**Travel Impact Model (TIM)**
ADVISORY COMMITTEE

**TECHNICAL BRIEF**

# Boosting model granularity: Literature review and preliminary analysis

**January 2025**

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## 1. SUMMARY

The goal of this workstream is to refine Travel Impact Model (TIM) fuel burn estimates by investigating how updates in aircraft technology and variations in real-world operations can be incorporated into the model, boosting TIM's granularity. TIM estimates are provided by the European Environment Agency's model, EEA 2023, for calculating aviation fuel burn and emissions. The model provides per-flight fuel burn estimates for many aircraft types (European Environment Agency [EEA], 2023), based on real-world aircraft data from Eurocontrol's Base of Aircraft Data (BADA) model. The only factors that can be specified by the user are aircraft type and stage length, which are defined in this study as first-order effects. All other factors, such as payload, winds, weather, and aircraft degradation, may be used by EEA to calibrate its estimates but cannot be changed by the user. We call those factors the second-order effects.

This technical brief presents the preliminary analysis developed to explore if and how these second-order effects can be incorporated into the TIM. The first step was to list all potential second-order effects and to identify if any literature had already analyzed the impact of these effects on fuel burn at the flight level. Data available to develop corrections to second-order effects for the model are also listed. Based on the literature and on inputs provided by the Task Group (TG), we developed a qualitative analysis, scoring each second-order effect based on its expected fuel-burn impact and on the availability of data. This analysis guided the selection of three second-order effects to be further analyzed—aircraft age, engine variant, and payload—as recommended by the TIM Advisory Committee at its sixth meeting (AC/6) in October 2024. The next step is to develop the correction factors for each second-order effect and to test if including the effect would improve fuel burn estimates by reducing modeling errors.

## 2. IMPACT OF SECOND-ORDER EFFECTS ON FUEL BURN

Fuel burn estimation models can have different levels of fidelity, depending on how the flight system is represented, as discussed by Yanto and Liem (2018). High-fidelity models use detailed trajectory and aircraft inputs to estimate fuel burn, while low-fidelity models may be based on empirical models or adopt simplifying assumptions. High-fidelity models are expected to be more accurate, but at the expense of intense computational usage and heavy reliance on detailed inputs. Low-fidelity models have a better computational performance, but usually with a lower accuracy. However, low-fidelity models can be refined by applying correction factors developed using high-fidelity models.

Given that the goal of the TIM is to provide emissions estimates of future flights for the global market, it is not appropriate to estimate fuel burn using a high-fidelity model with an assumed trajectory. Even if computational resources were available, data to perform these estimations are limited. Trajectory and weather conditions of future flights would need to be predicted to a high degree of accuracy. These predictions could be based on historical data, but they would be associated with a significant level of uncertainty given the stochastic and dynamic nature of the phenomenon, not to mention the lack of detailed data at global scale. This uncertainty in the input level would reduce the confidence of the estimations provided by a high-fidelity model.

Instead, the TIM estimates that emissions are based on the most probable fuel burn for a given mission, considering representative characteristics observed in past flights. The base model selected, EEA 2023, achieves this goal with reasonable accuracy, as discussed in the base model selection work (Travel Impact Model Advisory Committee [TIM AC], 2024). This study will assess the possibility of increasing the granularity level of the TIM by incorporating second-order effects to the model and then analyzing if these model additions would improve the TIM accuracy.

Figure 1 presents the influencing factors of a flight fuel burn estimation. According to Yanto and Liem (2018), an “ideal” high-fidelity fuel burn model would consider technology parameters (airframe and engine design), mission characteristics, atmospheric conditions, plus policy and market dynamics. Currently, the technology parameters in the TIM are only represented by the aircraft type. Mission characteristics are represented by the stage length. Together, these are our first-order effects. All other factors not yet included in the model are the second-order effects and the focus of this study.

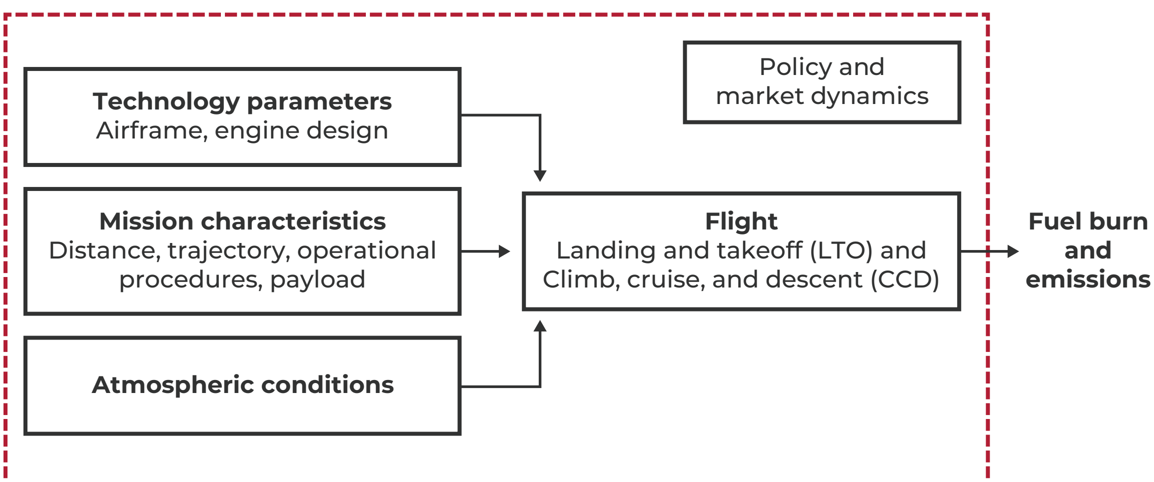


**Figure 1. Factors that impact a flight fuel burn estimation (adapted from Yanto & Liem, 2018)**

In this section, we discuss the second-order effects identified in the literature and their impact on fuel burn, as reported in previous studies. We also analyze how these effects could be implemented into the TIM, including the required data for each model change.

## 2.1 AIRCRAFT TECHNOLOGY

The Breguet Range Equation provides a simple way to estimate the fuel consumed in a flight. It can be rearranged, as shown in Equation 1, to determine the fuel weight required to fly a certain stage length.

$$W_{fuel} = W_o - W_f = \left[exp\left(R \frac{c_T}{V} \frac{D}{L}\right) - 1\right] \times (W_{OEW} + W_{payload}) \tag{1}$$

Where:

| | |
|---|---|
| $W_{fuel}$ | is the weight of the fuel burned; |
| $R$ | is the stage length; |
| $c_T$ | is thrust-specific fuel consumption (which is a property of the engine); |
| $V$ | is the airspeed; |
| $L/D$ | is the lift-to-drag ratio; |
| $W_{OEW}$ | is the aircraft operating empty weight; and |
| $W_{payload}$ | is the payload. |

This equation assumes that $c_T$, $V$, and $L/D$ are constant. $W_{fuel}$ is equal to the difference between the initial and final weight of the aircraft ($W_o$ - $W_f$), given that the gross mass of the aircraft falls during a flight as fuel is consumed.

