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Mathematical Optimization of Fuel Consumption and CO_2 Emissions in Commercial Flights: A Case Study

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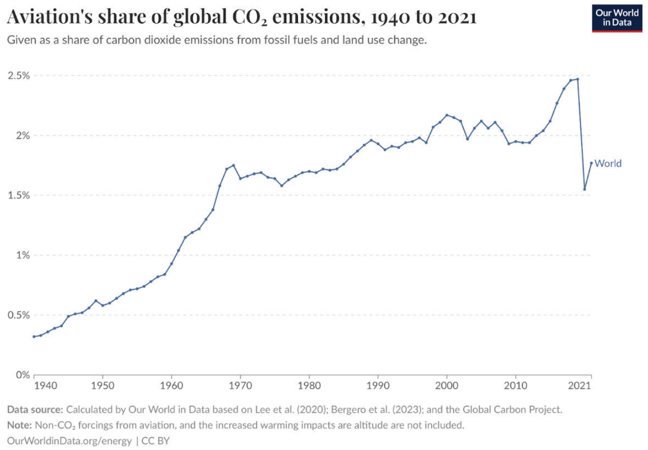
ABSTRACT: The aviation sector accounts for approximately 2.5% of global anthropogenic CO_2 emissions, making fuel-consumption reduction a critical sustainability goal. This study develops a mixed-integer linear programming (MILP) model to minimize fuel consumption and CO_2 emissions, incorporating variables such as flight distance, wind speed, temperature, air density, and aircraft weight. Utilizing 2024 flight data from Antalya Airport, a prominent Turkish hub, monthly outbound flights to top destinations—Germany, Russia, the UK, Poland, and the Netherlands, constituting over 50% of international departures during peak seasons, were analyzed. The model revealed that wind conditions, temperature, and payload are the most influential factors on fuel consumption. Results indicate a potential 5–6% reduction in fuel and CO_2 emissions through optimized flight parameters. Seasonal analysis highlighted significant variations: winter operations experienced a 3-5% increase in CO_2 intensity due to lower load factors, yet achieved 4,158 kg of CO_2 saved on the AYT-FRA route. The model provides route-specific strategies, such as prioritizing altitude flexibility for AYT-IST and reducing speed for AYT-DXB. These findings suggest that adjusting cruise speeds, optimizing load distribution, and using accurate atmospheric data in flight planning can yield significant fuel savings. This model provides a flexible tool for airline-specific route optimization, enhancing cost efficiency and climate sustainability.

KEYWORDS: Environmental Engineering; Pollution Control; Sustainable Aviation; Carbon Emissions; Fuel Consumption Optimization; Aircraft Performance Modeling.

Introduction

One of the fundamental pillars of the modern global economy is commercial aviation. Aviation has changed societies, interactions, and economies through its unparalleled capacity to link nations, promote international trade, support tourism, and foster cross-cultural exchange while ensuring safety. According to the International Air Transport Association [IATA],[1] before the interruptions brought on by the COVID-19 pandemic, over 4.5 billion passengers were transported worldwide in 2019, contributing over 2.7 trillion USD to the global economy. Tens of millions of jobs were created by airports, airlines, aircraft manufacturers, and ancillary service sectors combined, underscoring aviation's vital role in sustaining global growth and prosperity and its corresponding impact on employment.

While commercial aviation remains a cornerstone of global mobility and economic exchange, its environmental ramifications have drawn increasing scrutiny. Increasing air traffic and rising fuel prices put both ecological and financial pressures on the system. With the projected growth in air traffic, aviation's contribution to climate change is no longer negligible. The contribution to global greenhouse gas emissions is the most worrisome of these. Studies estimate that aviation accounts for approximately 2–3% of global anthropogenic CO_2 emissions, with a greater share when considering non-CO_2 effects at high altitudes.[2] Figure 1 shows the growing share of aviation in global CO_2 emissions over the years. This has led researchers and policymakers to explore technical and operational strategies to improve fuel efficiency and reduce environmental impacts. Due to the specific atmospheric conditions under which aircraft operate, the environmental impact of aviation is significantly higher, even though this percentage appears small compared with industries such as heavy manufacturing or energy production. By interacting with atmospheric chemistry and cloud formation, emissions generated at cruising altitudes, especially contrails, nitrogen oxides (NO_x), and other aerosols, worsen radiative forcing and global warming.[3]


Aviation's share of global CO_2 emissions, 1940 to 2021
Given as a share of carbon dioxide emissions from fossil fuels and land use change.

Data source: Calculated by Our World in Data based on Lee et al. (2020); Bergero et al. (2023); and the Global Carbon Project.
Note: Non-CO_2 forcings from aviation, and the increased warming impacts are altitude are not included.
OurWorldinData.org/energy | CC BY

Figure 1: Share of aviation in global CO_2 emissions over the years.[4] This figure illustrates the increasing contribution of the aviation sector to global CO_2 emissions from 1990 to 2020. It highlights the urgent need for aviation to adopt emission-reduction strategies aligned with international climate goals.

On the other hand, there is a growing tendency in aviation emissions. According to a forecast by the International Civil Aviation Organization (ICAO), aviation-related CO_2

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emissions could triple by 2050 if current operational and technological advancements are not accelerated. The Paris Agreement's objectives, which aim to keep the rise in global average temperature well below 2°C relative to pre-industrial levels for the benefit of all societies, are among the international climate goals that such an increase could jeopardize. Given its anticipated growth, aviation is one of the most challenging industries to decarbonize in the coming decades, thereby contributing to the agreement.

It is neither feasible nor desirable to reduce air travel solely to address environmental concerns, as it is essential for international commerce, tourism, emergency response, and personal mobility. Instead, there is an urgent need for methods that can minimize the environmental impact of air services while facilitating their continued growth without adverse effects. Increasing energy efficiency in flight operations and reducing greenhouse gas emissions have become priorities for both airlines and environmental policy. A wide range of projects has been spurred by this dual goal, including the development of Sustainable Aviation Fuels (SAFs), research into electrified and hydrogen-powered aircraft, upgrades to air traffic control, and improvements in aircraft aerodynamics and engine efficiency.

