Travel Impact Model (TIM)
ADVISORY COMMITTEE

TECHNICAL BRIEF

TIM base model selection and distance correction application

December 2024

1. SUMMARY

This technical brief presents two model changes recommended by the Travel Impact Model Advisory Committee (TIM AC) at its 5th meeting (AC/5) in June 2024. One of these changes was to update the TIM base fuel burn model from the 2019 European Environment Agency (EEA) model to EEA 2023. This decision resulted from a detailed comparison of the accuracy and precision of five alternative fuel burn models. The other change agreed was the inclusion of a distance correction factor to adjust the stage length input in the fuel burn estimation, previously represented by the direct distance between origin and destination airports, known as the Great Circle Distance (GCD). Actual flight paths are longer than the GCD due to several factors, including route path, airspace restrictions, adverse weather avoidance, and airport congestion. The adoption of these model changes increased the TIM market coverage from 97% to 99% and reduced the model average absolute error from 8% to 6.3%.

2. TIM BASE MODEL SELECTION

The fuel burn estimates of the TIM, considering the current TIM 1.9.1 version, are provided by the EEA 2019 model.[1] The EEA model is an accessible tool, based on real-world engine testing data from the International Civil Aviation Organization (ICAO)'s Engine Emissions Databank (EEDB) and aircraft performance from Eurocontrol's Base of Aircraft Data (BADA) model, that provides fuel burn and emissions estimates for many aircraft types. However, the user can only define the aircraft model and stage length. All other factors that impact fuel burn, such as flight trajectory and payload, cannot be modified. In addition, the model is infrequently updated and some aircraft types are not available. This section describes an evaluation of alternative fuel burn models that could potentially replace the EEA 2019 and improve the TIM estimation.

In a preliminary analysis, nine fuel burn models were compared considering several criteria, such as license, model coverage, and transparency. Of these nine models, five

1 EEA, EMEP/EEA Air Pollutant Emission Inventory Guidebook 2019: Annex 1.A.3.a Aviation 2019, October 17, 2019, https://www.eea.europa.eu/publications/emep-eea-guidebook-2019/part-b-sectoral-guidance-chapters/1-energy/1-a-combustion/1-a-3-a-aviation/view.

were selected for quantitative evaluation. We applied the TIM validation methodology[2] to assess how closely each model's fuel burn estimate matched real-world data. Some of the alternative models included other inputs besides aircraft type and stage length, such as trajectory and payload. Common assumptions based on real-world global flight data were adopted to the extent possible.

This assessment guided the decision to update the TIM base model from the EEA 2019 to the EEA 2023 model. The EEA 2023 was the only model that improved the fuel burn estimates in almost all distance bins compared to EEA 2019. Some alternative models could provide better estimates with some refinement of user-defined assumptions (e.g., of actual payload and trajectories). However, these and other factors are dynamic and vary with time and across aircraft, region, and airline. Defining global averages would require additional work and data that are not readily available, while these assumptions seem to be already tailored in the EEA model. In addition, some of the alternative models would require extra effort to increase the model coverage. EEA presents one of the highest market representations considering the models analyzed, and the aircraft coverage increased in EEA 2023 compared to EEA 2019. Finally, some of the other models presented license limitations.

The alternative model analysis was discussed in three Task Group meetings with AC experts or their delegates. These experts contributed data and support to the model simulations. The framework development and discussions took place in the second semester of 2023 and first semester of 2024. In June 2024, the AC agreed to incorporate the EEA 2023 as the TIM base model.

2.1. Scoring system for preliminary model evaluation

This section describes the criteria and scoring system applied to evaluate potential alternatives to the EEA 2019 model. For each criterion, each model received a score of either -1, 0, or 1, with a higher score indicating better performance. The numerical score was accompanied by a color code intended as a visual aid for comparing across models, whereby -1 mapped to red, 0 to yellow, and +1 to green. Models with the highest score summed across all the criteria were recommended for more detailed validation. Below is a short description of the criteria, followed by an explanation of the scoring system for each criterion in Table 1.

- **License:** Assesses the availability of the model for public use.
- **Coverage:** Compares the native coverage of aircraft types, calculated as the percentage of global flights that could be analyzed using the aircraft that are included in the model.[3]

2 Travel Impact Model Advisory Committee [TIM AC], 2024. AC/3-TB/1: Methodology for validating fuel burn model changes.

3 The aircraft coverage of emissions estimation models can often be extended by specifying fallback aircraft for types that are not specifically included in the model. For example, if a Boeing 737-900 aircraft is not included in the model, its performance could be approximated as a Boeing 737-800. Calculation of native coverage only considers aircraft types that are included in the emissions estimation model, without added approximations.

- **Input variables:** Compares the input variables available for the fuel burn calculation.
- **Non-CO_2 emissions:** Assesses whether the model provides emissions estimates for non-CO_2 pollutants, namely NO_x, SO_x, nvPM, and water vapor.
- **Transparency:** Assesses if all assumptions and calculations that underpin the model are accessible.
- **Maintenance:** Compares the maintenance and update schedule of the models.
- **Readiness:** Assesses whether the fuel burn model can be readily used as-is without further data manipulation or specialized aviation expertise.

Table 1: Scoring criteria for alternative base model evaluation

Dimension	+1	0	-1
License	Can be referenced and used by external validators	Licensing terms are dependent on the use-case	Requires a license purchase and would not be usable by external validators
Coverage	> 70% of global flights	> 50% and < 70% of global flights	< 50% of global flights
Input variables	Can use more input variables than just flight distance and aircraft model	Only uses flight distance and aircraft model as input variables	Uses fewer or less specific input variables
Non-CO2 emissions	Provides emissions estimates for NO_x, SO_x, nvPM, and water vapor	Provides emissions estimates for a subset of NO_x, SO_x, nvPM, and water vapor	Does not provide estimates for any non-CO_2 emissions
Transparency	All calculations and assumptions are accessible	Cannot access underlying calculations or assumptions, but has sufficient documentation	No access to or no documentation of the underlying assumptions or calculations
Maintenance	Annual or more frequent updates to the model	Less frequent than annual maintenance, but responsibility for maintenance is external	No maintenance schedule or the responsibility for maintenance is internal
Readiness	Can be used without aviation expertise	Requires data manipulation but does not require expertise in aircraft performance modeling	Requires aviation expertise to run the model

2.2. Initial assessment of alternative models

Nine alternative models were selected for this preliminary analysis based on discussions with the AC members. In this section, we introduce each model and score them across the dimensions presented above. Table 2 provides a summary of this evaluation.

EEA 2023 update

In October 2023, the EEA released an update to the EEA model that introduced more aircraft models and a new Landing and Takeoff (LTO) cycle calculator and changed the fuel burn estimates for some aircraft models.[4] It combines aircraft performance data from BADA with real-world engine testing data from ICAO's EEDB to provide fuel burn estimates for a large number of aircraft models. The model is presented as an Excel spreadsheet with emissions estimates for each aircraft model flying a discrete set of distances.

Similar to the 2019 version, the EEA 2023 model is freely available, provides emissions estimates for non-CO_2 emissions, and can be used with minimal aviation expertise. It has a native aircraft model coverage of 81%, up from roughly 72% in EEA 2019. The model still only uses the aircraft model and flight distance as inputs, does not disclose all underlying assumptions or calculations, and is not updated annually.

CO_2 Connect

CO_2 Connect is an emissions calculator from the International Air Transport Association (IATA).[5] The fuel burn estimates are based on operations data collected from airlines. The calculator provides a per-seat estimate for the fuel consumed on a flight. For a given origin-destination pair, the calculator queries flight schedules and allows the user to choose from one of the represented aircraft models. The calculator is time-based, rather than distance-based like the EEA model. This means that each aircraft model represented in the calculator has an associated fuel consumption rate, expressed in kg/min. This fuel consumption rate is multiplied by the average flight duration for the route. The total flight fuel burn is then apportioned by seat, considering cargo carriage, seating layout, and seating class.