Although dependent on some simplifying assumptions and applicable only to the cruise stage, this equation helps to analyze how aircraft technology impacts fuel burn. For a given stage length and payload ($R$ and $W_{payload}$), improvements in the aerodynamics (higher $L/D$ ratio), propulsion (lower $c_T$), and airframe weight (lower $W_{OEW}$) reduce the fuel burn per passenger-kilometer (Graham et al., 2014). Continuous developments in these three areas (aerodynamics, propulsion, and airframe) have contributed to improvements in aircraft fuel efficiency over the years (Benito & Alonso, 2018). Zheng & Rutherford (2020) analyzed the average fuel burn of new commercial aircraft from 1960 to 2019, considering two metrics: average block fuel intensity in grams of fuel per tonne-kilometer and the carbon dioxide ($CO_2$) metric value defined by the International Civil Aviation Organization (ICAO), as shown in Figure 2. The authors observed that the average block fuel intensity of newly delivered aircraft decreased more than 40% from 1970 to 2019. They highlight that steeper fuel burn reductions were observed in the last decade, from 2010 to 2019, due to the release of several fuel-efficient models, such as the Boeing 737 MAX, Airbus A320neo, Boeing 787 families, and Airbus A350.

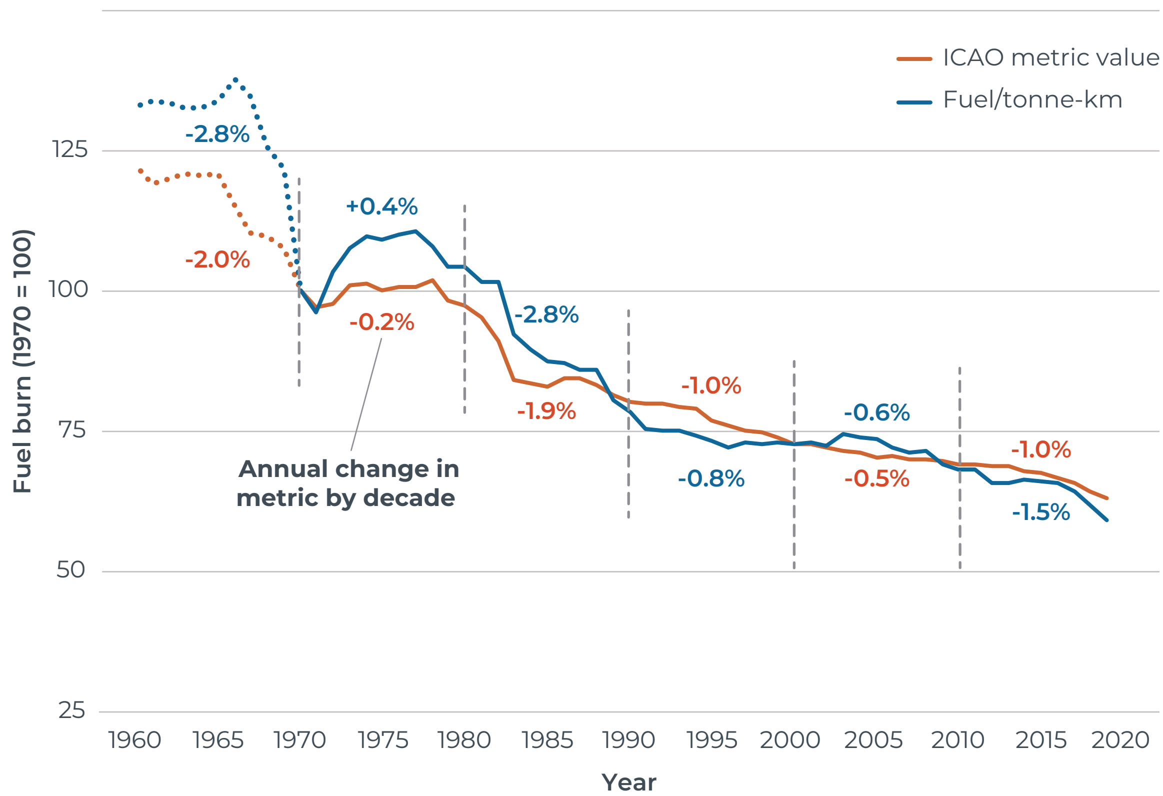


**Figure 2. Average fuel burn of new commercial jet aircraft, 1960 to 2019 (Zheng & Rutherford, 2020)**

Along with the technological improvements of aircraft and engines developed by manufacturers, the fuel efficiency of a carrier depends on fleet renewal. Brueckner and Abreu (2017) investigated the impact of several factors on airline fuel usage considering the United States market, including the impact of aircraft "vintage" or construction year. They observed that an older fleet is associated with a higher fuel consumption, and, on average, an aircraft-vintage reduction of 3 years is associated with a 2.2% decrease in fuel use.

In fact, the fleet renewal process includes the carrier's decision on when to introduce a new technology and the technology choice. Oliveira et al. (2021) explain that there are two strategies a carrier can adopt when deciding whether to introduce a new technology into its fleet:

***a)*** ***Fleet rollover***, which is the decision to reduce fleet age by replacing an older aircraft with a newer aircraft of the same type.

***b)*** ***Fleet modernization***, which is the decision to purchase a new-generation aircraft recently released by manufacturers.

Oliveira et al. (2021) analyzed how fuel price changes have motivated carriers to promote fuel savings by investing in fleet rollover and fleet modernization. While fleet modernization is associated with the introduction of new-generation aircraft, fleet rollover represents the replacement of older with newer aircraft of a similar generation. The authors considered the case of Brazilian carriers and developed an econometric model to estimate the impact of several factors on carriers' fuel efficiency. They found evidence that carriers may adopt a fleet planning strategy more targeted on fuel efficiency when fuel prices increase. Their results suggest that a 10% increase in fleet modernization of a carrier is associated with a 9%–10% overall fuel burn reduction. They also find that a 10% increase in the fleet age tends to increase its fuel burn by 1.4%–1.6%.

Aviation data and analytics firm Cirium corrects fuel burn estimations in its emissions model, EmeraldSky, to account for the deterioration of fuel efficiency with aircraft age (Cirium, 2024). The model assumes that the deterioration of fuel efficiency for narrowbody aircraft is more aggressive than for widebody aircraft. The age correction is based on the aircraft age range and varies from 2% to 6% for narrowbody aircraft (2% in year 1 and 6% starting in year 10), and from 0.5% to 2% for widebody aircraft (0.5% in year 0 and 2% starting in year 10).

An aspect that can influence the impact of technology on fuel burn is the engine selection when purchasing new aircraft. Ekici et al. (2023a) and Ekici et al. (2023b) investigated how much fuel and emissions reduction airlines can achieve with the aircraft-engine pairing. Both studies compared fuel burn and emissions of different combinations of aircraft and engine, modeling all flight phases for each combination in a single route using EUROCONTROL's aircraft noise and emissions modeling platform, known as IMPACT. Ekici et al. (2023a) analyzed a widely used narrowbody passenger aircraft combined with four commonly used engines and observed that the most inefficient engine emits 3.3% more $CO_2$ compared to the engine that emits the least for the flight analyzed. This would represent 666 kg of $CO_2$ in the route analyzed (a flight of 3h 50 min).