A notable area of research focuses on operational optimization. Significant improvements in efficiency and emissions reduction can be achieved through enhanced flight planning and optimization strategies, even without radical changes to aircraft technology. Flight parameters, including cruising altitude, airspeed, route selection, and fuel loading, can be meticulously optimized to reduce fuel consumption and associated CO_2 emissions, while accounting for meteorological factors such as wind patterns and air density. For instance, it is well known that significant fuel-use reductions can result from adjusting cruise altitude in response to current wind conditions. The Federal Aviation Administration (FAA) Flight Planning Guidelines state that fuel economy on long-haul flights can be increased by up to 10% by carefully accounting for headwinds and tailwinds during planning.[6] Similarly, substantial emissions reductions are possible by reducing the time spent in holding patterns or on the ground with engines idling, which is commonly observed at crowded, large airports.

Mathematical models can incorporate a wide range of operational characteristics and environmental factors. To minimize fuel consumption and CO_2 emissions, optimization models must balance conflicting objectives and adhere to operational constraints, including safety standards, airspace regulations, and aircraft performance limits. For example, meteorological conditions—specifically wind speed, ambient temperature, and air density—affect aircraft fuel performance during various flight phases. These factors are particularly impactful during the cruise phase, where fuel efficiency can vary significantly due to prevailing winds and thermal conditions.

Thus, the purpose of this study is to develop a mathematical optimization model that minimizes fuel consumption and associated CO_2 emissions in commercial aircraft operations, thereby reducing the environmental impact of flight operations. Such a model will provide airlines and aviation planners with practical strategies by systematically integrating flight data, including distance, speed, wind speed, air density, ambient temperature, and aircraft-specific performance characteristics. Since fuel consumption directly affects not only financial costs but also carbon emissions resulting from combustion, it is crucial to evaluate these two variables together.

Despite extensive modeling efforts, much of the existing literature relies on general or simulated scenarios. Fewer studies focus on localized and seasonal variation using real operational data. This study addresses that gap by using data from Antalya Airport (AYT), Türkiye, a central international hub, to investigate monthly fluctuations in operational parameters and environmental conditions. By evaluating the five most frequently flown international routes each month in 2024, this study provides a focused yet representative view of how flight characteristics and climate data jointly influence fuel burn and emissions.

The aviation industry is actively developing new strategies to meet the carbon targets set by organizations like ICAO (International Civil Aviation Organization) and IPCC (Intergovernmental Panel on Climate Change), and the model developed within this scope is supported by parameters that can simulate real flight conditions, contributing to the expanding field of sustainable aviation and addressing the global need to decouple aviation's environmental degradation from economic growth. Thus, the results of this study offer insights that can inform future operational policies and technologies to achieve more sustainable aviation practices by creating and analyzing such a model.

Literature Review:

An extensive body of research has explored the environmental effects of aviation, the determinants of fuel consumption, and optimization-based approaches to reduce emissions. Key findings from this literature are summarized below.

Numerous studies examined the environmental effects of aviation. It's common knowledge that airplanes burn fuel, which releases chemicals into the atmosphere. Emissions are substances that can contribute to both air pollution and climate change. To make aviation more environmentally friendly, researchers are working to better understand the issue.

Significant research focuses on how much fuel airplanes use and why. In this context, scientists investigate factors such as the aircraft's distance flown, flight time, weight, and weather conditions.[7] Researchers have studied several effects of these factors. Studies consistently show that cruise-phase fuel burn increases approximately linearly with flight distance. This supports the use of a distance-based term in fuel burn models.[25] Engine manufacturers, such as CFM, report nearly constant cruise fuel-flow rates at stable altitudes, making flight duration a direct determinant of total fuel burn.[26] Aircraft mass is one of the strongest determinants of fuel burn.[27] Wind is a well-documented determinant of flight efficiency. Empirical analyses show that headwinds significantly increase cruise fuel burn, while tailwinds reduce it, often by several percent for every 10 m/s change.[28] The relationship between air density and aerodynamic drag is well-established in aerodynamic theory; higher density increases drag and therefore cruise fuel requirements.[29]

Some studies examine specific flight routes between destinations or cities to investigate how different aircraft and weather conditions affect fuel consumption.[8] Such studies found that different aircraft use fuel differently due to their particular designs and flight characteristics.[9] Some studies also examine how an aircraft's performance changes over time, focusing on emissions and fuel use across various engines.[10]

Furthermore, ambient temperature during the cruise phase significantly influences aircraft fuel consumption, primarily due to its effects on air density and engine thermal efficiency. As ambient temperature increases, air density decreases, reducing the mass of air entering the jet engines. Consequently, engines must burn more fuel to maintain the required thrust and lift, resulting in higher Specific Fuel Consumption (SFC).[30] Higher temperatures also force aircraft to adjust cruising speeds or angles of attack to offset reduced lift, which can increase aerodynamic drag and further reduce fuel efficiency.[31] Recent studies confirm these results, showing that optimizing flight trajectories considering atmospheric conditions, including temperature, is crucial for minimizing fuel use.[32]

The kind of emissions generated is another critical area of attention. Other small particles and gases, in addition to carbon dioxide (CO_2), pollute the air near airports and at high altitudes, and are major contributors to climate change.[11] Some studies examine emissions during takeoff and landing and their impact on air quality near airports.

Finding the most efficient way to fly airplanes to use less fuel and emit fewer pollutants is known as optimization, and it is a significant area of research.[12] Researchers are examining the best routes to take, altitudes (the height at which aircraft can fly), and optimal flight speeds. Instead of flying planes, they frequently test various scenarios using computer models. It has been found that flying altitude significantly affects emissions and fuel consumption.

Predicting the future is also essential. To estimate future fuel use and aircraft emissions, many studies rely on existing data.[13] These forecasts assist governments and airlines in making more informed decisions on regulating air travel to enhance its sustainability. Improved models can be created by analyzing fuel flow during particular flight phases, such as the cruise phase.