This calculator is regularly updated with new data sources and is easy for non-experts to use. The exact aircraft model coverage is difficult to calculate, but it is said to represent 78 aircraft types, which is fewer than the EEA 2019 model. While the online calculator is free to use, access to the underlying calculator data would be required to use with the TIM. That would require a license, and the information would not be available to external validators. The fuel burn estimate is based on an origin-destination pair. Primary data are only available for a subset of aircraft models based on schedule data; averages are used otherwise. There is no estimation of non-

4 EEA, EMEP/EEA Air Pollutant Emission Inventory Guidebook 2023: Annex 1.A.3.a Aviation 2023, October 2, 2023, https://www.eea.europa.eu/publications/emep-eea-guidebook-2023/part-b-sectoral-guidance-chapters/1-energy/1-a-combustion/1-a-3-a-aviation.3/view.

5 IATA, CO_2 Connect, https://www.iata.org/en/services/statistics/intelligence/co2-connect/.

CO_2 emissions nor clear documentation of data, calculations, or the assumptions that underpin the fuel burn estimates.

ICAO Carbon Emission Calculator

The ICAO Carbon Emissions Calculator (ICEC) uses aircraft operating manuals and reported fuel burn data to estimate carbon emissions for a flight.[6] Fuel burn data reported to the U.S. Department of Transportation (DOT) are used to calculate an average fuel burn across discrete distances for all aircraft models represented in the database.[7] The calculator provides the CO_2 emissions per seat and per flight for an origin-destination pair for the mix of aircraft types that typically serve that pair. The calculator accounts for typical payload factors and seating layouts when apportioning the flight's emissions to each seat. The documentation of the methodology contains the averaged fuel burn data and assumptions that underpin the calculator.

Because the fuel burn values for all covered aircraft are listed in the publicly available documentation, they can be used by external validators.[8] The model covers over 200 aircraft types, corresponding to more than 98% of global flights. The calculator is easy to use and does not require aviation expertise to get fuel burn estimates. Similar to the EEA model, the input variables are limited to distance and aircraft model, the model does not disclose all the underlying data, and it is not updated annually. The model does not provide non-CO_2 emission estimates.

TASOPT

TASOPT is an aircraft modeling code developed by researchers at the Massachusetts Institute of Technology (MIT) that uses coupled aero-structural-propulsive modeling to estimate the fuel burn for an aircraft on any defined flight path.[9] It is the most complex aircraft model included in this assessment, requiring detailed definition of, amongst others, the aircraft geometry, construction materials, structural layout, and engine properties to define an aircraft's performance. Getting fuel burn estimates requires defining the aircraft parameters, payload, and trajectory.

TASOPT is an open-source software, which means that it can be accessed directly by external validators and that the entire code base, along with all assumptions and calculations, can be examined. It gives the user immense control over the input variables, with options to define the aircraft, engine, trajectory, and payload. There are regular updates and ongoing maintenance of the code. It can provide NO_X emissions based on engine performance characteristics but does not provide other non-CO_2 emission estimates. Because aircraft definitions are so detailed, only six aircraft models

6 ICAO, Carbon Emissions Calculator (ICEC), https://www.icao.int/environmental-protection/Carbonoffset/Pages/default.aspx.

7 See ICAO, *ICAO Carbon Emissions Calculator Methodology*, Version 13.1, August 2024, https://applications.icao.int/icec/Methodology%20ICAO%20Carbon%20Emissions%20Calculator_v13_Final.pdf.

8 ICAO, *ICAO Carbon Emissions Calculator Methodology*, Appendix C.

9 The TASOPT code is available at https://github.com/MIT-LAE/TASOPT.jl.

are natively supported, with a coverage of 37% of global flights in 2019. The model requires aviation expertise to run.

OpenAP

OpenAP is an open-source aircraft modeling code developed by researchers around the world (and maintained by researchers at Delft University of Technology) that uses publicly available aircraft and engine data to estimate aircraft emissions.[10] It uses aerodynamic performance data derived from trajectory analysis of real-world operations, aircraft geometry data gathered from open literature, and engine data from the ICAO EEDB. Once the aircraft parameters are defined, generating fuel burn estimates requires the definition of a trajectory using altitude and the true airspeed.

Because OpenAP is an open-source software, it can be accessed directly by external validators and the entire code base, along with all assumptions and calculations, can be examined. In addition to distance and aircraft model, it allows for the definition of different trajectories, payloads, and engines. It provides emission estimates for all relevant non-CO_2 emissions. It is regularly updated with new features and aircraft models. Defining a new aircraft model entails populating roughly 25 parameters, which requires aviation expertise. As of July 2024, the model supported 34 models natively with a coverage of 57% of global flights.

Poll-Schumann method

The Poll-Schumann method is a set of equations developed by researchers at Cranfield University and the German Aerospace Center (DLR) to describe the aerodynamic and propulsive performance of aircraft.[11] These equations have been used as an aircraft performance module in the open-source pycontrails project.[12] Fuel burn estimates require specifying an aircraft and running the model with trajectory data that include latitude, longitude, and altitude. The application in pycontrails includes provisions to use Automatic Dependent Surveillance-Broadcast (ADS-B) recorded flight trajectories and historical weather data to model wind conditions.

That the method is open-source means that it can be accessed directly by external validators and the entire code base, along with all assumptions and calculations, can be examined. Custom flight trajectories and payload weights can be defined. It provides all relevant non-CO_2 emission estimates by linking aircraft to engines in the ICAO EEDB. The project is regularly updated and maintained by the developers. The

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10 OpenAP model and additional information are available at: https://openap.dev/.

11 The model is described in two papers: Ian Poll and Ulrich Schumann, "An Estimation Method for the Fuel Burn and Other Performance Characteristics of Civil Transport Aircraft in the Cruise. Part 1 Fundamental Quantities and Governing Relations for a General Atmosphere," The Aeronautical Journal 125, no. 1284 (2020): 257–295, https://doi.org/10.1017/aer.2020.62; and Ian Poll and Ulrich Schumann, "An Estimation Method for the Fuel Burn and Other Performance Characteristics of Civil Transport Aircraft During Cruise: Part 2, Determining the Aircraft's Characteristic Parameters," The Aeronautical Journal 125, no. 1284 (2020): 296–340, https://doi.org/10.1017/aer.2020.62.

12 More information about the pycontrails project is available at https://py.contrails.o rg/.

initial definition of equations also included aircraft parameters for 54 aircraft models, covering 66% of global flights. To add a new aircraft model would require the definition of approximately 35 parameters. The model requires aviation expertise to run.

SUAVE

SUAVE is an open-source aircraft modeling code developed by researchers around the world (and maintained by researchers at Stanford University) that uses linearized aerodynamic and 1-D propulsive modeling equations to estimate the fuel burn on any defined flight path.[13] It requires a detailed definition of the aircraft geometry to estimate aerodynamic performance. The aircraft model can be flown through arbitrary flight trajectories to get fuel burn for a flight.

That the code is open-source means that it can be accessed directly by external validators and the entire code base, along with all assumptions and calculations, can be examined. There is considerable discretion in the definition of input variables, with control over payload, flight trajectory, and engine modeling. The code is maintained regularly with yearly releases of new versions. It does not provide any non-CO_2 emission estimates. As of July 2024, it only supported four aircraft, covering 28% of global flights. It requires aviation expertise to run.

