relevant features (e.g., aircraft type), we trained several ML models to estimate the aircraft's take off weight, drag polar coefficients (both parasitic and lift induced), and thrust settings (multiplier applied to the maximum engine thrust). The chosen flights are from three of the most common aircraft types (B738, B737, and A320) arriving at four airports (LAX, DEN, MSP, and DFW).

Our ML approach is comprised of two different solutions: 1- using a subset of features that are known prior to the flight departure and do not change during flight (such as engine type, current temperature at departure & destination airports, aircraft type) and 2 - using a subset of temporal features of the flight trajectory (such as cruise altitude, Mach, airspeed, and rate of climb) in addition to the pre-departure features from the first solution. The labels or target variables are the APM parameters that were obtained by an optimized ordinary differential equations (ODE) fitting process (applied to individual flights). The ODE-fitting is very time intensive and is therefore performed offline. Thus, training an ML model to learn the relationship between the flight features and ODE-generated labels enables faster estimation of the APM parameters and is therefore amenable to real-time prediction. Various ML models including linear regression, random forest, XGBoost, and neural network were trained, and the results are compared. After model validation and hyperparameter-tuning, we observed that the Random Forest model outperformed the other three models by the overall mean square error (MSE) of 2% for the first solution and 1.5% for the second solution.

Finally, the ML-derived parameters are compared against default BADA APM parameters using NASA’s Autonomy Development toolkit (ADK) simulation software. The simulation results for one of each aircraft type is shown and discussed.