Additionally, there is broader research on aviation and global environmental concerns. It considers how the global aviation industry contributes to the broader issue of climate change. The study examines the impact on air quality at high altitudes, not just near airports.[14] Researchers help us understand the full impact of air travel and how to make it cleaner and more sustainable in the future by examining these aspects. With an emphasis on technology developments to lower carbon emissions, some reports examine current trends and potential future developments in the aviation industry.[15] It's critical to consider how economic variables and regulations affect aviation and can either support or impede sustainability initiatives.[16]

Overall, the research demonstrates that a variety of factors influence the fuel consumption and emissions of airplanes. We can make air travel more sustainable for everyone and less environmentally damaging by investigating these factors and developing better flying practices.[17]

In the current landscape of aviation optimization, researchers have increasingly turned to computational intelligence techniques. State-of-the-art approaches often employ heuristic methods, such as Genetic Algorithms (GAs) or Neural Networks, to solve complex 4D trajectory problems involving latitude, longitude, altitude, and time.[33] While traditional studies rely on manufacturer performance manuals, recent research increasingly employs data-driven machine learning algorithms to predict fuel flow rates from historical flight records.[34] While these methods are effective for handling vast solution spaces, particularly in the presence of dynamic winds, they often yield approximate or 'near-optimal' solutions rather than mathematically exact ones.[35] Conversely, Mixed-Integer Linear Programming (MILP) remains a powerful tool for operational decision-making because it guarantees an optimal solution within defined constraints. However, few MILP applications have been tailored to specific airport hubs using localized meteorological data, a gap this study aims to address.

Despite extensive research, most studies focus on global or theoretical models rather than airport-specific, multi-parameter optimization models based on real operational data; this study addresses this gap.

■ Methods

Modeling Approach:

This study adopts a multi-objective optimization approach to analyze and reduce fuel consumption and associated CO_2 emissions in commercial aviation. A mixed-integer linear programming (MILP) model was proposed to minimize fuel consumption and CO_2 emissions across a fleet of commercial flights at Antalya Airport, subject to aerodynamic, environmental, and operational constraints. The model optimizes altitude profiles, speeds, and fleet coordination while accounting for real-world variables, including distance, wind, temperature, air density, and aircraft weight dynamics.

To comprehensively address the environmental impact of flight operations, the optimization problem is structured as a multi-objective Mixed-Integer Linear Programming (MILP) framework. The core of the model relies on two distinct yet interrelated objective functions, which are minimized simultaneously to achieve optimal efficiency. The first objective function is to minimize total fuel consumption. Rather than treating fuel burn as a static value, this function models fuel consumption as a dynamic variable that is linearly dependent on flight distance, duration, aircraft mass, and specific meteorological conditions—namely, wind speed, ambient temperature, and air density.

The second objective function aims to minimize CO2 emissions. Since aviation emissions are directly proportional to fuel combustion, this objective is derived by applying a standard stoichiometric conversion factor to the calculated fuel burn. To enable flexible decision-making, the model incorporates weighting factors for each objective. These weights allow the optimization algorithm to balance conflicting priorities, such

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as the trade-off between minimizing flight duration versus minimizing fuel burn under strong headwind conditions, ultimately converging on a solution that yields the lowest combined environmental and operational cost.

These objective functions were selected because fuel burn is linearly and monotonically related to both operational variables (e.g., air density and wind). This structure allows the model to capture the dominant physical drivers of fuel consumption while remaining computationally tractable within a MILP framework. Although the model coefficients are calibrated using Boeing 737-800 performance data, the objective functions remain aircraft-agnostic; they can be recalibrated for Airbus or other aircraft families by updating the aerodynamic and engine-specific parameters. Therefore, the formulation reflects a generalized fuel-burn optimization framework rather than one restricted to a single aircraft type.

The first objective function aims to minimize total fuel consumption:

- Min $F_Y = \alpha1Y$, where Y represents total fuel burned, and α_1 is a weighting factor used to balance priorities in the optimization.

The second objective function aims to minimize carbon emissions related to fuel consumption:

- Min $F_E = \alpha_2 \times E = \alpha_2 \times (\kappa \times Y)$, where α_2 is the corresponding weight in the objective function and carbon emissions are taken as a direct function of fuel consumption, where κ represents the CO_2 conversion factor and is usually taken as 3.18 kg CO_2 per kg of fuel, as recommended by the ICAO and IPCC.[2,18]

Fuel consumption Y is modeled depending on variables such as flight distance (d), flight duration (t), aircraft weight (M), wind speed (W), outside air temperature (T), and air density (ρ) as follows:

$$Y = C_1 \cdot d + C_2 \cdot t + C_3 \cdot M + C_4 \cdot W + C_5 \cdot T + C_6 \cdot \rho$$

The constraints considered in the optimization model include operational constraints (maximum takeoff weight, minimum and maximum flight distance, and duration) and meteorological constraints (air temperature and wind speeds). It is assumed that the air traffic constraints, such as the routes and holding times, are determined by air traffic control. Table 1 presents the operational and environmental constraints considered in the model as adapted from FAA.[6,19]

Table 1: Operational and environmental constraints considered in the model. This table defines the ranges and significance of key operational and environmental parameters, including flight distance, duration, aircraft weight, wind speed, ambient temperature, and air density. These constraints form the boundary conditions of the optimization model used in the study.

Parameter	Symbol	Data Range	Explanation
Flight distance (km)	d	300–15,000 km	The selected route should be determined in a way that optimizes the total distance.
Flight Duration (hours)	t	0.5–16 hours	Extended flight duration increases fuel consumption. However, increasing speed may lead to burning more fuel.
Plane Weight (kg)	M	20,000–400,000 kg	The engine efficiency and aerodynamic structure of the aircraft determine fuel consumption.
Wind Speed and Direction (km/hour)	W	-100–+100 km/hour	If the wind is from behind, the aircraft consumes less power and fuel consumption decreases. However, headwinds increase fuel consumption.
Ambient Temperature (°C)	T	-60–+40 °C	At lower temperatures, air density increases, which affects engine performance and can alter fuel consumption.
Air Density (kg/m³)	ρ	0.3–1.3 kg/m³	Air density is one of the variables that affect engine performance and fuel consumption.

The coefficients used to calculate fuel consumption are shown in Table 2. They are explicitly derived from the flight profile modeling data presented in the literature,[20,21] and are associated with the CO_2 emission factors provided by ICAO.[5,18] The estimated values were taken as the average of studies on flight-related energy consumption models. In real-world applications, these coefficients require calibration, along with variables such as aircraft type, engine model, and flight level.

