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# Aircraft Black Carbon Particle Number Emissions – A New Predictive Method and Uncertainty Analysis

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## 1. Introduction

- Black Carbon (BC) particle number emissions contribute to contrail formation and subsequent induced cirrus cloudiness, leading to an indirect radiative forcing (RF) component with a significant but highly uncertain magnitude.
- The number of contrail ice particles is strongly correlated to the number of emitted aircraft BC particle per kg of fuel burned ($EI_n$ - #/kg-fuel) [1].
- Previous BC $EI_n$ estimation methodologies do not include a dependence on engine thrust settings and differences in BC aggregate morphologies.
- This research project aims to:
  1. Develop a new BC $EI_n$ predictive model with uncertainty analysis
  2. Specify predictive relations for the $EI_n$ model input parameters
  3. Apply the new model to an aircraft activity dataset to estimate BC $EI_n$ emissions and its implication to initial contrail characteristics.

## 2. Theory – Development of a new $EI_n$ Predictive Model

- BC aggregate morphologies such as Geometric Mean Diameter (GMD), Geometric Standard Deviation (GSD) and mass-mobility exponent ($D_{fm}$) are highly dependent on thrust settings.
- Based on the morphology of fractal aggregates, a new methodology, called the Fractal Aggregates (FA) approach is developed to estimate BC $EI_n$ from BC mass emissions index ($EI_m$ – g/kg-fuel):

$$EI_n = \frac{EI_m}{\rho_0(\frac{\pi}{6})(1.6212\times10^{-5})^{3-D_{fm}}\mathrm{GMD}^{\varphi}\exp(\frac{\varphi^2\ln(\mathrm{GSD})^2}{2})}$$

where $\varphi$ = 1.17 + 0.61$D_{fm}$, and $\rho_0$ is the material density of BC.

- The full derivation of the equation above was presented in [2].

## 3. Data & Methodology

- To model input values for $EI_m$, different BC mass estimation methods (FOA3 [3], FOX [4] and ImFOX [5]) are assessed using a compiled database from five different experimental campaigns.
- Since GMD & GSD values are only available for a small number of aircraft, its predictive relations for model inputs are specified in *Fig.1* using data from previous literatures [6], [7], [8].
- Uncertainty analysis performed using a Monte Carlo 1000-member ensembles.
- The new $EI_n$ FA model is applied to a sample of aircraft activity from the Aviation Environmental Design Tool (AEDT).