BADA

BADA is an aircraft performance dataset maintained by EUROCONTROL.[14] It comprises a mix of aircraft performance modeling informed by real-world aircraft testing data to improve its accuracy. It does not automatically provide fuel burn estimates; rather, the performance modeling yields throttle settings for the engines that then are converted into fuel burn rates using the ICAO EEDB. BADA is one of the aircraft performance model choices in the pycontrails project but requires a separate license to access.[15]

The model has representations of nearly all aircraft-engine combinations and can provide 100% global flight coverage.[16] It provides control over payload, engine, and trajectory. Linking it with the ICAO EEDB provides information on all relevant non-CO_2 emissions. It has detailed documentation of its methods and calculations and is maintained regularly by EUROCONTROL. The license to use BADA depends on the application; aircraft manufacturers approve access to the most recent version of BADA on a case-by-case basis for specific projects. Its applicability to the TIM, and potential use by third parties for verification, were unconfirmed as of the publication of this study. It requires aviation expertise to run.

13 More information about the SUAVE model is available at https://suave.stanford.edu/.

14 More information about the BADA model is available at https://www.eurocontrol.int/model/bada.

15 More information about the pycontrails project is available at https://py.contrails.org/.

16 Roger Teoh et al., “The High-Resolution Global Aviation Emissions Inventory Based on ADS-B (GAIA) for 2019–2021,” *Atmospheric Chemistry and Physics* 24, no. 1 (January 18, 2024): 725–44, https://doi.org/10.5194/acp-24-725-2024.

Piano 5

Piano 5 is an aircraft modeling tool created and maintained by Lyssis Ltd. that can be licensed to model aircraft emissions.[17] The ICCT's global aviation emissions inventory[18] uses Piano 5 as the underlying fuel burn model. This emissions inventory was within 3% of what was predicted by Teoh et al.[19] and within 2% of what was predicted by Quadros et al.[20] following calibration using DOT Form 41 data. The key selling points of this model are the predefined library of aircraft models (which includes multiple versions of the same aircraft with different mass characteristics) and functions that automate trajectory generation and fuel burn analysis.

The extensive library of aircraft models provides near-total coverage of global flights, with additional differentiation in performance and weight estimations for different engine options. There is significant freedom to define input variables such as payload, engine, and trajectory. The model provides estimates for non-CO_2 emissions. The underlying calculations cannot be accessed, but most assumptions are listed and are changeable. It is uncertain whether the tool will be continually maintained. Running the model does require some data manipulation but the presence of a graphical user interface makes it more accessible than some of the more academic codes. However, Piano 5 requires a paid license which prevents its direct access by external validators.

Table 5 summarizes the initial assessment of alternative fuel burn models. The EEA 2023, OpenAP, and Poll-Schumann models were clear front-runners with four points each and were selected for a more detailed comparison. Piano 5 was also recommended to be analyzed as it provides estimates comparable to other aviation emission inventories developed using sophisticated models and inputs. Finally, ICAO ICEC was also included due to its prominent use in the United Nations' aviation carbon calculator. Because BADA also scored well, its quantitative analysis and potential application in TIM will be further investigated in future work.

17 More information about the Piano 5 model is available at https://www.lissys.uk/.

18 Brandon Graver, Dan Rutherford, and Sola Zheng, *CO_2 Emissions from Commercial Aviation: 2013, 2018, and 2019* (International Council on Clean Transportation, 2020), https://theicct.org/publication/co2-emissions-from-commercial-aviation-2013-2018-and-2019/.

19 Teoh et al., "The High-Resolution Global Aviation Emissions Inventory."

20 Flávio D. A. Quadros et al., "Global Civil Aviation Emissions Estimates for 2017–2020 Using ADS-B Data," *Journal of Aircraft* vol. 59, no.6 (2022): 1394-1405, https://doi.org/10.2514/1.C036763.

Table 2: Initial assessment of alternative fuel burn models

Model	License	Coverage	Input variables	Non-CO_2 emissions	Transparency	Maintenance	Readiness	Total
EEA 2023 update	+1	+1	0	+1	0	0	+1	**4**
CO_2 Connect	-1	0	-1	-1	-1	+1	+1	-2
ICEC	+1	+1	0	-1	0	0	+1	**2**
TASOPT	+1	-1	+1	0	+1	+1	-1	2
OpenAP	+1	0	+1	+1	+1	+1	-1	**4**
Poll-Schumann	+1	0	+1	+1	+1	+1	-1	**4**
SUAVE	+1	-1	+1	+1	+1	+1	-1	2
BADA	0	+1	+1	+1	+1	+1	-1	4
Piano 5	-1	+1	+1	+1	0	0	0	**2**

Legend: +1 0 -1

The five models ultimately chosen for quantitative analysis were:

a. EEA 2023

b. ICAO ICEC

c. OpenAP

d. Poll-Schumann

e. Piano 5

2.3. Methodology for fuel burn estimation comparison

For the detailed evaluation, we applied the TIM validation framework to compare fuel burn estimates from the five alternative models and analyzed how close the estimates were to actual fuel burn data. We considered the flight data sample collected in the validation work, which combines public data from Brazil with the anonymized version of private flight data provided by around a dozen of Google's partner airlines. The combined sample contains historical flights operated between 2019 and 2023 in different countries and by different airlines, with actual fuel burn reported.

As described above, each model has its own estimation methodology and input needs. EEA 2023 and ICAO ICEC require the fewest inputs among the models analyzed, using only distance and aircraft type definition. OpenAP and Poll-Schumann require additional trajectory data and the definition of aircraft characteristics. Piano 5 has many aircraft models in its predefined library and default parameters for several inputs, such as aircraft engine and payload; these default parameters can be changed as required by the user. To deal with this imbalance in input requirements across models, we adopted similar assumptions to the extent possible. This section describes these assumptions and how the fuel burn estimates of each model were structured and provides a summary of the validation framework used to compare estimates with real-world fuel burn.

To allow for the application of the validation methodology and comparison across models, the fuel burn estimates of each model were organized in the EEA style (i.e., at a minimum as a fuel burn list for a set of distances by aircraft type). Fuel burn was differentiated by other variables if the alternative model supported additional inputs, such as payload. We also associated the fuel burn estimates with the corresponding flight phase: Climb, Cruise, and Descent (CCD), Landing and Takeoff (LTO), or FF (Full Flight, combining CCD and LTO). EEA 2019 fuel burn estimates by aircraft type and stage length were then replaced with those from the alternative model, and TIM was run using the flight schedules from the validation dataset. The last step was to compare real-world fuel burn data, available for the flights in the validation sample, with modeled fuel burn using the TIM validation framework.

The ICAO ICEC already provides data organized in the EEA style; these data tables were used instead of running the calculator itself. OpenAP and Poll-Schumann require flight trajectory data to estimate fuel burn. To maintain common trajectory assumptions, we used trajectory data of real-world flights provided by Imperial College London (ICL) collected by ADS-B telemetry.[21] The aircraft codes represented in the dataset are listed in Table 3. The dataset uses ICAO codes while the validation process uses IATA codes, hence both are provided here. We used trajectories of the relevant aircraft class (narrowbody, widebody, or regional) or of a similar type for aircraft types that are not in the list.

Table 3: Aircraft classes and types supported in ICL's trajectory data

Narrowbody		Widebody		Regional	
IATA Code	**ICAO Code**	**IATA Code**	**ICAO Code**	**IATA Code**	**ICAO Code**
320	A320	333	A333	E7W	E75L
738	B738	77W	B77W	E70	E170
321	A321	332	A332	E95	E195
319	A319	789	B789		
737	B737	788	B788		
32N	A20N	772	B772		
752	B752	359	A359		
734	B734	763	B763		
739	B739	343	A343		

ICL sampled 100 unique flights by aircraft type, randomly selected from global flights operated between January 7 and January 14, 2019. In total, the dataset contains trajectory and meteorological data for 2,100 flights. Figure 1 presents an example of these data, showing flight altitude and flight distance for three prominent aircraft types. Figure 2 shows two examples of trajectories and corresponding meteorological data, including air temperature, winds, humidity, and real airspeed.