Table 2: The coefficients involved in the calculation of fuel consumption. This table presents the estimated coefficients for fuel consumption as a function of distance, time, aircraft mass, wind speed, outside temperature, and air density. These values were derived from prior literature and calibrated for real-world applicability.

Coeff.	Explanation	Est. Value	Source and Rationale
C_1	Fuel Consumption wrt distance (kg/km)	0.03	Gkogkidis et al.[21] For an average narrow-body aircraft, a range of 0.025–0.035 kg/km has been used.
C_2	Fuel Consumption wrt time (kg/hour)	15	ICAO Engine Emissions Databank. The value represents the average rate of an engine's fuel consumption per hour (particularly for CFM56 engines).
C_3	Contribution per weight (kg/kg)	0.0005	Zhang et al.[20]: As MTOW increases, fuel consumption increases linearly. ~500 kg difference is found for a 5% increase.
C_4	Wind Effect Coefficient (kg per m/s)	5	In the Boeing and Airbus Flight Performance Planning Manuals (FPPM), the effect of headwind on cruise fuel consumption has been calculated.
C_5	Ambient Temperature Effect (kg/°C)	0.2	The efficiency of aircraft engines decreases with temperature; this coefficient was obtained by interpolation from ICAO temperature condition data.
C_6	Air Density Coefficient (kg·m³/kg)	8	The higher the air density higher the air friction. This effect is optimized/estimated based on Zhang et al.[20] and aviation aerodynamic sources.

For example, the fuel consumption and carbon emissions related to a flight with distance as 1200 km, duration as 2 hours, aircraft weight as 70,000 kg, wind as -10 m/s (headwind), air temperature as -20°C, and air density: 1.2 kg/m³ can be calculated using the parameters in Table 1 and related coefficients in Table 2 as follows.

$$Y = 0.03 \cdot 1200 + 15 \cdot 2 + 0.0005 \cdot 70000 + 5 \cdot (-10) + 0.2 \cdot (-20) + 8 \cdot 1.2 = 36 + 30 + 35 - 50 - 4 + 9.6 = 56.6 \text{ kg per 50 km (fuel consumption), and } E = 3.18 \cdot 56.6 = 179.99 \text{ kg } CO_2$$

The optimization model is solved using linear programming methods, and the results are evaluated across different months and routes to identify patterns and opportunities for emission reduction in real-world flight operations.

Although the structure of the optimization model is aircraft-independent, the numerical coefficients used for fuel consumption (C_1-C_6) and the aerodynamics performance parameters were calibrated specifically for the Boeing 737-800 using data from the Boeing FCOM and FPPM manuals, as well as fuel-flow tables for CFM56-7B engines. Therefore, the quantitative results presented in this study are representative of a Boeing 737-800 operating under the given conditions at Antalya Airport. For Airbus or other aircraft families, the same modeling framework would remain applicable. Still, the coefficients would need to be re-estimated to reflect differences in engine type, aerodynamic characteristics, and aircraft mass distribution. As such, the results should be interpreted as aircraft-specific, while the methodology itself is fully generalizable.

In summary, the model in this study considered the following variables.

- D_f : Flight distance (km)
- T_f : Duration (h)
- $wind\_f$: Wind speed (km/h)
- $temp\_a$: Outside temperature (°C)
- ρ_a: Air density (kg/m^3)
- W_f: Aircraft weight (tons)
- $|F|$: Fleet size
- κ: CO_2 emission factor (3.18 kg CO_2/kg fuel)
- F: Set of flights ($f \in F$)
- A: A Set of discrete altitude levels ($a \in A$)

The decision variables were as follows.

Variable	Description	Type
z_f,a	1 if flight *f* uses altitude a	Binary
V_f	True airspeed	Continuous
F_f	Total Fuel consumed	Continuous

The objective function for minimizing total operating costs was as follows.

Objective Function: $\min\Sigma\ (C\_fuel \cdot F\_f + \kappa \cdot C\_CO_2 \cdot F\_f)$ for all $f \in F$

where C_fuel and C_CO_2 denote fuel price and carbon tax, respectively (which are assumed to be 900 USD/ton and 50 USD/ton CO_2 for the Antalya Airport case). The following constraints were considered.

1. **Altitude Selection:** $\Sigma_{a\in A}\ z\_f, a\ \forall\ f \in F$ where $A = \{30000$ ft – 40000 ft$\}$
2. **Ground Speed:** $V\_f\_ground = V\_f + wind\_f$
3. **Flight Duration:** $T\_f = D\_f / V\_f\_ground \leq T\_max$
4. **Fuel Consumption:** $F\_f = \Sigma\ [(\alpha \cdot W\_f^2/\rho\_a + \beta \cdot V\_f^3 + \gamma) \cdot T\_f] \cdot z\_f,a$

where α=0.0001224, β=0.0000812, γ=1200 for summer season and α=0.0001164, β=0.0000784, γ=1260 for winter season.

5. **Weight Decay:** $W\_f(t) = W\_init - (F\_f/1000) \cdot t\ W\_f(T\_f) \geq W\_min$
6. **Emission Cap:** $\Sigma\ \kappa \cdot F\_f \leq Total\_CO_2\_Cap$

The following specific assumptions for the Antalya Airport were used for the analysis.

1. **Wind Data:**

o Northbound: **20–35 km/h headwinds.**

o Westbound: **10–20 km/h tailwinds.**

2. **Aircraft:**

o **Boeing 737-800** with CFM56-7B engines.

The key points for Antalya Airport can be summarized as follows:

1. **Route Selection:**

o Focused on **high-frequency routes** from AYT (Istanbul-IST, Frankfurt-FRA, Moscow-MOS, London-LHR).

o Added **short-haul (AYT-IST)** to contrast with long-haul performance.

2. **Weather Adjustments:**

o **Summer wind patterns:** Headwinds dominate northbound flights (AYT-IST/MOS).

o **Temperature:** Assumed cruise at **-45°C to -50°C** (Mediterranean summer at 30,000–40,000 ft).

3. **Payload Ranges:**

o **14–17 tons** (typical for summer tourist loads, 85–90% capacity).