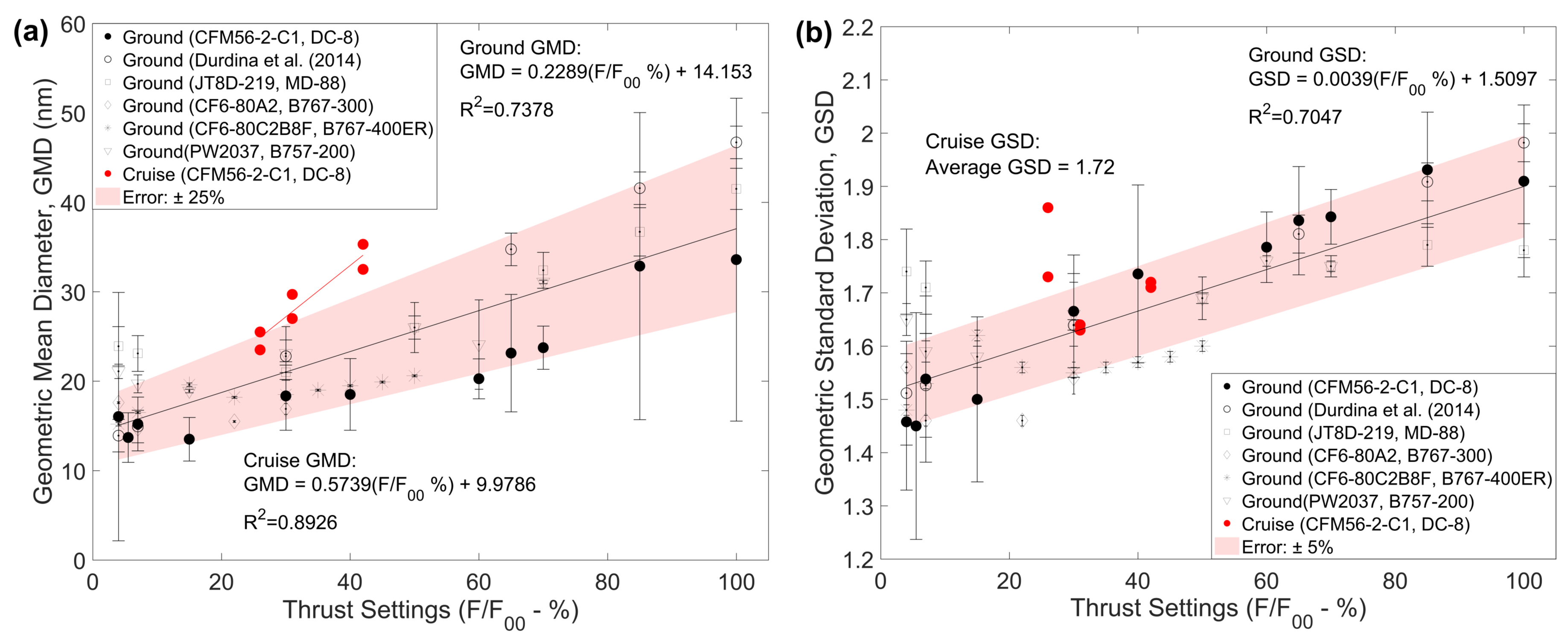


*Fig. 1*: (a) GMD and (b) GSD vs. Thrust Settings ($F/F_{00}$ -%) compilation for ground and cruise conditions from different turbofan engines.

## 4. Model Validation for New $EI_n$ Predictive Model

- To evaluate the performance of the new FA model, measurements of $EI_n$ are only included for validation when corresponding BC $EI_m$, GMD and GSD observations are available.
- For ground conditions (*fig. 2a*), estimated $EI_n$ agrees well with measured data from the NASA APEX ($R^2$ = 0.852) & SAMPLE III.2 ($R^2$ = 0.985) campaigns.
- For cruise conditions (*fig. 2b*), a lower $R^2$ value ($R^2$ = 0.537) is recorded when compared with the NASA ACCESS data.

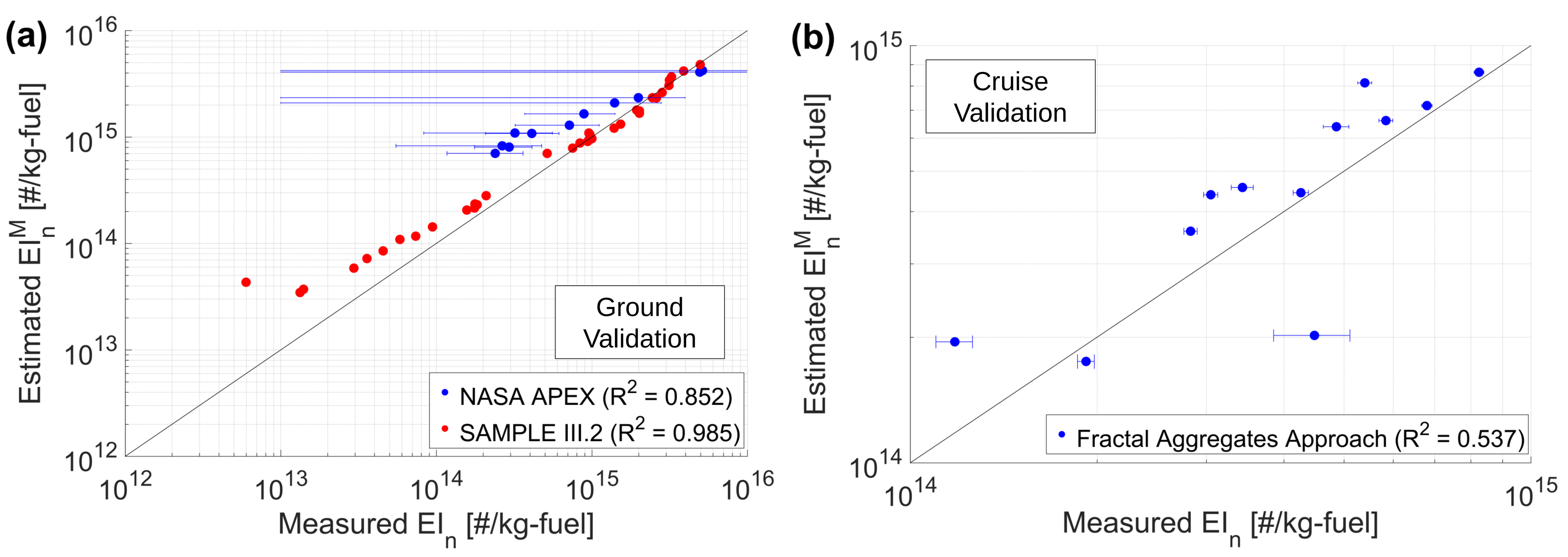


*Fig. 2*: Validation of the new $EI_n$ Predictive Model for (a) Ground and (b) Cruise conditions