In contrast, Ekici et al. (2023b) compared two different aircraft (narrowbody vs. widebody) considering two engine types for each. The fuel burn difference across engines was 5% for the widebody and 13% for the narrowbody aircraft, which is equivalent to 5,044 kg and 3,455 kg of $CO_2$, respectively, considering the Ankara–London route analyzed. The authors also found that the widebody aircraft—even though it has twice the passenger capacity of the narrowbody aircraft—emits 4 to 7 times more emissions than the narrowbody plane depending on the flight phase for the route analyzed.

Retrofitting existing aircraft can also affect fuel burn. These changes can bring fuel-saving opportunities, including engine replacements and airframe improvements such as installing winglets or sharklets. In fact, winglets improve the aircraft aerodynamics, reducing the lift-induced drag and reducing fuel burn. McConnachie et al. (2013) interviewed some airlines about their efforts to modernize the fleet, including retrofitting aircraft with winglets to improve fuel consumption. One of the interviewed airlines shared that winglets have improved fuel efficiency by about 2% in short flights and 3% in longer flights. Airbus (2017) reported that the sharklets developed for the A320 family can reduce fuel burn by up to 4%. Flight tests developed by Boeing observed a 4%–5% reduction in fuel burn with winglets, and that winglets also contribute to improved takeoff performance (Freitag & Schulze, 2009).

Reducing the aircraft's operational empty weight (OEW) is another technological development that contributes to fuel saving given that the empty weight directly impacts the fuel burn, as presented in Equation 1. Manufacturers have been achieving weight reductions with the adoption of lighter material in the aircraft structure, such as extending the use of composites (Benito & Alonso, 2018). Airlines also invest in strategies to reduce the aircraft weight and save fuel, such as reducing the weight of catering service, seats, and imposing baggage weight limits (Morris, 2018). Tsai et al. (2014) interviewed stakeholders from the airline industry in China and observed that during periods of high fuel prices and high flight occupancy, airlines increase their efforts to save fuel, including reducing the aircraft built-in weight.

The Tsai et al. (2014) study proposed a method to reduce fuel burn by reducing the weight of seats in the aircraft. The authors explained that an airline could adjust the number of seats if the flight is not fully booked or replace existing seats with lighter versions. However, they highlight that a fuel efficiency improvement will not necessarily reduce the overall environmental impact. If the energy savings provided by weight reductions lower ticket prices, this may attract more passengers, which can lead to fully booked flights, and thus the final weight reduction will not be as high as expected. $CO_2$ emissions per ticket, however, would fall due to the higher load factors.

TIM already uses variations in the payload mass of passengers and cargo to apportion the fuel burn and $CO_2$ from a given flight to individual passengers. But it does not yet modify the fuel burn per flight due to those variations in payload. Thus, TIM overestimates variation in $CO_2$ per ticket due to load factor differences across airlines.

## 2.2 OPERATIONAL FACTORS

As we have discussed in the previous section, the classical range equation (Equation 1) shows that a flight's fuel consumption depends on some technological and operational factors. The operational factors included are the stage length and flight payload, which considers passengers, baggage, and belly freight.

As described in Equation 1, the higher the payload, the higher the fuel burn. Oliveira et al. (2021) estimated that a 10% increase in the payload is associated with a 1.7%–2.8% increase in the fuel burn. Some studies consider the number of passengers as a representation of the aircraft load. Quadros et al. (2022) have shown that the influence of payload on fuel burn is relatively small: +/- 1.1% global fuel burn for +/- 7.7% load from a baseline of 62.8%, assuming an industry-wide average load factor from the International Air Transport Association. Brueckner and Abreu (2017) estimated that a 5% increase in the airline's load factor is associated with an 8.2% increase in fuel use. When analyzing at the aircraft-type level, Brueckner and Abreu (2020) found that a 10% rise in the load factor is associated with an 8.8% increase in fuel consumption.

In general, reducing the aircraft's weight means reducing fuel burn, emissions, and costs. Given that the fuel itself is an additional weight, reducing unnecessary fuel contributes to saving fuel. Kang and Hansen (2018) explain that fuel planning is performed by flight dispatchers before every mission using a flight planning system. The fuel predictions provided by this system are based on forecasted conditions and historical flight data and thus come with a level of uncertainty. Tang et al. (2020) comment that although fuel loading requirements vary across countries, they tend to be similar and to comply with ICAO standards. ICAO divides fuel requirements into seven categories (International Civil Aviation Organization, 2022):

- Taxi fuel: fuel to be burned before takeoff.
- Trip fuel: fuel needed to fly from takeoff to the destination airport.
- Contingency fuel: fuel to compensate for unforeseen factors, such as unexpected deviations and extended delays.
- Destination alternate fuel: fuel to fly to one or two alternate airports, if required and depending on flight conditions.
- Final reserve fuel: fuel that should remain in the aircraft after landing.
- Additional fuel: supplementary fuel required if previous fuel categories are not enough to ensure that the aircraft is able to reach an alternate airport in case of an engine failure or a pressurization loss.
- Discretionary fuel: extra fuel uplift requested by the pilot in command.

Much of the fuel required as a safety margin depends on airlines' fuel policies and dispatchers' experience. Given that the main priority of airlines is safety, dispatchers generally overload discretionary fuel to minimize the risk of fuel exhaustion. Trujillo (1996) performed a survey with pilots and dispatchers and observed that discretionary fuel is always above the value suggested by airlines. Ryerson et al. (2015) observed that 4.5% of the fuel burn of an average flight by a U.S. airline is from the weight of carrying unused fuel. Some studies (Ryerson et al., 2015; Kang et al., 2018; Kang & Hansen, 2018) have observed that inaccurate fuel burn predictions may result in excess fuel consumption, and that it is possible to reduce unnecessary fuel while minimizing the risk of fuel exhaustion. Kang & Hansen (2018) proposed an improved procedure to predict fuel burn, which is estimated to save 1%–2% of fuel while achieving the same safety level.

Another factor that undoubtedly impacts fuel burn is the stage length. Although higher fuel burn is expected for longer flights, this relation is not linear. Fuel consumption varies by flight phase, and aircraft burn more fuel per unit distance in the landing and takeoff (LTO) phase than in the cruise, climb, and descent (CCD) phase. For this reason, longer flights—which have a higher proportion of the CCD phase in their total flight time—tend to be more fuel efficient than shorter flights. Babikian et al. (2002) show that regional aircraft usually fly shorter routes than large aircraft and spend a greater fraction of their time in non-cruise, non-optimum flight stages.