21 For the trajectory data collection methodology, see Teoh et al., "The High-Resolution Global Aviation Emissions Inventory."

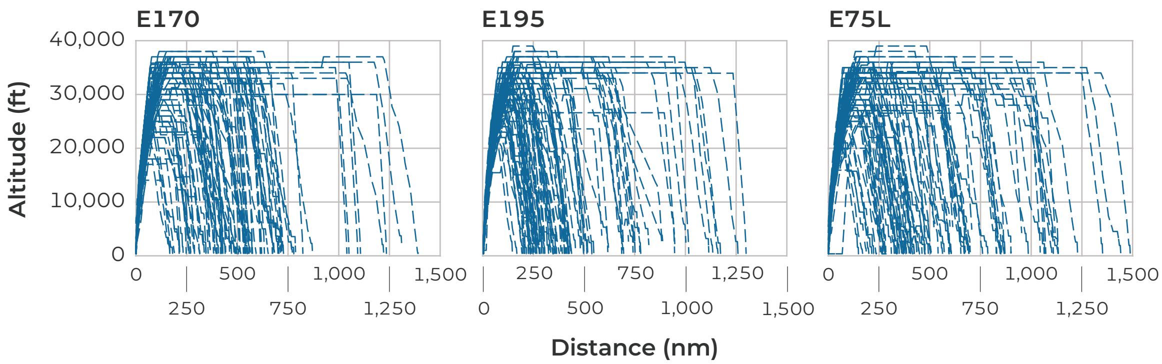


Figure 1: Flight profiles of the regional aircraft extract in ICL's trajectory dataset

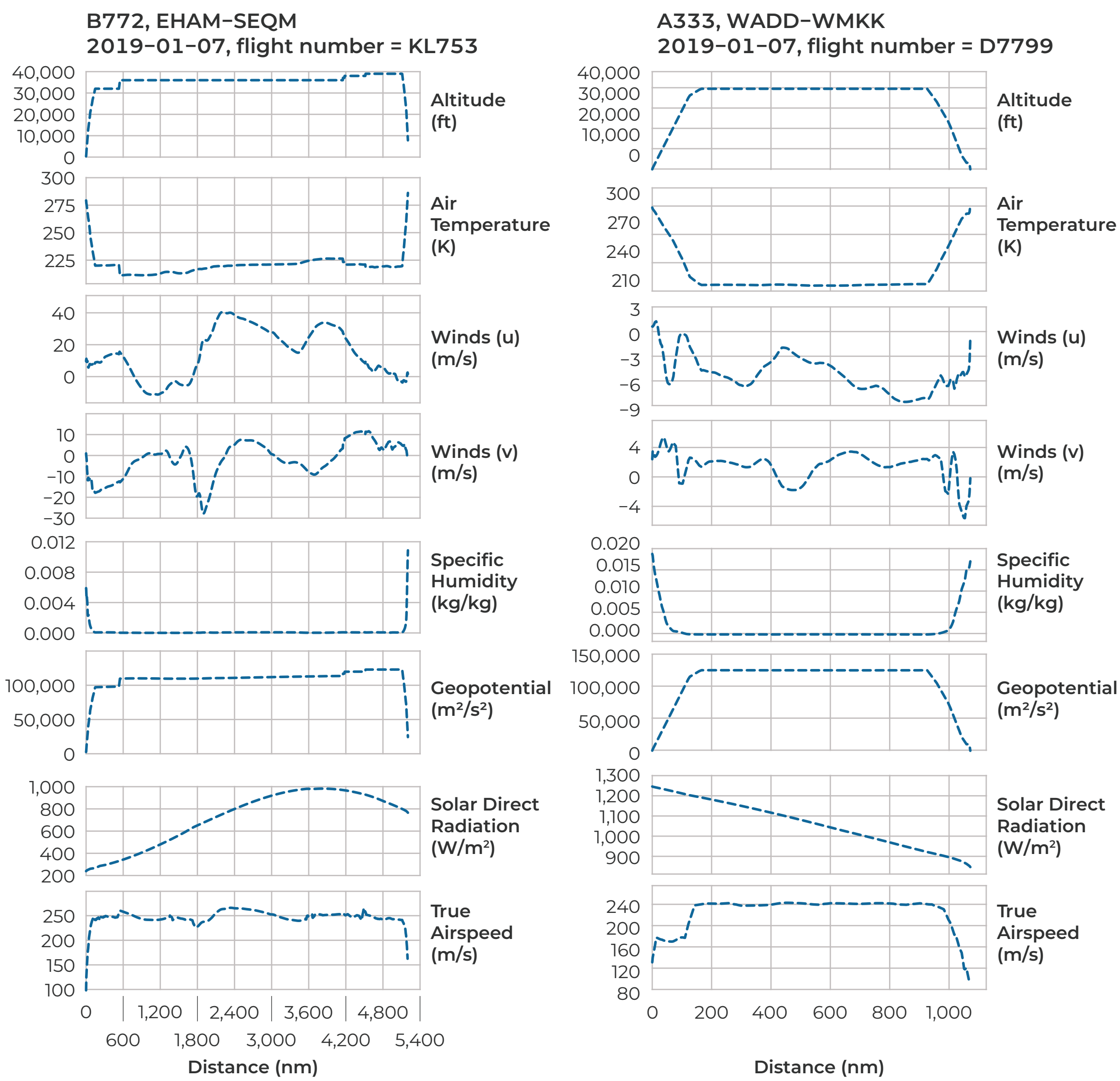


Figure 2: Examples of trajectories and meteorological data in ICL's dataset

Table 4 summarizes the assumptions adopted for each model analyzed. As detailed above, OpenAP and Poll-Schumann require flight trajectories. For these two models, we first estimated fuel consumption for each flight within the ICL real-world trajectory sample set. Using these provided estimates, a linear regression was applied to generate representative fuel burn values for each aircraft type across various distance bins (125 nm, 250 nm, 500 nm, 750 nm, etc.). The resulting data were then structured according to the EEA framework. EEA 2019 and 2023 have predefined trajectories based on real-world global operations that cannot be modified by the user. Piano 5 also provides estimates based on predefined trajectories, but the user can also define a trajectory, if needed; for our comparison, we prioritized testing Piano's default trajectory assumptions.

For payload assumptions, EEA 2019, EEA 2023, and ICAO ICEC use default values that cannot be modified by the user; EEA's default payload assumptions are unknown, while ICAO ICEC assumes that aircraft operate at maximum takeoff weight (MTOW), which corresponds to maximum payload for most flights. For Piano 5 and OpenAP, evaluators provided fuel burn estimates considering several scenarios, varying from 0% to 100% of maximum payload by aircraft type. Poll-Schumann also supports user payload definition; we examined one payload scenario, considering the historical passenger load factor and not including cargo.[22]

Table 4: Assumptions adopted for each model analyzed

Model	Assumptions		
	Payload	**Trajectory**	**Flight phase**
EEA 2019 (base model)	Default	Default	FF (LTO + CCD)
EEA 2023	Default	Default	FF (LTO + CCD)
ICAO ICEC	Default (assumes MTOW)	Default	FF (LTO + CCD)
Piano 5	User defined (0% to 100% of payload fraction, with a 10% interval)	Default adopted (supports user-definition)	FF (LTO + CCD)
OpenAP	User defined (10%, 30%, 50%, 70%, 90%, and 100% of payload fraction)	User-defined (ICL sample adopted)	FF (LTO + CCD)
Poll-Schumann	User defined (one scenario analyzed based on historical passenger load factor data from ICAO and IATA)	User-defined (ICL sample adopted)	CCD

22 See Teoh et al., "The High-Resolution Global Aviation Emissions Inventory."

For all models except Poll-Schumann, fuel burn estimates correspond to the full flight—that is, the fuel consumed during LTO and CCD. Poll-Schumann estimates consider only the CCD phase, so direct comparisons with other models should be made carefully.