## 5. Assessment of Different $EI_m$ Estimation Methods

- For ground BC $EI_m$ estimates (*fig. 3a*):
  1. FOA3 underestimates $EI_m$ by over 90% for most engines with an overall $R^2$ of -0.20.
  2. FOX estimates agree well with older engines ($R^2$ = 0.433) but over-predicts $EI_m$ from newer engines by an order of magnitude, giving an overall $R^2$ of -0.068.
  3. ImFOX has the highest overall $R^2$ (0.273), but underestimates $EI_m$ from older engines by a factor of 5.
- For cruise BC $EI_m$ estimates (*fig. 3b*):
  1. Although the $R^2$ from the ImFOX (0.504) is higher than the FOX (0.052), the same database was used by the ImFOX for model calibration, potentially leading to a bias.
  2. Only 8 data points from 3 engines are available. More $EI_m$ cruise data is needed.
- Given the uncertainties listed above, both the FOX & ImFOX are selected to estimate BC $EI_n$.

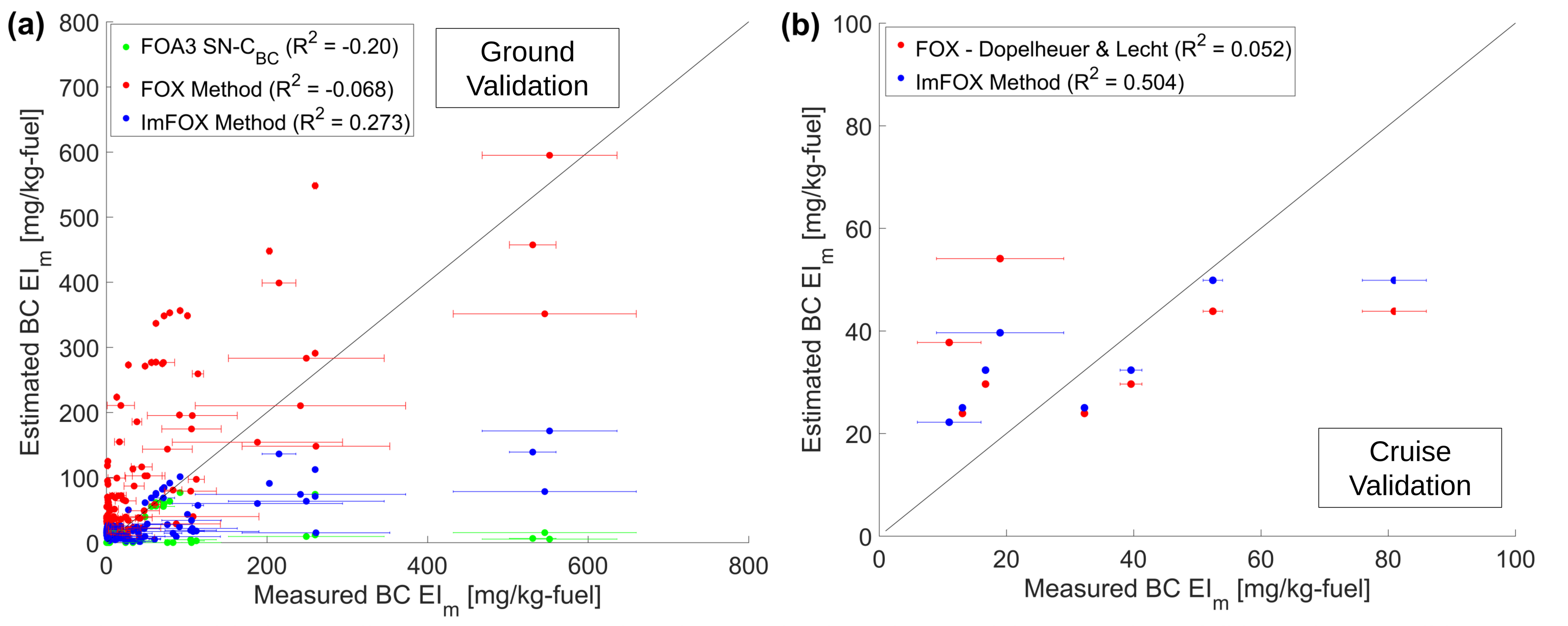


*Fig. 3*: Validation of different BC $EI_m$ estimation methodologies for (a) Ground, and (b) Cruise conditions

## 6. Uncertainty Analysis & Aircraft Activity Dataset Application

- The new FA model outputs ($EI_n^E$) has a ± 62% uncertainty.
- Average cruise $EI_n^E$ is around 1.2x$10^{15}$ #/kg-fuel [4.4x$10^{14}$ – 1.9x$10^{15}$ #/kg-fuel]
- The FA model has a 65% higher estimated $EI_n$ relative to previous methods (*fig. 4a*).
- Both *fig. 4a* and *fig. 4b* show that the estimated $EI_n$ and thrust settings is inversely proportional at certain thrust intervals (24% to 42% $F/F_{00}$).
- The CoCiP contrail model assumes $EI_n$ to be fixed at 2.8x$10^{14}$ #/kg-fuel [9].
- A higher $EI_n$ by a factor of 3 imply that young contrails will have a 36% smaller ice particle diameter and 76% larger optical depth [1], thereby likely to increase contrail lifetime & RF [10].