Also, in actual operations, aircraft do not necessarily fly the most direct path to the destination airport. An important flight performance metric adopted by ICAO is horizontal inefficiency, which is the actual distance flown en route compared to a reference ideal distance.[1] Liu et al. (2021) explain that the reference distance can be the direct path between origin and destination, called the great circle distance (GCD), or a non-direct distance that is optimal due to favorable winds. Although the GCD is not necessarily the most optimal route, it is commonly chosen as the reference distance due to its computational ease. Teoh et al. (2024) estimated the horizontal inefficiency of flights in different regions. They observed a global increase in the average horizontal inefficiency from 5.2% in 2019 to 5.6% in 2020/21. By region, they estimated a horizontal inefficiency of 5.1% in the United States, 7.5% in Europe, and 9.5% in East Asia in 2021.

Reynolds (2008) identified that horizontal inefficiencies can be caused by congestion, restrictions in the airspace, departure and arrival procedures, vectoring and holding in the terminal airspace, and adverse weather conditions. Liu et al. (2021) observed that flights have a higher probability to choose more inefficient paths with the presence of convective weather and headwinds. The authors also found that some routes tend to have a higher horizontal inefficiency due to the presence of airspace flow programs, miles-in-trail restrictions, and special activity airspace.

In effect, improvements in trajectory planning can contribute to reducing airlines' fuel consumption. Trajectory planning can take advantage of favorable winds and improved technologies of satellite communications. Wells et al. (2023) propose dynamic programming to find time-minimal and fuel-minimal routes considering wind fields, which are then compared with real-world trajectories. They study the case of the route between London's Heathrow and New York City's John F. Kennedy airports, accounting for the differences among wind directions, velocities, and temperatures. The fuel-efficient route could provide 4.6% fuel reduction when flying east (New York City to London) and 3.9% when flying west (London to New York City), on average, without significantly changing flight duration.

Brueckner et al. (2024) investigate how airlines adjust their aircraft utilization and fleet composition to save fuel as a response to fuel price variations. Evidence on fuel conservation efforts was already found by Fukui and Miyoshi (2017) and by Brueckner and Abreu (2017, 2020), but the evidence is indirect given that these efforts were not directly measured. These previous studies mention that this indirect evidence can be the result of various strategies, such as taxiing on one engine, reducing reserve fuel, flying at lower speeds, retrofitting the aircraft with winglets, and prioritizing more efficient aircraft in the fleet. One of the findings of Brueckner et al. (2024) is that airlines tend to fly at slower speeds as a strategy to conserve fuel when fuel cost per seat-mile is higher. The authors highlight, however, the complexity of connecting speed and fuel consumption with factors that are interconnected with speed, such as ton-miles and distance.

1 Flight horizontal inefficiency indicator is KPI 05 from ICAO. More information is at https://www4.icao.int/ganpportal/ASBU/KPI?IDs=5

Airlines usually define the cruise speed of a flight using the cost index parameter (CI), the ratio between cost per unit of time and cost per unit of fuel. As described by Cook et al. (2009), a low CI indicates that the cost of time is low or that the cost of fuel is high, favoring the adoption of lower speeds to save fuel at the expense of a longer flight duration. A high CI indicates that the time cost is high or that the fuel cost is low, leading to higher speeds and shorter flight duration, and therefore higher fuel consumption.

Airlines' efforts to reduce fuel consumption can be strengthened with air traffic management (ATM) improvements (Ryerson et al., 2014). Eurocontrol (2020) reported that inefficiencies in the European ATM network resulted in an additional fuel burn of 8.6%–11.2%, on average, in 2020. ATM directly impacts operations and flight trajectories to guarantee safety and an efficient air traffic flow; ATM manages how the network will absorb delays en route and at the gate, airspace restrictions, adverse weather conditions, terminal inefficiencies, and demand and capacity imbalances in general. Ryerson et al. (2014) analyzed the operations of two commonly operated aircraft models by a major U.S. airline; they estimated that 1.0%–1.5% of flight fuel burn is attributed to ATM delays and 1.5%–4.5% to inefficiencies at the airport terminal.

Initiatives to improve ATM, such as performance-based navigation (PBN) and trajectory-based operations (TBO), aim at increasing the efficiency, flexibility, and predictability of flight operations with more precise trajectories and delay redistribution, contributing to fuel saving (Federal Aviation Administration, 2022). TBO is a key part of air navigation systems modernization programs, such as NextGen in the United States and SESAR in Europe. Chu and Zhou (2023) estimated that the implementation of NextGen has provided an average reduction of 4 minutes in travel time per flight, which was associated with $60 in fuel saved per flight in 2017. These ATM modernization efforts also include the implementation of more fuel-efficient climb and descent procedures, such as continuous climb and descent operations. Szenczuk and Gomes (2022) analyzed the 20 most-flown domestic routes in Brazil in 2019. They estimated that if the flights in their sample adopted continuous climbs and descents, in addition to flying over the great circle distance, 189–231 liters of fuel could be saved per flight.

Aircraft ground operations can also be optimized and contribute to reducing fuel burn. Cao et al. (2023) compared the conventional method of using all engines to taxi with alternative methods that have been implemented or experimented with in several airports. The alternative methods included single-engine taxiing and ground traffic optimization (two procedures that improve conventional taxiing), and dispatch towing and onboard systems (methods that do not use engines for taxiing). Considering the six aircraft types analyzed, taxiing using a single engine provided fuel burn reductions ranging from 29% to 33%, while using onboard systems to provide electric power to aircraft wheels reduced fuel burn from 52% to 62%. Stettler et al. (2018) analyzed flights operated at London Heathrow, where single-engine taxiing is commonly adopted. They found that using both engines during taxi-in would use 50% more fuel compared with using just one engine. They also noted that single-engine taxiing could save even more fuel if started earlier during the taxi-in. If all aircraft initiated single-engine taxiing at the 25th percentile of the observed start times for single-engine taxiing, fuel consumption could be reduced between 3% and 12%, depending on the aircraft-engine pair.

This is by no means an exhaustive list of factors that influence the fuel burn of a flight. Fuel burn can also be affected by aircraft maintenance, which is important to guarantee an aircraft's safety and performance from degradation. Airport infrastructure—including airport elevation, runway configuration, and the presence of high-speed exit taxiways—will influence LTO fuel burn. Market-related factors are also very relevant. Fuel price, as mentioned above, directly impacts the cost index of time and fuel, therefore affecting aircraft speed. Fuel price can also influence airlines' fleet renewal process. Other market dynamics, such as the differences between low-cost and full-service airlines, may be important to understanding variations in technological and operational factors.

## 2.3 IMPLEMENTATION STATUS OF INFLUENCING FUEL BURN FACTORS INTO THE TIM

Table 1 presents the implementation status of first- and second-order effects into the TIM. We consider the factors identified in the literature, discussed in the previous section.