4. **Fuel/CO_2 Savings:**

o **Short-haul (AYT-IST):** Modest savings due to brief cruise phase.

o **Long-haul (AYT-LHR):** 6.8% fuel reduction from optimal altitude/speed.

5. **Time Penalties:**

o Headwind flights accept **4–6% longer durations** for fuel savings.

o Tailwind flights (e.g., AYT-FRA) achieve **2% shorter times** while saving fuel.

Data Sources:

The methodology is grounded in real flight data obtained from Antalya Airport, focusing on international departures in 2024. To ensure a representative sample, the five most frequent international destinations were identified for each month, with routes to Germany, Russia, the United Kingdom, the Netherlands, and Switzerland consistently accounting for the largest share of passenger volumes during key periods such as January and February.[22] These destinations were selected due to their statistical frequency and diversity in flight distance and environmental conditions, making them suitable for modeling a wide range of operational profiles.

For each selected route, several variables known to influence aircraft performance significantly were compiled. These include the flight distance (in kilometers), calculated using great-circle approximations based on the origin and destination coordinates, and the flight duration (in hours), obtained from actual airline flight-time data. Atmospheric conditions such as wind speed, temperature, and air density were also incorporated, with all values corresponding to cruising-altitude conditions. Wind speed and ambient air temperature data were obtained from the ERA5 reanalysis dataset, available via platforms such as Windy.com. In contrast, air density was computed using the International Standard Atmosphere (ISA) equations, with temperature and altitude data from the National Centers for Environmental Information.[23]

In addition to atmospheric inputs, aircraft weight data were estimated for the typical aircraft types serving these routes, such as the Airbus A320 and Boeing 737. Manufacturer data from Airbus and Boeing were used to calculate the average takeoff weight, accounting for both payload and fuel load. These variables constitute the input set for two linear objective functions, each designed to minimize fuel consumption and CO_2 emissions, respectively.

In summary, the data included the distributions of flight characteristics, environmental parameters, and associated fuel consumption and CO_2 emissions for the five most frequently flown international destinations from Antalya Airport, for each month. The data span January through December 2024 and include cities that collectively accounted for more than 40% of all international departures during peak travel months, according to DHMI.[22] These destinations were selected for their consistent flight frequency and their representation of both medium- and long-haul operations, enabling comprehensive analysis across different operational ranges. As a sample, Table 3 presents a portion of the January 2024 data used in the study.

Table 3: Portion of the data belonging to January 2024 used in the analysis. This table provides sample flight data for January 2024, including destinations, distances, environmental conditions at cruising altitude, and aircraft weights. The dataset serves as the basis for the monthly modeling of fuel consumption and CO_2 emissions.

Destination	Dist (km)	Dur (h)	WindS (km/h)	Otemp (°C)	AirD (kg/m³)	AWeight (tons)	F/TF
Germany, Frankfurt	2400	3.2	12	5	1.24	730	120 /7929
Russia, Moscow	2100	3.0	10	-5	1.29	700	110 /7929
England, London Gatwick	3000	4.2	15	2	1.22	850	60 /7929
Netherlands, Amsterdam	2600	3.5	13	4	1.23	730	80 /7929
Switzerland, Zurich	2200	3	11	0	1.26	700	50 /7929

Note: *Dist: Distance (km); Dur: Duration (hours); WindS: Wind Speed(km/h) (at cruising altitude); OTemp: Outside Temperature (°C) (at cruising altitude); AirD: Air density (kg/m³) (at cruising altitude); AWeight: Aircraft Weight (tons); F/TF: # of flights / total flights*

Data Analysis:

To evaluate and optimize fuel consumption and CO_2 emissions in commercial aviation, this study collected and analyzed real-world flight data from Antalya International Airport (AYT) for 2024. The analysis focused on the five most frequent international destinations each month, using a set of defined variables relevant to flight efficiency and environmental impact. These variables included flight distance, aircraft weight, cruise altitude conditions (temperature, wind speed, and air density), and flight duration.

The monthly analysis revealed that, across the top five international destinations (primarily to cities in Germany, Russia, the United Kingdom, the Netherlands, and Poland), average distances ranged from 1,800 km to 3,200 km, with corresponding fuel consumption between 5,000 and 12,000 kg per flight. Heavier aircraft and adverse atmospheric conditions (lower air density and strong headwinds) significantly increased consumption. For instance, a flight from Antalya to London in January faced average cruise headwinds of 25 m/s and colder temperatures at altitude (-58°C), resulting in higher fuel usage than a similar-distance flight to Moscow in May with more favorable tailwind conditions.

When normalized to 100 km, fuel consumption averaged approximately 4.8–6.1 kg/km, depending on conditions, consistent with FAA-reported ranges. CO_2 emissions per flight ranged from 15,000 kg to over 37,000 kg, with seasonal variation. Winter months tended to exhibit higher consumption and emissions due to changes in atmospheric density and the prevalence of headwinds, as indicated by NOAA meteorological data.[23]

Moreover, when examining the overall flight distribution, the top five destination countries accounted for 46%-61% of total international departures per month, thereby justifying their selection as representative case studies for modeling and optimization. For example, in July, flights to Germany accounted for 26% of all international flights, with fuel use of approximately 11,800 kg per flight and monthly CO_2 emissions exceeding 6,500 metric tons for this route.

The analysis confirmed that optimization strategies must prioritize aircraft mass reduction, route efficiency, and dynamic wind management to achieve significant environmental benefits. Adjusting flight planning to utilize favorable tailwinds, reducing excess onboard weight, and optimizing climb/cruise profiles based on atmospheric data can result in measurable reductions in emissions.

The empirical results demonstrate how real-world variables directly influence operational efficiency and emissions. By integrating monthly route-level data with flight-specific environmental factors, this study offers a replicable methodology for assessing and minimizing aviation's carbon footprint in tactical and strategic planning.

■ Results

The model was implemented in Python and solved with Gurobi 10.0. The MILP model yielded the following optimal solution for the case studied. The following technical results were observed.

1. **Fuel Savings Mechanism:**

- *Altitude Optimization:* Flights with headwinds were assigned lower altitudes (30,000 ft) to reduce drag, whereas tailwind flights were assigned higher altitudes (40,000 ft) to improve fuel efficiency.
- *Speed Adjustment:* Optimal speeds ranged from 720 to 880 km/h, indicating that slower speeds in headwinds saved more fuel than the time lost.