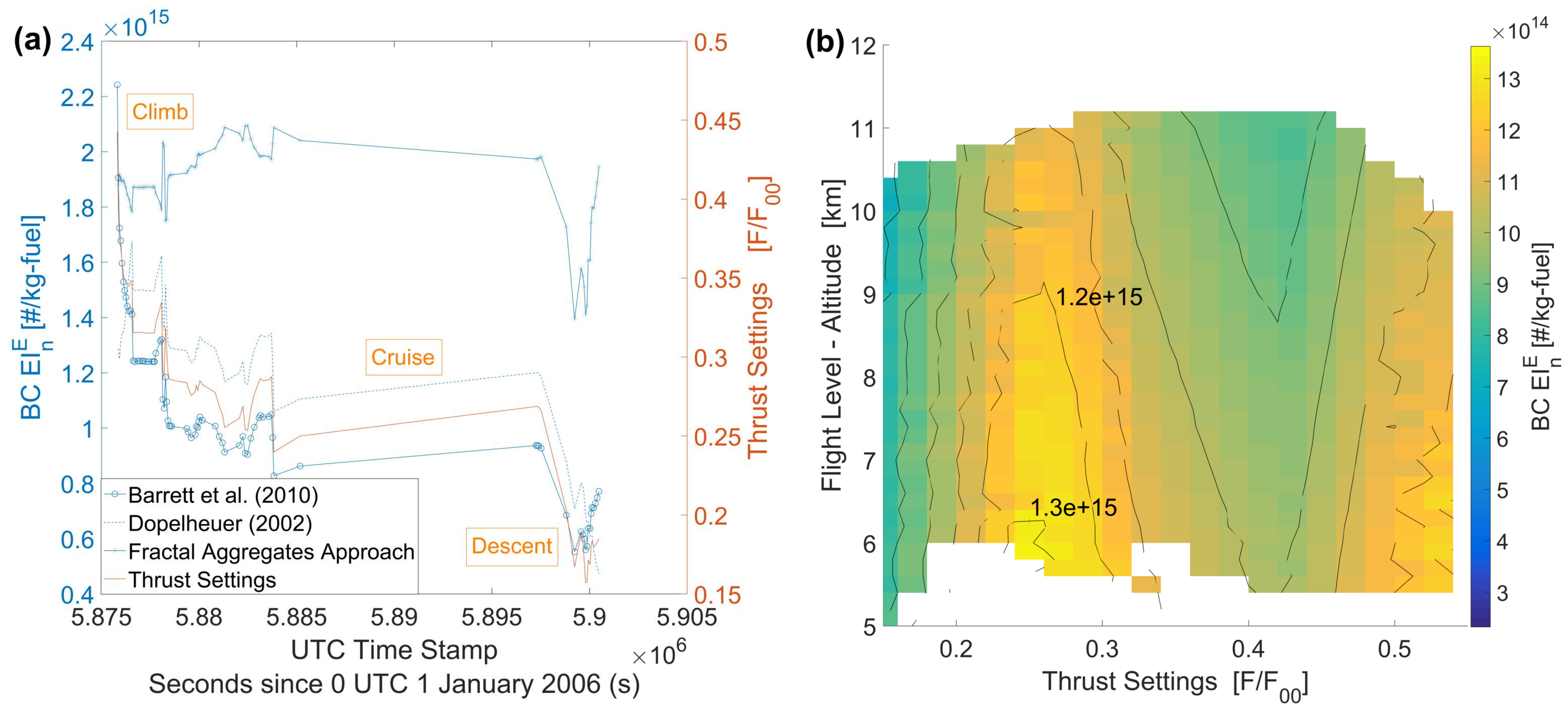


*Fig. 4*: AEDT sample dataset analysis, (a) Comparison of outputs from different $EI_n$ methodologies for a transatlantic flight profile (A330-300), and (b) Surface/Contour plot for $EI_n^E$ vs. thrust and flight level for a B737-300. (BC $EI_m$ estimated using the FOX Method, burning conventional fuel)

## 7. Summary

- A new method to estimate $EI_n$ for global civil aviation is developed and applied to an aircraft activity dataset.
- The new $EI_n$ predictive model can be incorporated into a contrail model.

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