2.4. Fuel burn estimation comparison

Using the fuel burn estimates provided for each alternative model, we calculated the aircraft coverage considering the 2019 global flights. If a given aircraft type was represented in the alternative model, its market share (based on the flight frequency of global flights in 2019 provided by OAG Aviation Worldwide Limited)[23] was included in the aircraft coverage calculation. Table 4 presents the aircraft coverage of each alternative model. Most common aircraft types are supported by the EEA model, but the TIM includes some fallback types or correction factors for the missing aircraft. This model extension is considered in the aircraft coverage calculation of EEA and all alternative models analyzed, which results in higher coverage numbers for the EEA model compared to those quoted as native coverage in Section 2.2.

Table 4: Model coverage based on global flights from 2019

TIM current implementation (EEA 2019 as base model)	EEA 2023	ICAO ICEC	Piano 5	OpenAP	Poll-Schumann
97.28%	99.03%	99.81%	89.83%	67.40%	74.91%

Figure 3 presents the validation sample coverage (i.e., the number of flights from the validation sample with aircraft types supported by each model) by distance bin (in gray), compared with EEA 2019 (in blue).

23 Historical flight schedules data provided by OAG Aviation Worldwide Limited, available at https://www.oag.com/airline-schedules-data.

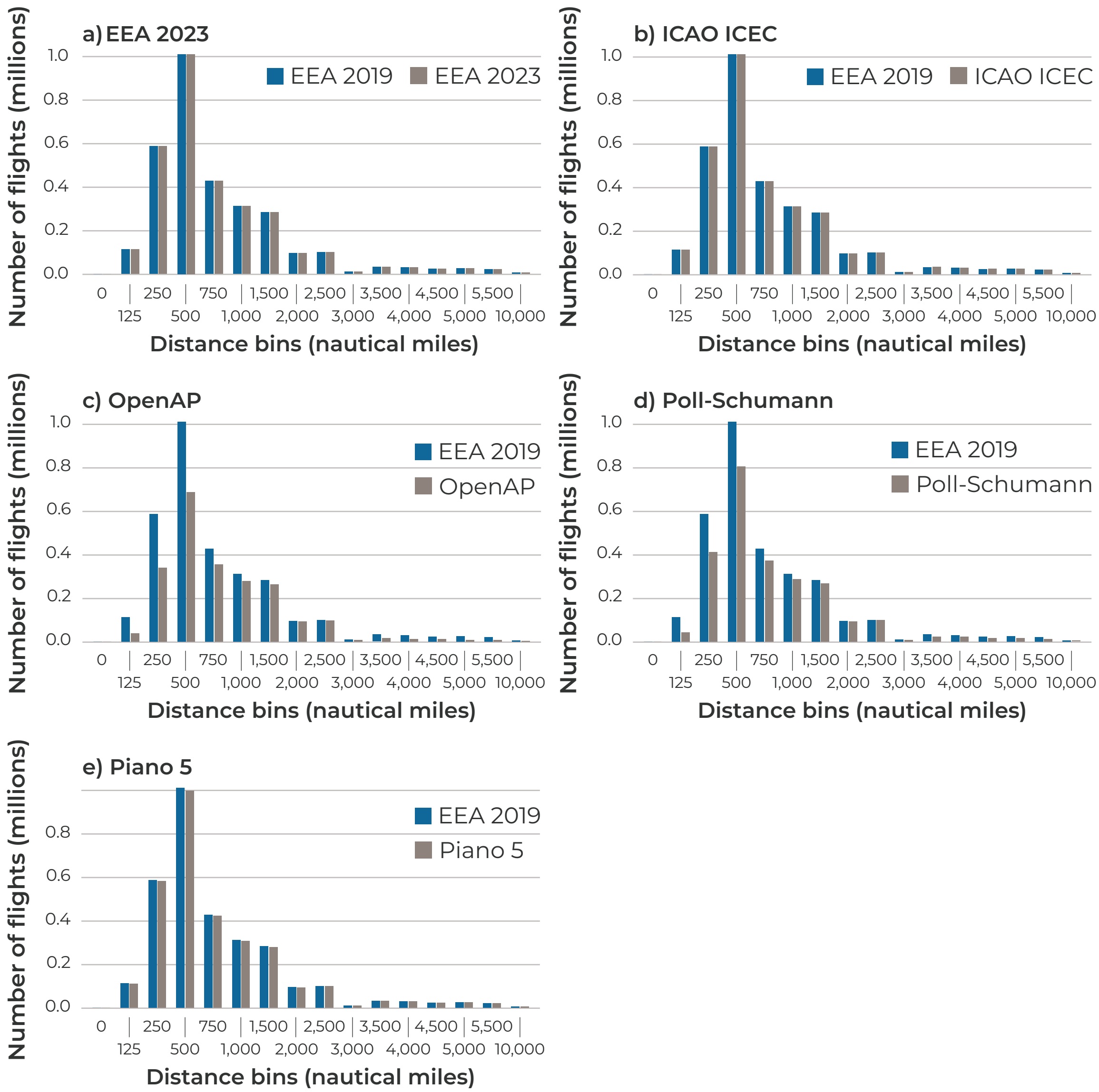


Figure 3: Number of validation flights covered by alternative model, compared with EEA 2019

Figure 3 shows that EEA 2023 and ICAO ICEC covered all flights covered in EEA 2019. Piano 5 provided the next best validation sample coverage, with nearly 100% of flights from the validation sample covered. Poll-Schumann ranked fourth and OpenAP fifth.

We then applied the model validation framework[24] to compare the estimated fuel burn with real-world values from the validation dataset.[25] Table 5 presents the comparison of

24 Travel Impact Model Advisory Committee [TIM AC], 2024. AC/3-TB/1: Methodology for validating fuel burn model changes.

25 A flight was only included in the validation analysis if its aircraft type was supported by the alternative model. However, the alternative models that include payload as an input variable have an additional mission limitation: given the trade-off effect between payload and range, some long-distance flights may not be operational for higher payloads. Ideally, we would impose this limitation to define the validation sample and consider only flights with range lower than the maximum distance allowed for each payload scenario and each aircraft. This limitation is minor and we do not expect it to influence the relative merits of a given model.

the error distribution across alternative models compared to the base model. EEA 2019 had a median absolute error of 8.0% and presented a small overestimation trend for the shortest distance bin (125 nm) and an underestimation trend for longer distance bins. We observed that the median absolute error of the EEA 2023 model was slightly lower, at 7.8%, and that the over- and underestimation trends were the same as those of EEA 2019, but with smaller errors across almost all distance bins.

The ICAO ICEC model had a median absolute error of 14.8%. It showed an overestimation trend across all distance bins that could result from using the MTOW as the payload in its estimation. When compared to EEA 2019, the absolute error increases for the shorter distances (from 125 nm to 1,500 nm) but decreases for the longer distances (> 1,500 nm).

For OpenAP, only the 70% payload fraction scenario was analyzed, and it presented a median absolute error of 20.2%. We observed that the model tended to underestimate fuel burn for short distance flights (from 250 to 2,000 nm) and overestimate fuel burn for long distance flights (> 2,000 nm). The absolute error was higher than EEA 2019 for all distance bins.

Poll-Schumann presented a median absolute error of 15.2% and tended to underestimate emissions, especially for short distance flights. Compared to EEA 2019, Poll-Schumann reduced the fuel burn absolute errors for long distance flights (> 2,000 nm) but presented higher absolute errors for shorter flights (from 150 nm to 2,000 nm). However, as noted above, Poll-Schumann only models the CCD phase and does not account for the LTO phase. This likely explains the stronger underestimation trend for short-distance flights, which tended to gradually reduce with increases in distance, as LTO fuel burn is relatively smaller for longer distances.