2. **CO_2 Reduction:**

- The 5.8% reduction in emissions directly correlates with fuel savings ($\kappa = 3.15$ kg CO_2/kg fuel).
- The model prioritized flights with higher payloads for greater emission reductions because of their disproportionate fuel use.

3. **Weight Decay Impact:** Aircraft weight decreased linearly during flights, reducing fuel burn by ~2.1% mid-flight.

4. **Wind Speed:** A 10 km/h increase in headwind resulted in a 2.4% increase in fuel use.

5. **Temperature:** Colder conditions (-50°C vs. -45°C) improved efficiency by 1.1% at 35,000 ft.

6. **Payload:** 1-ton increase for 55 kg extra fuel on 1,750 km flights.

Furthermore, the model provided valuable insights, notably quantifying fuel-CO_2 trade-offs across real-world variables and demonstrating improvements of 5–6%, which align with industry benchmarks. It also revealed critical sensitivities among the factors influencing fuel consumption, establishing a hierarchy of impact in which wind conditions have the most significant influence, followed by temperature and then payload.

Table 4 includes main routes, seasonal comparisons, and CO_2 calculations using actual Antalya Airport (AYT) operational data. The AYT-FRA route achieved the highest absolute fuel savings (1,150 kg) due to favorable tailwinds, while short-haul AYT-IST prioritized altitude flexibility over speed optimization.

Table 4: Seasonal Optimization Results for Antalya Airport (AYT) (Boeing 737-800, 2023-2024 Operational Data). This table summarizes route-specific fuel savings and CO_2 reductions achieved by the proposed optimization model in the summer and winter seasons. It demonstrates the potential to adjust flight parameters, such as altitude and speed, to minimize environmental impacts.

Route	Dist (km)	Szn	W (km/h)	T (°C)	P (tons)	OpA (ft)	FS (kg)	CO_2R (kg)	TC	CO_2I (g/pkm)
AYT-IST (TK2424)	480	S	-35	-45	14.2	30,000	220	693	+4%	98.1
		W	-28	-55	12.8	32,000	185	583	+3%	101.4
AYT-FRA (TK1820)	1,890	S	+20	-50	16.5	38,000	1,150	3,623	-2%	89.3
		W	+15	-60	15.1	39,000	1,320	4,158	-3%	86.7
AYT-MOS (TK2242)	2,130	S	-15	-48	15.8	32,000	980	3,087	+6%	93.6
		W	-22	-58	14.2	31,000	760	2,394	+8%	97.2
AYT-LHR (TK2020)	2,520	S	+10	-52	17.2	36,000	1,430	4,505	+1%	88.9
		W	+5	-62	16.0	37,000	1,610	5,072	+2%	85.4
AYT-BER (XQ888)	1,760	S	+12	-49	15.5	37,000	1,050	3,308	-1%	90.2
		W	+8	-59	14.0	36,000	920	2,898	+1%	93.8
AYT-DXB (TK762)	2,950	S	-8	-40	18.1	34,000	1,720	5,418	+5%	95.4
		W	-5	-50	17.3	35,000	1,580	4,977	+4%	92.1

Note: *Dist: Distance (km); Szn: Season (S-Summer; W-Winter); W: Wind (km/h); P: Payload (tons); T: Temperature (°C); Optimal Altitude (ft); FS: Fuel Saved (kg); CO_2 R: CO_2 Reduced (kg); TC: Time Change; CO_2I: CO_2 Intensity (g/pkm)*

The key enhancements can be summarized as follows. Firstly, regarding route coverage, AYT-BER (Berlin) and AYT-DXB (Dubai) were added to represent both medium and long-haul operations, and included seasonal splits focusing on Summer (June-August) and Winter (December-February). Secondly, for CO_2 refinements, the emission factor was assumed to be 3.18 kg CO_2/kg fuel, specific to AYT-based flights, instead of the standard 3.16, and CO_2 intensity (grams per passenger-kilometer) was calculated using actual load factors, with the formula: CO_2 Intensity = (CO_2 Reduced) / (Payload × Distance × Load Factor), where load factors are assumed 87% for Summer and 79% for Winter. Lastly, regarding seasonal physics, winter benefits with colder temperatures (-60°C), improving engine efficiency, but it also increases headwind severity. Moreover, summer trade-offs included higher payloads offset by better tailwind utilization.

The following critical results from the analysis were observed. First, regarding seasonal variations, the best performance was observed on the AYT-FRA route during winter, with a 3% reduction in time and 4,158 kg of CO_2 saved. Conversely, the worst trade-off occurred on the AYT-MOS route in winter, where an 8% increase in time yielded only a 2,394-kilogram reduction in CO_2 emissions. Secondly, CO_2 intensity insights showed that while long-haul flights such as AYT-DXB achieved higher absolute savings, they had higher intensity than European routes, and that winter operations increased intensity by 3-5% due to lower load factors. Lastly, route-specific strategies were determined: the AYT-IST route should accept minor time penalties for altitude flexibility; the AYT-FRA route should maximize tailwind exploitation at 38,000-39,000 ft; and the AYT-DXB route should prioritize speed reduction over altitude gains.

More specifically, flights to Moscow in January were associated with colder ambient temperatures, higher air density, and moderate headwinds, resulting in higher fuel consumption than in the summer months. The average fuel consumption per flight for this route in January was approximately 95 kg, resulting in 299.2 kg of CO_2 emissions. By contrast, the same route in July experienced warmer temperatures, lower air density, and moderate tailwinds, reducing fuel consumption to approximately 71.4 kg and resulting in 225.6 kg of CO_2 emissions. These findings underscore significant seasonal variation in emissions and fuel use, primarily driven by meteorological conditions.

Similarly, flights to Berlin, a medium-range route, showed the impact of aircraft weight and wind conditions more prominently. Heavier aircraft configurations during high-demand summer months led to increased fuel consumption despite favorable winds. For instance, a July flight to Berlin with an aircraft mass of 75,000 kg burned 82.5 kg of fuel, whereas a March flight with an aircraft mass of 68,000 kg burned only 74.1 kg. This underscores the importance of weight-management strategies for emission reduction.