**Table 1. Implementation status of influencing fuel burn factors**

| Factors that influence flight fuel burn | Status in the TIM |
|---|---|
| **Aircraft technology factors** | |
| **Aircraft type** | ***Captured*** by aircraft type selection in the TIM estimation as one of EEA model inputs. |
| **Fleet rollover**<br>Replacing older aircraft with newer aircraft of a similar generation | ***Not captured*** by the current model, but aircraft aging is expected to impact fuel burn. Oliveira et al. (2021) observed that a 10% increase in the fleet age on a route tends to increase fuel burn by 1.4%–1.6%. |
| **Fleet modernization**<br>Introduction of new-generation aircraft | ***Captured*** by aircraft type selection in the TIM estimation as one of the EEA model inputs. However, any completely new aircraft design brought to the commercial market will not be added to the EEA model inputs until the next EEA model update. |
| **Engine selection**<br>Specific aircraft may be equipped with various engine types across fleets of different airlines | ***Not captured*** by the current model. TIM currently models only one engine variant per aircraft type, but previous studies suggest that fuel burn varies by engine type. Ekici et al. (2023a) calculated a maximum fuel burn difference of 3% when comparing four engines for a single narrowbody aircraft on a single route. Ekici et al. (2023b) observed a 5% difference when comparing two engines for a single widebody aircraft on a single route, and a 13% difference when comparing two engines for a single narrowbody aircraft on that same route. |
| **Retrofits (winglets/sharklets)** | ***Captured*** by the current model beginning with TIM Version 1.10. Some correction factors based on a literature review were developed to account for aircraft types with winglets/sharklets that are not available in the EEA model and are instead represented in the model by non-winglet aircraft from the same family. Winglets installed as retrofits and not followed by an IATA code change are not captured by the TIM. |
| **Operating empty weight (OEW)** | ***Not captured*** by the current model, beyond the average OEWs of different aircraft types. Adoption of lighter materials in aircraft structure and other strategies deployed by airlines may reduce OEW and therefore reduce fuel burn. |

| Operational factors | |
|---|---|
| **Distance flown** | ***Captured*** by the distance definition in the TIM estimation as one of the EEA model inputs, and adjusted from great circle distance to real-world distance with the application of distance corrections. This change was implemented in TIM Version 2.0. |
| **Payload** | ***Not captured*** by the current model. TIM's base model, EEA, has defined a payload scenario but its assumptions are unknown. The static payload setting cannot be modified by the user. Estimated payload is used to apportion the fuel burn of a flight to passengers and freight in the TIM, although not to estimate the fuel burn itself. Oliveira et al. (2021) estimated that a 10% increase in payload is associated with a 1.7%–2.8% increase in fuel burn. Quadros et al. (2022) observed that 7.7% variation in payload is associated with a 1.1% variation in global fuel burn. |
| **Speed** | ***Not captured*** by the current model. The speed at which the aircraft travels has a significant impact on fuel burn. TIM's base model, EEA, has defined speed settings but its assumptions are unknown. Speed is partially captured by ongoing fuel burn correction work. |
| **Congestion** | ***Partially captured*** by the current model, with the distance correction developed by Google and Imperial College London (ICL). Congestion at airports can lead to longer taxi times and longer holding times and also affects aircraft speeds. Congestion can be considered in TIM through distance flown and taxi times. More aspects of congestion can be captured with ongoing fuel burn correction work. |
| **Fuel loading practices** | ***Not captured*** by the current model. Varies from airline to airline, with airlines choosing to uplift more or less fuel for reserves or to take advantage of fuel price differences across airports, known as tankering. Both approaches will make the aircraft heavier and therefore increase fuel burn. Fuel loading data is difficult to access, so it is out of the scope of this effort. |
| **Air traffic management (ATM)** | ***Partially captured*** by the current model with the distance correction developed by Google and ICL. The correction reflects the average horizontal inefficiency, a variable that is impacted by ATM. However, ATM inefficiencies and improvements are not all represented by the distance correction, as ATM also impacts other variables that influence cruise fuel burn, such as speed, and LTO fuel burn, such as climb and descent procedures and taxiing. Ongoing fuel burn correction work being developed by Google takes into account additional factors that influence ATM and may impact aircraft speed, such as winds and weather, and their effect on fuel burn. |
| **Winds** | ***Not captured*** by the current model. Headwinds require extra fuel burn while tailwinds reduce fuel burn. The impact of winds is partially captured by the ongoing fuel burn correction work. |
| **Weather** | ***Not captured*** by the current model. Weather conditions can require specific routing or trigger flight diversions. Partially captured in the TIM through the ongoing fuel burn correction work. |
| **Taxi times** | ***Not captured*** by the current model. TIM's base model, EEA, assumes a static taxi time of 26 minutes in accordance with ICAO definitions for takeoff and landing for every flight. In real-world scenarios, taxi times can vary depending on the airport, the time of year, and the time of day. Real-world data on taxi times that could be integrated in TIM for improved LTO estimates is available from Eurocontrol for EU airports and the FAA for U.S. airports, and potentially from other sources. |
| **Airport elevation** | ***Not captured*** by the current model. TIM's base model, EEA, assumes two flight phases: the LTO phase with landing, takeoff, and climbing that happens below 3,000 ft; and the CCD phase with climbing to cruising altitude, cruising, and descending, all above 3,000 ft. EEA assumes that all airports are located at an altitude of 0 ft. This not the case in reality, and it leads to an overestimation of how much fuel-intense climbing and descending is required. Airport altitude data is readily available; the details on how to apply the data in the TIM for improved LTO estimates are still to be developed. |

Below we detail how some second-order effects described in Table 1 are included in the research being conducted by Google.

**Distance correction** is a strategy to incorporate aggregated historical flight-tracking data from Automatic Dependent Surveillance-Broadcast (ADS-B) technology about actual distance flown as a result of airspace restrictions, temporary airspace closures, bad weather conditions, and airport congestion. The incorporation of a distance correction factor into the TIM was agreed at AC/5 and implemented and launched in TIM Version 2.0. More details about this work can be found in the TIM base model selection and distance correction application technical brief (TIM AC, 2024).

A **fuel burn correction** is under investigation by Google. Fuel burn correction builds on top of distance correction to additionally include corrections for the following real-world conditions: average true airspeed on the route, average flight trajectory on the route, average wind and weather conditions—including but not limited to the east/west effect—and the aircraft/engine mix used on the route. The fuel burn effects are calculated using the global aviation emissions inventory (GAIA) approach developed by Imperial College London (ICL), which uses Eurocontrol's BADA as the underlying base model for aircraft performance. The correction for fuel burn happens relative to the fuel burn for the great circle distance between origin and destination airport on the route as estimated by the EEA aircraft performance model dataset. A prototype for fuel burn correction has been developed as part of another workstream. It will be developed into a final version for potential incorporation in TIM in a further collaboration starting in Q4 2024.

## 2.4 PRELIMINARY SELECTION OF SECOND-ORDER EFFECTS AND DATA REQUIREMENTS

Even though some of the second-order effects described in Table 1 are already being considered in the ongoing distance and fuel burn correction work, there are still several other influencing factors not addressed by the model. In this section, we explore the potential to include additional second-order effects to improve the model's granularity and to increase the TIM's precision and accuracy.

At AC/5, the group agreed to update the TIM base model from EEA 2019 to EEA 2023. This choice was made following the assessment of alternative fuel burn models and of the data available for the TIM application. Given the findings of this analysis, we assume that the adoption of a high-fidelity base model in the short or medium term is unlikely. Thus, instead of being implemented directly as a model input, a second-order effect will be implemented as a correction factor, similar with the approach taken to correct the stage length.