For Piano, we analyzed three payload fraction scenarios: 70%, 90%, and 100%. The median absolute errors were 15.5%, 11.8%, and 10.1%, respectively. The model had a general underestimation trend that reduced as payload fraction increased.

Table 6 summarizes the full validation metrics results, including the median absolute error, error threshold analysis, frequency- and emissions-weighted distance metrics, and the distance and aircraft error metric.[26] Both EEA 2019 and EEA 2023 performed well across most metrics, while OpenAP (with a 0.7 payload fraction) performed poorly on most. ICAO ICEC, Poll-Schumann, and Piano 5 had intermediate performance, with ICEC being the worst among the three and Piano 5 matching the validation better as the payload fraction increased. This effect suggests that improving the representation of masses in the TIM will improve its accuracy, a point to return to in future work.

26 See AC/4-TB/1 for definition of these terms.

Table 5: Comparison of the error distribution across alternative models

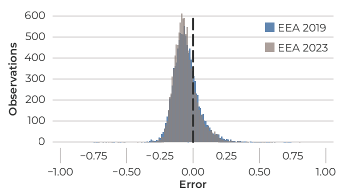
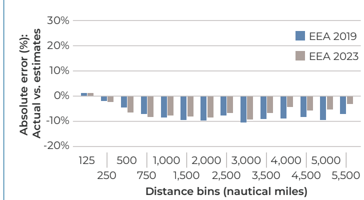
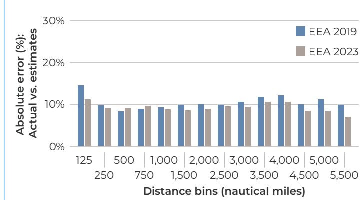
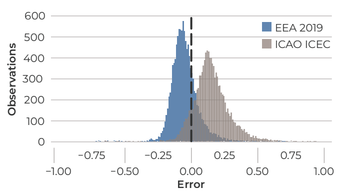
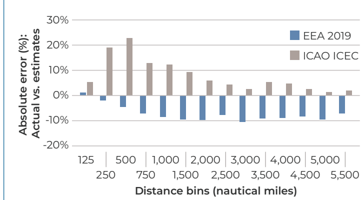
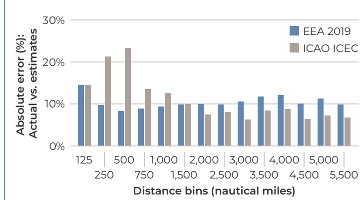
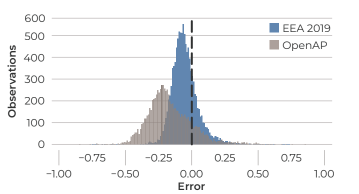
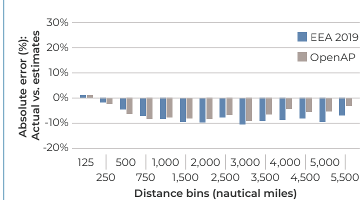
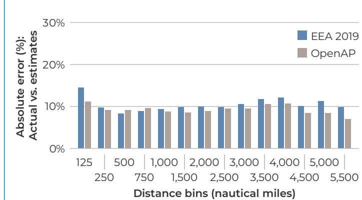
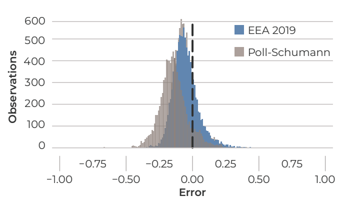
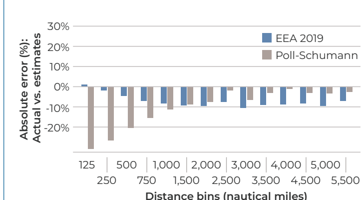
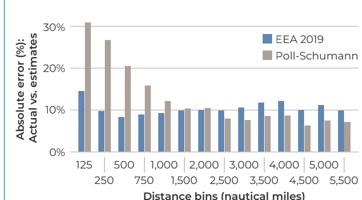
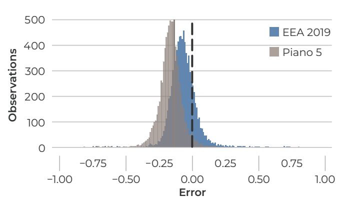
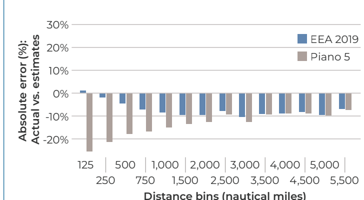
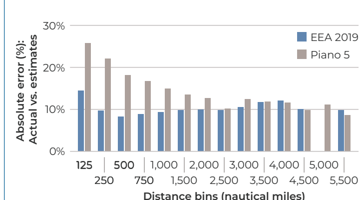
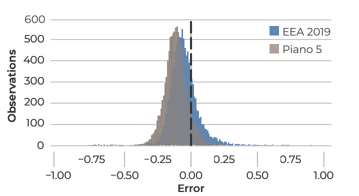
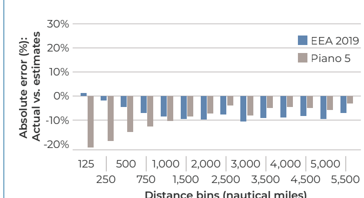
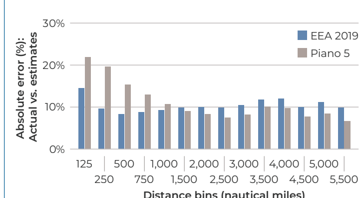
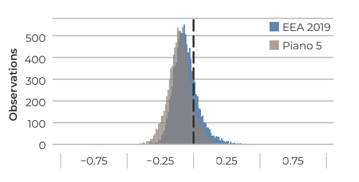
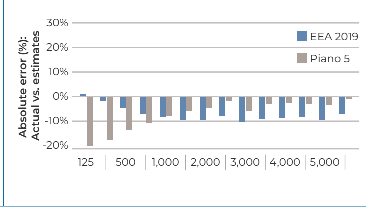
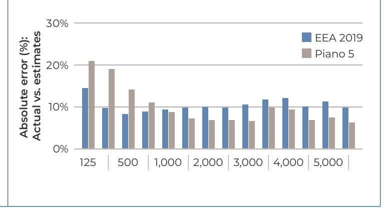
Model	Error distribution	Weighted average of errors by distance bin	Weighted average of absolute errors by distance bin
EEA 2023			
ICAO ICEC			
OpenAP (70% of payload fraction)			
Poll-Schumann			
Piano 5 (70% payload fraction)			
Piano 5 (90% payload fraction)			
Piano 5 (100% payload fraction)			

Table 6: Comparison of fuel burn error metrics across alternative models

	EEA 2019	EEA 2023	ICAO ICEC	OpenAP (Payload = 0.7)	Poll-Schumann	Piano 5 (Payload = 0.7)	Piano 5 (Payload = 0.9)	Piano 5 (Payload = 1)
Error metric	**Baseline**	**Baseline**	**Baseline**	**Baseline**	**Baseline**	**Baseline**	**Baseline**	**Baseline**
Median absolute error **Ideal value: 0%**	8.00%	7.80%	14.80%	20.20%	15.20%	15.50%	11.80%	10.10%
Error threshold analysis **Ideal value: 100%**	63.80%	65.10%	39.80%	29.50%	39.30%	38.00%	50.10%	55.40%
Frequency-weighted distance metric (absolute errors) **Ideal value: 0%**	9.54%	9.02%	16.38%	24.51%	18.32%	17.63%	14.22%	12.86%
Emissions-weighted distance metric (absolute errors) **Ideal value: 0%**	9.79%	8.79%	11.90%	20.60%	12.57%	14.20%	10.84%	9.51%
Distance and aircraft error metric **Ideal value: 1.0**	0.88	0.90	0.76	0.83	0.85	0.85	0.90	0.92