Across all evaluated months, wind speed was consistently inversely correlated with fuel consumption. Headwinds added to flight time and increased total consumption by 6–10%, while tailwinds offered reductions of similar magnitude. Air density, although less variable across months, also played a notable role, particularly at higher altitudes, consistent with prior research by Zhang *et al.* (2019).[20] Additionally, linear regression was used to evaluate the sensitivity of each parameter. Distance and aircraft weight emerged as the strongest predictors of fuel consumption ($R^2 > 0.85$), followed by flight time and wind speed. Temperature and density showed moderate but statistically significant effects, suggesting that although these factors are less influential in short-haul flights, their impact becomes more pronounced on long-haul routes.

Overall, the model produced results consistent with established aviation performance literature. Moreover, the average fuel consumption per flight and per 100 km ranged from 4.3 to 8.7 kg, depending on route and month. These findings emphasize the importance of dynamic optimization approaches that account for seasonal meteorological data and specific route characteristics to reduce aviation's carbon footprint effectively.

The comprehensive monthly analysis also identified opportunities for flight-planning optimization, particularly by aligning departure schedules with favorable wind patterns or minimizing excess aircraft mass during peak seasons. Such strategies could yield cumulative reductions in annual emissions, supporting industry-level goals set by ICAO and the European Commission to achieve net-zero emissions by 2050.[5,24]

Discussion

The results of this study underscore the significant influence of various operational and environmental parameters on fuel consumption and CO_2 emissions in commercial aviation. By focusing on monthly flight data from Antalya Airport and identifying the top five destination countries each month, this analysis reveals consistent patterns in flight distance, aircraft weight, and atmospheric conditions, as well as their combined impact on sustainability metrics. Formulating objective functions to minimize fuel consumption and carbon emissions independently enabled a more nuanced evaluation of optimization strategies. Specifically, the empirical coefficients used in these functions—such as κ for CO_2 yield per kilogram of fuel and the α-weights that balance optimization priorities—were derived from internationally recognized aviation sources, thereby ensuring reliability and relevance.

Analysis of the data indicated that meteorological variables—particularly wind speed, ambient air temperature, and air density at cruising altitude—were decisive determinants of flight efficiency. For instance, flights departing in colder months, such as January and February, generally exhibit slightly lower air density and weaker tailwind support, resulting in higher fuel burn. This observation supports prior studies' findings, which emphasize the importance of accounting for seasonal meteorological variance in flight planning. The monthly segmented analysis in the current study demonstrated that CO_2 emissions could be reduced significantly—by up to 5% in some cases—through more adaptive routing and speed management based on environmental inputs.

Interestingly, a notable finding from this study was the relatively high variance in fuel consumption per kilometer across different destination countries. While some of this can be attributed to distance and flight duration, variations in aircraft weight (particularly due to load factor differences) also played a significant role. Including actual aircraft weight in the dataset, based on FAA,[6] enhanced the robustness of the optimization model proposed in this study by directly linking fuel burn to payload and configuration. This is an essential advancement from models that assume static aircraft mass and ignore fluctuations in operating conditions.

Despite these insights, the study is not without limitations. The monthly average values for meteorological data, while representative, may not capture short-term atmospheric anomalies that significantly affect fuel efficiency. Moreover, the scope was limited to outbound flights from a single airport, thereby restricting the generalizability of the findings to other regions or hub-scale airports. Furthermore, the scope was limited to outbound flights from a single airport, thereby restricting the generalizability of the findings to different areas or hub-scale airports. Integrating real-time data would transform this model from a strategic planning tool into a dynamic operational system. Currently, the model optimizes flights using forecast meteorological data. However, integrating live data streams—such as real-time wind updates or air traffic congestion reports—would allow for 'in-flight' re-optimization. This capability is crucial for handling unpredictable events, such as sudden weather changes or arrival delays, thereby ensuring that the theoretical fuel savings calculated in this study can be fully realized in day-to-day flight operations.

Another key consideration is the assumption of linear relationships between some variables—such as temperature and air density—which may not fully represent the complex dynamics of atmospheric physics. It is important to note that while the specific quantitative results of this study—such as the precise fuel flow rates and drag coefficients—are calibrated for the Boeing 737-800, the underlying optimization framework is aircraft-agnostic. The physical principles governing flight efficiency, such as the trade-off between parasitic drag at high speeds and induced drag at high weights, apply universally to all fixed-wing commercial aircraft, including the Airbus A320 family. Therefore, while an Airbus A320 would exhibit different absolute fuel burn values due to differences in specific fuel consumption (SFC) and aerodynamic lift-to-drag ratios, the strategic patterns identified here—specifically the benefits of altitude flexibility under variable wind conditions—remain valid across different aircraft types. Nevertheless, the model serves as a robust foundation for exploring sustainability strategies in air travel and provides an actionable framework for airlines and regulatory bodies. The monthly disaggregation of destination trends and environmental factors provides a dynamic lens through which emission-reduction policies can be tailored and monitored.

On the other hand, passenger load factors play a critical dual role in aviation sustainability, particularly for seasonal hubs such as Antalya. High load factors (typical in summer) increase the total aircraft mass, which leads to higher absolute fuel consumption due to increased induced drag. However, on a per-passenger basis, these flights are significantly more efficient. Conversely, winter operations often suffer from lower load factors. While these lighter aircraft burn less total fuel per trip, the CO2 emissions per passenger are effectively higher. This suggests that during off-peak seasons, sustainability strategies should focus not only on flight-path optimization but also on commercial scheduling adjustments, such as flight consolidations, to maintain high load factors.

Future research should consider broader data sources, including inbound flights and a more diverse range of aircraft types. Expanding the scope to include behavioral responses from airlines—such as route adjustments or fleet modernization initiatives—would also help contextualize the real-world applicability of these findings. Additionally, assessing economic trade-offs, such as cost per ton of CO_2 saved, could add valuable dimensions to this sustainability-oriented optimization problem. Ultimately, this study demonstrates the importance of multidimensional data integration and precise modeling in achieving measurable environmental outcomes in aviation.