To implement a second-order effect, we need to first estimate its impact on fuel burn, and then—based on the factor's variation across airlines and routes and the data availability— estimate the correction factors. Table 1A in the appendix presents a summary of the methods and data required to estimate the impact of each second-order effect on fuel burn. Table 2A summarizes how each second-order effect could be incorporated into the TIM, including the required data and aggregation of correction factors.

We then ranked the second-order effects based on certain criteria. We divided the criteria into two categories: (a) those evaluating the expected fuel burn impact and variation of the factor, as described in Table 2, and (b) those assessing the data availability for their implementation, described in Table 3.

For each criterion from category (a), each factor received a score of 0 or +1, with 0 indicating no expected or relevant impact (or variation across airlines), while +1 represents an expected impact (or relevant variation). Separate scores for the likely impact on cruise and LTO fuel burn are provided because the former dominates most flights and is also more controllable by airlines. For each criterion from category (b), each factor received a score of -1, 0, or +1, with -1 representing the case in which the data is not available, 0 when there is incomplete data or data in a non-ideal format, and +1 when all the needed resources are available.

**Table 2. Criteria for qualitative analysis on impact and variance**

| | | Score | |
|---|---|---|---|
| **Criteria** | **Description** | **0** | **+1** |
| **Likely impact on cruise fuel burn** | Indicates the expected impact level of this factor on the cruise fuel burn | Very low or no expected impact | Expected impact |
| **Likely impact on LTO fuel burn** | Indicates the expected impact level of this factor on the LTO fuel burn | Very low or no expected impact | Expected impact |
| **Likely variance (across airlines)** | Assesses how much a given factor varies across airlines | Very low variation | Expected variation |

**Table 3. Criteria for qualitative analysis on data availability**

| Criteria | Description | Score: -1 | Score: 0 | Score: +1 |
|---|---|---|---|---|
| **Availability of input data to estimate the impact** | Assesses the availability of the data needed to estimate the isolated impact of a given factor on fuel burn | Not available at all | Partially available (incomplete data and/ or non-ideal aggregation and/or in limited markets) | Adequate data available at a global scale |
| **Need for a new license** | Modeling software may be needed to estimate the impact, which may require purchase of a new license | Require a new license | Does not require a new license and can be developed by Google with support from ICCT and/or other third parties | Does not require a new license and can be developed by Google without any new models |
| **Availability of data on future flights for the TIM application** | Given that the TIM estimates fuel burn of future flights, this criterion assesses the availability of corresponding second-order data for future flights | Not available at all | Possible to develop forecasts based on historical data or to adopt averages based on airline and aircraft, with option to include region and/or season | Data available along with schedule data for future flights |
| **Availability of validation data** | Analyze the availability of real-world data needed for model validation, including second-order effect data and fuel burn | Not available at all | Partially available (incomplete data and/ or non-ideal aggregation) | Adequate data available |

The results of this scoring are detailed in Table A3 in the appendix.

Table 4 presents the final results for all the second-order effects considered, including the representative variable chosen for each factor, the expected aggregation of the corresponding correction factors (to be developed), the total score based on the analysis described above, and if Google has relevant work ongoing. Three additional factors that could be taken forward in further analysis—fleet rollover, engine variant, and payload—are highlighted in the table.

**Table 4. Down selection of second-order effects for further analysis**

| Effect category | Second-order effect | Representative variable | Correction factor aggregation | Total score | Google's work status |
|---|---|---|---|---|---|
| **Technology** | Retrofits | Presence of winglets/ sharklets | Correction factor by airline/aircraft type | 5 | Completed (correction for fallback aircraft) |
| **Operation** | Airport elevation | Airport elevation | Correction factor by airport | 4 | Ongoing (via airport elevation correction) |
| **Technology** | Fleet rollover | Aircraft age | Correction factor by airline/aircraft type | 3 | — |
| **Technology** | Engine selection | Engine type | Correction factor by airline/aircraft type | 3 | — |
| **Operation** | Payload | Payload (passengers + baggage + cargo) | Correction factor by airline/aircraft type | 3 | — |
| **Operation** | Taxiing | Taxi time | Correction factor by airport | 3 | Ongoing (via taxiing fuel burn correction) |
| **Operation** | Real distance flown | Distance flown/GCD | Correction factor by route | 2 | Ongoing (via distance correction) |
| **Operation** | ATM | Impact on several variables (distance flown, cruise speed, take off/landing procedures, taxi times, etc.) and is impacted by others (winds, weather, etc.) | Correction factor by route | 2 | Ongoing (via fuel burn correction) |
| **Operation** | Winds | Wind speed and direction | Correction factor by route | 2 | Ongoing (via fuel burn correction) |
| **Operation** | Weather | Occurrence of adverse weather in the airport region or along the route. Special attention to convective weather | Correction factor by route | 2 | Ongoing (via fuel burn correction) |
| **Operation** | Speed | Cruise speed | Correction factor by route | 1 | Ongoing (via fuel burn correction) |
| **Technology** | OEW | OEW | Correction factor by airline/aircraft type | 0 | — |
| **Operation** | Fuel loading practices | Initial and final fuel of a flight | Correction factor by airline/route | -1 | — |
| **Operation** | Maintenance | Maintenance frequency | Correction factor by airline/aircraft type | -2 | — |

## 2.5 METHOD OF ANALYSIS

The effect of engine selection and payload can be modeled using a high-fidelity model, such as BADA, Piano, Poll-Schumann or another model that considers these variables as inputs. In an ideal modeling scenario, we would analyze the variation of each variable across airlines considering a global fleet data set at the aircraft level (identified by its tail number). For each effect, we would then be able to model differences in fuel burn across various scenarios. Using the estimation results, we would be able to develop the correction factors and then test their impact in the TIM by applying the validation framework. The main challenge for this work is to have data at the global scale, either for the engine type by airline/aircraft (tail number), or for the payload, especially including cargo information.

The fleet rollover requires a different approach. As far as we are aware, this variable is not a typical input in high-fidelity fuel burn models, so modeling the impact of its variation is not possible. The approach chosen is to derive age-correction factors from the literature and test if their application improves the TIM fuel burn estimation, considering the validation framework.

# 3. DATA AVAILABLE

In this section we present the potential flight data to be considered for the development of the correction factors described above, considering the three second-order effects selected. Some of the data was previously adopted in other steps of the TIM refinement work.

### Actual operations data:

- Microdata from Brazil's civil aviation authority ANAC (Agência Nacional de Aviação Civil):
  - Aggregation: flight level
  - Region: Brazil (only Brazilian airlines provide fuel burn data)
  - Variables: flight number, airline, aircraft type, tail number (last 3 digits), number of passengers, cargo mass, baggage mass, mail mass, departure/arrival time/date, route, seats, fuel burn
  - Time availability: Since 2000
- Private data provided to Google by partner airlines:
  - Aggregation: varies by airline; some airlines provide flight-level data and others provide route/month/aircraft type aggregates
  - Region: global operations
  - Variables: fuel burn, aircraft type, date, route, passengers (in some cases), cargo (in some cases)
- ICAO data+ M2:
  - Yearly aggregates for carrier-specific total cargo carried (in addition to seats and passengers); broken down by city pairs and aircraft. Requires complex mapping of aircraft, carrier, and city names, but this was already done in the belly cargo workstream, so can be reused.