Legend: Best performance Midpoint (percentile = 50%) Worst performance

The colors in Table 6 indicate the best (green), midpoint (yellow), and worst (red) performance for each model against each error metric. The final ranking, considering the results of the validation analysis, is:

1. EEA 2023
2. EEA 2019
3. Piano 5 (payload fraction = 1)
4. Piano 5 (payload fraction = 0.9)
5. Poll-Schumann
6. Piano 5 (payload fraction = 0.7)
7. ICAO ICEC
8. OpenAP (payload fraction = 0.7)

We conclude that only EEA 2023 completely satisfies the immediate needs of the TIM. OpenAP, Piano 5, and Poll-Schumann could probably perform better after adjusting the user-defined assumptions. For OpenAP and Piano 5, for example, we analyzed multiple scenarios of payload fractions, but always adopted a fixed fraction across aircraft in each scenario. The actual payload fraction, however, varies with time and across aircraft, region, and airline, and would require additional effort to be refined. This assumption appears to be already tailored in the EEA model.

In addition, OpenAP and Poll-Schumann would require additional work to increase the aircraft coverage. For Piano 5, the best performance obtained considered a 100% payload fraction for all aircraft, which is clearly a weak assumption, showing a general underestimation trend of the model. This trend could be a consequence of other assumptions (such as flight trajectory). Moreover, even if Piano assumptions were refined, its license would still be an issue.

3. DISTANCE CORRECTION APPLICATION

The other change adopted in the TIM, as recommended by the Advisory Committee at AC/5, was the inclusion of a correction factor to adjust the distance input in the fuel burn estimation. Previously, the distance of each route was represented by the Great Circle Distance (GCD), meaning the direct distance between the origin and destination airports. Stage length was, therefore, underestimated in the TIM, given that actual flight paths are usually longer than the GCD due to several factors, including the actual route path, airport congestion, airspace restrictions, and bad weather avoidance.

The distance correction factors derive from research developed by Teoh et al.,[27] and are based on historical flight tracking data. Teoh et al. observed that actual distance flown is around 5% higher than the GCD on a global level, but this percentage varies across regions and distances. Given this finding, for the TIM application, this factor is represented by the ratio between the average real-world distance and the GCD for each airport pair.

One of the main challenges in defining distance correction factors is that flight distance and fuel consumption do not always have a direct relationship. A lateral inefficiency may lead to lower fuel consumption if there are advantageous tailwinds in the longer path. Another challenge is that the TIM provides emissions estimation for future flights, based on planned flight schedules, with unknown weather conditions or airspace and airport restrictions. Even with these uncertainties, we consider the average distance flown of past flights as the best approximation for the expected distance flown for future flights.

ICL provided historical flight data, collected with ADS-B telemetry, from global flights operated in 2019. The sample includes more than 40 million flights that, combined, traveled 61 billion kilometers. Figure 5 presents the distance correction factors calculated for major airports in Europe and North America. The distance correction factors for transatlantic flights are symmetric, as shown by the green-dominated boxes on the lower left and upper right of the diagram on the left-hand side.

27 Teoh et al., “The High-Resolution Global Aviation Emissions Inventory.”

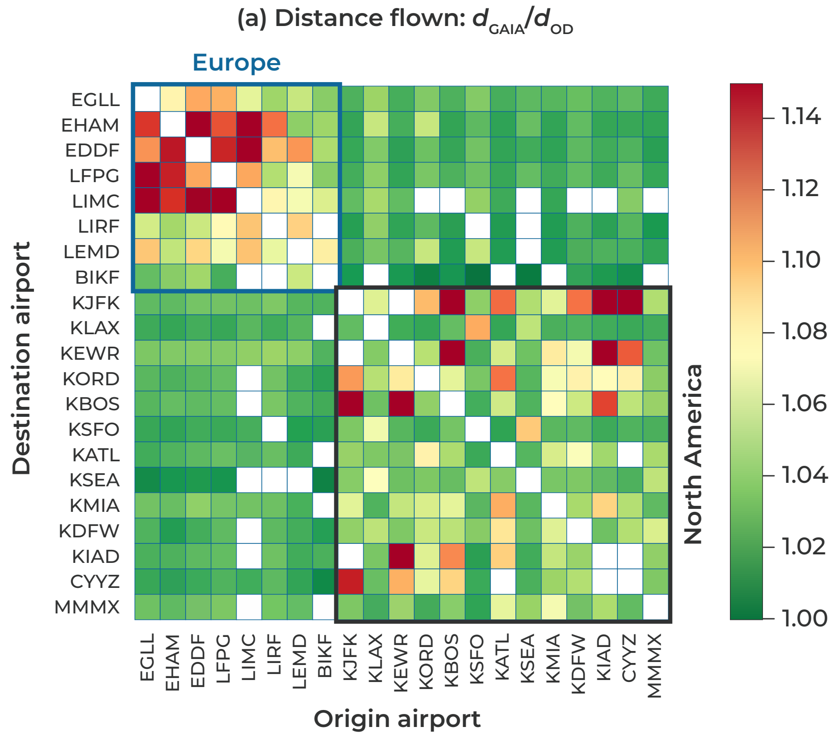


Figure 5: Distance correction factors considering routes between major airports in Europe and North America. Source: Teoh et al., "The High-Resolution Global Aviation Emissions Inventory," Fig. 8; reproduced with permission.

As mentioned previously, the EEA model separates the fuel burn for the LTO and CCD stages of flights. According to its documentation, the EEA model assumes that the aircraft travels 17 nm during the LTO cycle. The reference stage length, which is used as an input for the CCD fuel burn estimation, is calculated by subtracting 17 nm from the Great Circle Distance.[28] The current version of TIM (1.9.1) does not include this 17 nm correction to account for the distance traveled during the LTO cycle. The distance correction factor updates the TIM calculations to be consistent with the EEA documentation by subtracting 17 nm from each itinerary before calculating CCD fuel burn using the EEA model. For routes not covered by the ADS-B data, the distance correction factor was represented by the average distance correction of the corresponding country pair. In the rare case when a country pair correction factor was not available (~2.5% of the flight schedule as of October 2024), an ultimate fallback of the global mean lateral inefficiency in 2019 of 5.2% was used.[29]

28 European Organisation for the Safety of Air Navigation, *EUROCONTROL Method for Estimating Aviation Fuel Burnt and Emissions: EMEP/EEA Air Pollutant Emissions Inventory Guidebook 2016*, https://www.eurocontrol.int/archive_download/all/node/10913, 21.