- U.S. Bureau of Transportation Statistics, Air Carrier Statistics (T-100) database:
    - Aggregation: route/aircraft/airline/month
    - Region: origin and/or destination in the United States
    - Variables: airline, route, aircraft type, service class for transported passengers, freight and mail, available capacity, scheduled departures, departures performed, aircraft hours, load factor (only for domestic flights)
    - Time availability: since 1990
    - Taxi times: ASPM data
- Spire ADS-B data: Exact 3D flight trajectories by tail number for all covered flights
    - Aggregation: flight level
    - Region: global
- FlightAware ADS-B data: Exact 3D flight trajectories by tail number for all covered flights
    - Aggregation: flight level
    - Region: global

### Fleet data:

- ANAC RAB (Registro Aeronáutico Brasileiro):
    - Aggregation: aircraft level (by tail number)
    - Variables: aircraft type, manufacturer, aircraft owner, model specification, manufacturing date, seats
    - Region: Brazil (only Brazilian airlines)
- IBA:
    - Aggregation: aircraft level (by tail number)
    - Variables: tail number, operator, owner, aircraft type, engine model, MTOW, winglets/sharklets (yes/no), build date, original delivery date, seating capacity
    - Region: global
- Ch-aviation:
    - Level: aircraft level
    - Variables: engine type, hours of operation, cycle count, winglets

## 4. NEXT STEPS

In conclusion, to boost the model's granularity, the TIM Advisory Committee has decided to prioritize further analysis of **aircraft age, engine variants, and payload** as second-order effects influencing fuel burn. These areas were selected following the qualitative review of their impact, which is summarized in the appendix. The next step is to develop a correction factor for each second-order effect and to test if including these corrections would reduce the fuel burn modeling errors.

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# APPENDIX

## Table A1. Estimating the impact of second-order effects on fuel burn

| Effect category | Second-order effect | Representative variable | Method type | Method description | Required data | Software supporting the second-order effect as an input | Main challenges |
|---|---|---|---|---|---|---|---|
| Technology | **Retrofits** | Presence of winglets/ sharklets | Literature review | Google developed correction factors for the presence of winglets or sharklets based on the literature, but only for aircraft types with winglets/sharklets that are not available in the EEA model but can be represented by a fallback aircraft. The fallback was a non-winglet aircraft from the same family. These correction factors were implemented starting in the TIM Version 1.10.0. However, winglets installed in aircraft retrofits are not going to be captured by the model if the retrofit does not trigger an aircraft type code change. | Ideal: presence of winglets or sharklets by tail number<br>Alternative: fleet averages by airline/aircraft type could be adopted if aircraft-level data is not available. | No modeling adopted | Data |
| | **Fleet rollover** | Aircraft age | Empirical analysis | Consider the isolated effect of age on fuel burn as reported in the literature or estimate this effect by analyzing an empirical model (can be developed with the application of an econometric model). | Ideal: aircraft age by tail number + flight operations and market data (including fuel burn) at the flight level (and tail number)<br>Alternative: fleet averages by airline/aircraft type + flight operations and market data (including fuel burn) | — | Data |
| | **Engine selection** | Engine type | Modeling | Model differences in fuel burn across various engine variants using BADA or another high-fidelity model that supports engine type as an input in the fuel burn modeling. | Ideal: engine type by tail number<br>Alternative: fleet averages by airline/aircraft type could be adopted if aircraft-level data is not available. | BADA, PS, PIANO (limited) | Data and model license |
| | **OEW** | OEW | Modeling | Model differences in fuel burn across various OEW scenarios using BADA, PIANO or another high-fidelity model that supports weight as an input in the modeling. | Ideal: OEW by tail number<br>Alternative: fleet averages by airline/aircraft type could be adopted if aircraft-level data is not available. | PIANO, BADA, PS | Data and model license |
| Operation | **Airport elevation** | Airport elevation | Modeling | Model fuel burn of actual trajectories using a high-fidelity model such as BADA or PIANO, while taking into account elevation changes between origin and destination airports. | Airport altitudes | Manual integration in the EEA model | Isolating the impact |
| | **Payload** | Payload (passengers + baggage + cargo) | Empirical analysis or modeling | • Estimate the isolated effect of payload on fuel burn by analyzing an empirical model (this can be developed with the application of an econometric model), or<br>• Model differences in fuel burn across various payload scenarios using BADA. | Ideal: payload information of past flights; ideally, payload would include weight of passengers, baggage, and cargo.<br>Alternative: incomplete payload (number of passengers only, for example) by flight or by combination of aircraft type/airline/ route/month | PIANO, BADA, PS | Data and model license |
| | **Taxiing** | Taxi time | Modeling | Model the impact of variations in taxi time using the ICAO Engine Emissions Database (EEDB) or a high-fidelity model like BADA or PIANO that references the EEDB. | Ideal: taxi time by flight and tail number<br>Alternative: taxi time by airline/aircraft type/airport | Manual integration in the EEA model | Data and isolating the impact |
| | **Real distance flown** | Distance flown/ GCD | Empirical analysis | Correct distance input in the TIM model, considering the lateral inefficiency of global flights. Distance correction developed by Google and ICL is based on the GAIA approach (which uses BADA) and is incorporated in TIM 2.0.0. | ADS-B data and GCD by route | EEA, PS, PIANO, BADA | Data and model license |
| | **ATM** | ATM impacts several variables (distance flown, cruise speed, take off/landing procedures, taxi times, etc.) and is impacted by others (winds, weather, etc.) | Empirical analysis and/or modeling | The impact of some ATM-related factors on flight trajectories and speed is considered in the distance correction and the fuel burn correction work. This correction is based on GAIA approach (which uses BADA for fuel burn modeling). | Ideal: airline flight computer data<br>Alternative: aggregate ADS-B data | Modeled via flight parameters (distance, speed) using EEA, PS, PIANO, BADA | Data variability and complexity |
| | **Winds** | Wind speed and direction | Modeling | The impact of wind conditions on fuel burn is considered in the fuel burn correction work. This correction is based on the GAIA approach (which uses BADA for fuel burn modeling). | Ideal: airline flight computer data + winds directions and velocity data (in route)<br>Alternative: aggregate ADS-B data | Modeled via flight parameters (speed) using PS, BADA | Data variability and complexity |
| | **Weather** | Adverse weather in the airport region or along flight route; special attention to convective weather | Empirical analysis and/or modeling | Adverse weather conditions can impact choice of route path and other operational variables. This impact is considered in the fuel burn correction work. The correction is based on the GAIA approach (which uses BADA for fuel burn modeling). | Ideal: airline flight computer data + weather conditions by flight<br>Alternative: aggregate ADS-B data + average weather or information only about adverse weather occurrences | Modeled via flight parameters (distance, speed) using EEA, PS, PIANO, BADA | Data variability and complexity |
| | **Speed** | Cruise speed | Modeling and/or empirical analysis | Speed is one of the factors considered in the fuel burn correction work under development. Fuel burn effects are calculated using the GAIA approach (which uses BADA). | ADS-B and weather data to define speed scenarios | PS, BADA | Data and model license |
| | **Fuel loading practices** | Initial and final fuel of a flight | Modeling | Model differences in fuel burn across various fuel loading scenarios | Ideal: fuel uplift and reserves data by flight<br>Alternative: fuel uplift and reserves data by aircraft type/airline | PIANO (directly as an input), BADA and PS (through takeoff and waypoint inputs) | Data and model license |
| | **Maintenance** | Maintenance frequency | Empirical analysis | Maintenance impact on aircraft weight and aircraft performance (and consequently on fuel burn) needs to be empirically analyzed based on proprietary data. | Maintenance interventions reports, registration of OEW changes | | Data |

## Table A2. Incorporating the second-order effects into the TIM

| Effect category | Second-order effect | Representative variable | Required data | Correction factor aggregation | Main challenges |
|---|---|---|---|---|---|
| **Technology** | **Retrofits** | Presence of winglets/ sharklets | Global data on aircraft information (age/engine type/sharklets or winglets/OEW)<br>Ideal: by tail number, but fleet averages by airline/aircraft can be adopted | Correction factor by airline/aircraft type | Data at the global scale (winglets/ sharklets by aircraft/airline) |
| | **Fleet rollover** | Aircraft age | Global data on aircraft information (age/engine type/sharklets or winglets/OEW)<br>Ideal: by tail number, but fleet averages by airline/aircraft can be adopted | Correction factor by airline/aircraft type | • Extrapolate from the empirical model to the airline/aircraft type level<br>• Tail number not available for future flights. If there is a lot of variation within an airline, airline/aircraft averages may be inaccurate. |
| | **Engine selection** | Engine type | Global data on aircraft information (age/engine type/sharklets or winglets/OEW)<br>Ideal: by tail number, but fleet averages by airline/aircraft can be adopted | Correction factor by airline/aircraft type | Data at the global scale (engine type by aircraft/airline) |
| | **OEW** | OEW | Global data on aircraft information (age/engine type/sharklets or winglets/OEW)<br>Ideal: by tail number, but fleet averages by airline/aircraft can be adopted | Correction factor by airline/aircraft type | Needs proprietary data (OEW) at the global scale |
| **Operation** | **Airport elevation** | Airport elevation | Global data on airport altitudes | Correction factor by airport | Model integration |
| | **Payload** | Payload (passengers + baggage + cargo) | Global data on payload<br>Ideal: at flight level, but fleet averages by airline/aircraft can be adopted. Also, ideally cargo + passenger load would be considered, but passenger data can be used as a proxy if cargo data is not available. Seasonal variance should be analyzed. | Correction factor by airline/aircraft type | Data at the global scale, especially including cargo information; unsure how frequently this analysis would need to be updated. |
| | **Taxiing** | Taxi time | Global data taxi times per airport (EU from EEA, U.S. from FAA) | Correction factor by airport | Model integration |
| | **Real distance flown** | Distance flown/GCD | Global data on actual distance flown (at flight level) | Correction factor by route | Fallback options for the routes not captured by the ADS-B data need to be defined; unsure how frequently this analysis needs to be updated. |
| | **ATM** | Impact on several variables (distance flown, cruise speed, take off/ landing procedures, taxi times, etc.) and is impacted by others (winds, weather, etc.) | Global data on flight trajectories | Correction factor by route | Fallback options for the routes not captured by the ADS-B data need to be defined; unsure how frequently this analysis needs to be updated. |
| | **Winds** | Wind speed and direction | Global data on flight trajectories | Correction factor by route | Fallback options for the routes not captured by the ADS-B data need to be defined; unsure how frequently this analysis needs to be updated. |
| | **Weather** | Occurrence of adverse weather in the airport region or along the route; special attention to convective weather | Global data on flight trajectories | Correction factor by route | Fallback options for the routes not captured by the ADS-B data need to be defined; unsure how frequently this analysis needs to be updated. |
| | **Speed** | Cruise speed | Global data on cruise speeds<br>Ideal: at flight level (ADS-B data) | Correction factor by route | Fallback options for the routes not captured by the ADS-B data need to be defined; unsure how frequently this analysis needs to be updated. |
| | **Fuel loading practices** | Initial and final fuel of a flight | Airline data on fuel loading practices | Correction factor by airline/route | Needs proprietary data on fuel loading practices at global scale |
| | **Maintenance** | Maintenance frequency | Airline data on maintenance | Correction factor by airline/aircraft type | Needs proprietary data |

## Table A3. Qualitative assessment of second-order effects

| Effect category | Second-order effect | Representative variable | Qualitative analysis on impact (0, +1): Likely impact on cruise fuel burn | Likely impact on LTO fuel burn | Likely variance across airlines | Qualitative analysis on data (-1, 0, +1): Availability of input data to estimate the impact | Need for a new license | Availability of data for the TIM application (future flights) | Availability of validation data | Total score |
|---|---|---|---|---|---|---|---|---|---|---|
| Technology | **Retrofits** | Presence of winglets/ sharklets | 1 | 0 | 1 | 1 | 1 | 1 | 0 | **5** |
| | **Fleet rollover** | Aircraft age | 1 | 1 | 1 | 0 | 0 | 0 | 0 | **3** |
| | **Engine selection** | Engine type | 1 | 1 | 1 | 1 | -1 | 0 | 0 | **3** |
| | **OEW** | OEW | 1 | 1 | 1 | -1 | 0 | -1 | -1 | **0** |
| Operation | **Airport elevation** | Airport elevation | 0 | 1 | 0 | 1 | 1 | 1 | 0 | **4** |
| | **Payload** | Payload (passengers + baggage + cargo) | 1 | 1 | 1 | 0 | 0 | 0 | 0 | **3** |
| | **Taxiing** | Taxi time | 0 | 1 | 0 | 1 | 1 | 0 | 0 | **3** |
| | **Real distance flown** | Distance flown/ GCD | 1 | 0 | 0 | 1 | 0 | 0 | 0 | **2** |
| | **ATM** | Impact on several variables (distance flown, cruise speed, take off/landing procedures, taxi times, etc.) and is impacted by others (winds, weather, etc.) | 1 | 1 | 0 | 0 | 0 | 0 | 0 | **2** |
| | **Winds** | Wind speed and direction | 1 | 1 | 0 | 0 | 0 | 0 | 0 | **2** |
| | **Weather** | Occurrence of adverse weather in the airport region or along the route; special attention to convective weather | 1 | 1 | 0 | 0 | 0 | 0 | 0 | **2** |
| | **Speed** | Cruise speed | 1 | 0 | 1 | 0 | -1 | 0 | 0 | **1** |
| | **Fuel loading practices** | Initial and final fuel of a flight | 1 | 1 | 1 | -1 | -1 | -1 | -1 | **-1** |
| | **Maintenance** | Maintenance frequency | 1 | 0 | 1 | -1 | -1 | -1 | -1 | **-2** |