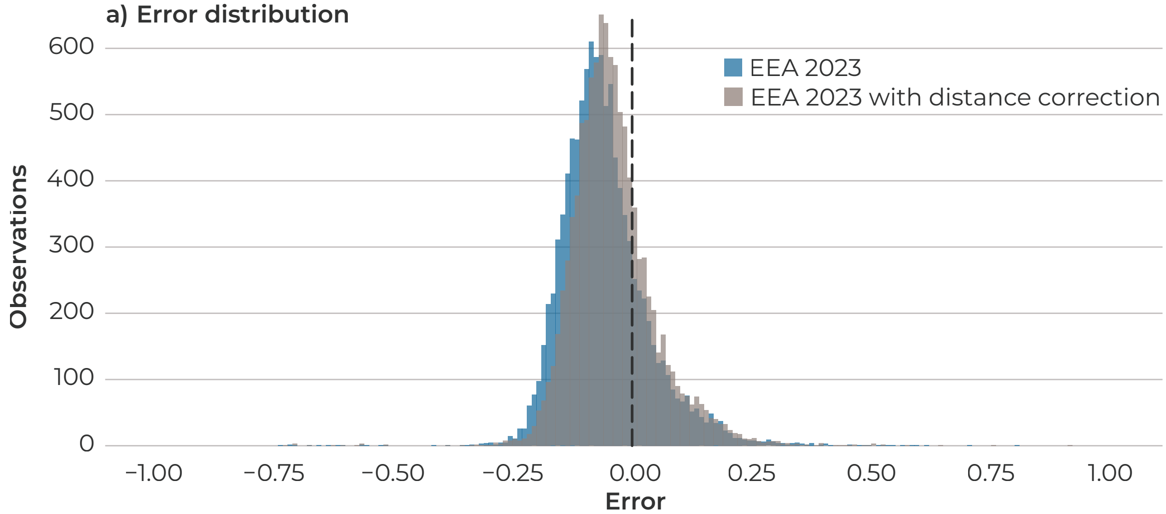
29 Teoh et al., "The High-Resolution Global Aviation Emissions Inventory."

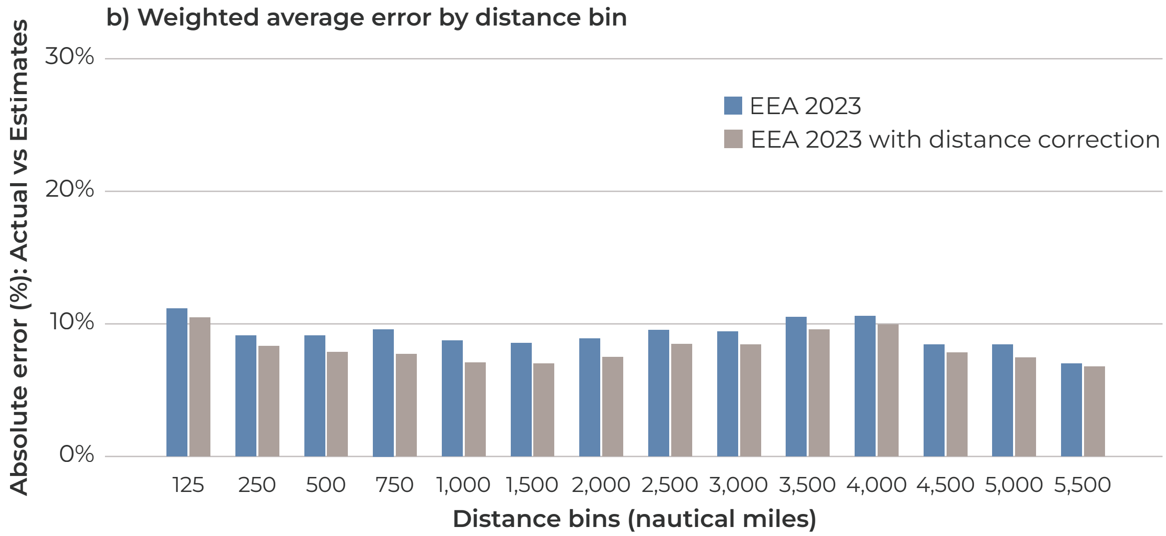
The adjusted distances, calculated by multiplying the GCD by the distance correction factors, were adopted as the distance input in the TIM. We then applied the validation framework to assess if the TIM estimation improved with the adoption of this model change.

Tables 7 and 8 show the validation charts and metrics, comparing the error distribution of EEA 2023 with and without distance correction. We observe that the application of the distance correction factor cut the median absolute error from 7.8% to 6.3%. As seen in Table 7 (b), we observed that the EEA 2023 had similar trends with and without the distance correction except for the shortest distance bin, in which the model presented a slight overestimation trend without the distance correction and a small underestimation trend with the correction. We observed an underestimation trend for the remaining distance bins for both models.

Table 7 (c) shows that the distance correction factor reduced the errors for all the distance bins. That the underestimation trend fell with the application of the distance correction is also observed in Table 7 (a), given that the error distribution has slightly shifted to the right. This general model improvement is supported by the validation metrics of Table 8, which indicates that the distance correction improves the accuracy of the EEA 2023 model on all error definitions analyzed. In summary, the validation results support the application of the distance correction in the TIM.

Table 7: Validation results for the distance correction application





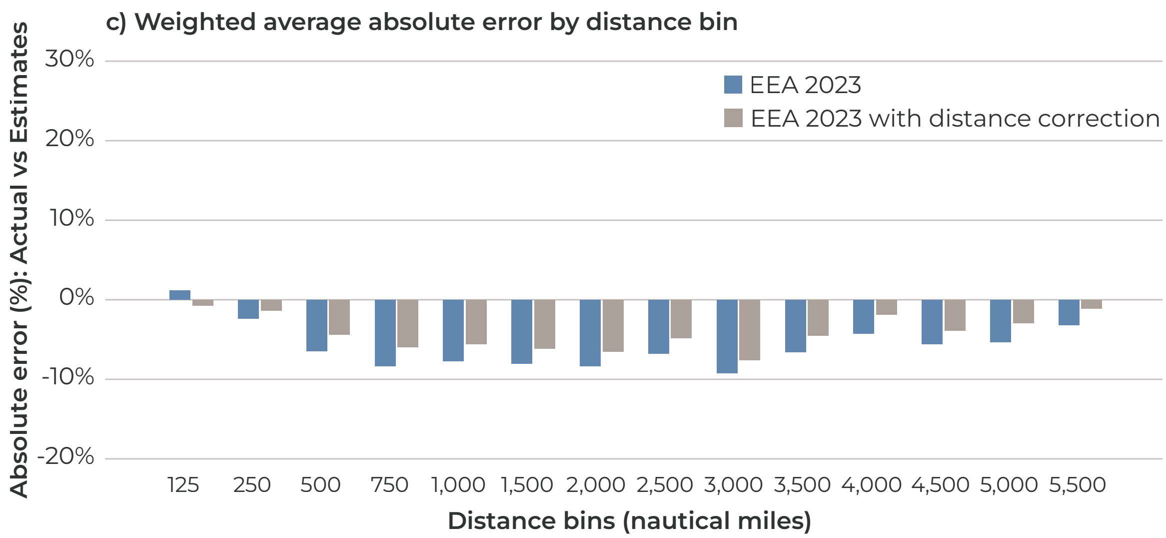


Table 8: Validation metrics for the distance correction application

Error metric	EEA 2023 Baseline	EEA 2023 Distance correction
Median absolute error **Ideal value: 0%**	7.80%	6.30%
Error threshold analysis **Ideal value: 100%**	65.10%	70.10%
Frequency weighted distance metric (absolute errors) **Ideal value: 0%**	9.02%	7.78%
Emissions weighted distance metric (absolute errors) **Ideal value: 0%**	8.79%	7.59%
Distance and aircraft error metric **Ideal value: 1.0**	0.9021	0.9087

4. NEXT STEPS

Considering the analysis presented in this document and the model changes agreed in AC/5, EEA 2023 will be adopted as the new base model, replacing EEA 2019, and the distance correction factor will be implemented to adjust the stage length input in the fuel burn estimation. These changes will be implemented as TIM v2.0.0.

The TIM AC will continue to monitor the evolution of the alternative models presented in this study and the release of new models in the market. Any potential model can be analyzed following the structure presented in this document. As a next step, the AC will evaluate the performance of BADA and its potential as a TIM base model. Also, the impact of additional factors influencing fuel burn, such as payload, engine type, and wind direction and intensity, will be explored under a future workstream. Incorporating those second-order fuel burn effects to distinguish more and less emitting flights may help improve the precision of the TIM.