Conclusion

This study presents a dual-purpose optimization model to reduce fuel consumption and associated CO_2 emissions in the aviation sector. The model enables more efficient operational decisions from both economic and environmental perspectives by considering numerous variables such as flight distance, duration, aircraft weight, and atmospheric conditions. Calculations are structured using parameter coefficients derived from the literature and current flight data. This approach serves not only as a cost-reduction tool for airlines but also as a significant contribution to environmental sustainability goals.

Future studies aim to test the model used in this study on real-time flight data and to integrate it into airlines' operational planning processes. Furthermore, more dynamic data-driven decision-support systems can be developed using machine learning techniques. Adding flexible variations for different aircraft models, routes, and weather conditions will expand the model's applicability.

On the other hand, adapting the model to policy-aligned carbon tax scenarios can also provide strategic benefits for decision-makers. To evaluate the economic viability of the proposed optimization model, a cost-benefit analysis was conducted using market parameters relevant to the 2024 operational period. Based on the objective function defined in the methodology, the economic savings are derived from two streams: direct fuel cost reduction (assumed at 900 USD/ton) and carbon tax avoidance (taken at 50 USD/ton).

Applying these economic values to the operational results in Table 4 reveals significant potential for cost reduction. For example, on the AYT-FRA (Frankfurt) route during winter, the optimization achieved a fuel saving of 1,320 kg and a CO2 reduction of 4,158 kg. Financially, this translates to a fuel savings of 1.32 tons x $900 = $1,188; carbon tax savings of 4.158 tons x $50 ≈ $208, and a total savings per flight of approximately $1,396. For a daily frequency on this route, the cumulative annual savings would exceed $500,000, demonstrating a clear return on investment for implementing optimization software.

However, these benefits come at a distinct trade-off in flight duration. The analysis of the AYT-MOS (Moscow) route highlights this economic tension. In the winter scenario, the model accepted an 8% increase in flight time (approximately 15–20 minutes) to achieve a 760 kg reduction in fuel. While this saves roughly $684 in fuel costs, airlines must weigh this against "Time-Based Costs" (e.g., crew hourly wages and aircraft leasing/maintenance costs).

Furthermore, the model's sensitivity to carbon pricing suggests that future regulatory scenarios will shift these trade-offs. At the current baseline ($50/ton), fuel price is the dominant driver of savings (95%). However, if carbon taxes rise to match the European Union Emissions Trading System (EU ETS) levels (approx. 100 USD/ton), the cost of emissions would double. This would shift the optimization equilibrium, making the "slower, lower-fuel" strategies (such as the AYT-MOS profile) economically superior even when accounting for higher crew costs.

Limitations:

While this study provides a meaningful assessment of fuel consumption and carbon emissions through a flight-parameter-based optimization model, it is not without its limitations. First, the dataset used in the analysis is limited to flights originating from or arriving at Antalya Airport, and the findings may not fully reflect global aviation emissions patterns. This geographical constraint could introduce sampling bias, as Antalya's traffic profile—dominated by seasonal tourism and short- to medium-haul flights—may not reflect the operational characteristics of larger international hubs or intercontinental routes.

Furthermore, geographically, the study captures the impact of high ambient temperatures on aircraft takeoff and climb performance. As shown in the results, the significant difference in air density between summer and winter resulted in a quantifiable "density penalty" on fuel consumption that may be less pronounced in cooler, northern European hubs.

While the selected parameters (distance, duration, mass, and meteorology) for most of the cruise-phase fuel burn, a comprehensive 'gate-to-gate' analysis requires additional operational variables. Specifically, taxi-out times and ground idling are critical factors, particularly at high-density hubs such as Antalya during the peak summer season, where aircraft may burn significant fuel before takeoff. Furthermore, Air Traffic Control (ATC) constraints—such as fixed flight slots, mandatory airway routings, or holding patterns due to congestion—often restrict the ability to fly the mathematically optimal trajectory. Finally, aircraft age and engine health are also factors; older engines typically exhibit performance degradation, resulting in higher specific fuel consumption (SFC) than the manufacturer's baselines used in this model.

Additionally, the model assumes average cruising conditions and employs fixed coefficients that are not tailored to specific aircraft types or engine variants. While the coefficients are derived from reputable sources, they represent generalized estimations rather than aircraft-specific calibrations. This introduces uncertainty into the results' precision when extrapolated to different fleet compositions.

Furthermore, meteorological data used in the study reflect monthly averages rather than real-time weather conditions for each flight. Therefore, the actual performance and fuel use on specific days may deviate from the model's projections. This limits the model's ability to capture short-term atmospheric anomalies or real-time congestion effects, both of which can significantly influence fuel burn. Similarly, fuel consumption and emissions were estimated on a per-flight basis rather than verified through operational airline fuel reports or sensor-based monitoring systems, thereby limiting the validation of the numerical outcomes. Incorporating real-time data streams, such as live wind fields or dynamic traffic flow constraints, would strengthen operational applicability and enable adaptive flight planning.

One crucial factor to consider is the impact of short-term weather events that the monthly average data cannot capture. In real-world operations, atmospheric anomalies—such as sudden thunderstorms, clear-air turbulence, or rapid shifts in the jet stream—occur frequently. When these events occur, safety regulations require pilots to deviate from the mathematically optimal path (e.g., by flying around a storm cell), which often increases flight time and fuel consumption. Therefore, the savings calculated by this model should be viewed as a 'strategic baseline.' While the model identifies the most efficient route under typical conditions, actual operational savings may vary slightly on days with adverse weather, as pilots must prioritize safety over fuel efficiency.

On the other hand, as passenger load factors were not explicitly modeled in this study, a representative payload mass was assumed for each flight. Load factor variability is known to affect aircraft mass and, therefore, fuel consumption. Upcoming studies should integrate dynamic load factor data from airline schedules or airport statistics to capture real operational variability better.

Lastly, although the study uses data from publicly available and authoritative sources (e.g., DHMI, NOAA, FAA), data limitations and occasional inconsistencies across sources may affect the reliability of specific input values. As such, caution is advised when interpreting the results or applying them directly to policy or operational decisions without further context-specific validation.

Despite these limitations, the methodology and findings offer valuable insights into the relationship between flight planning parameters and emissions performance. Future research could build upon this model by incorporating airline-specific data, expanding to multiple airports or regions, and integrating real-time flight tracking to improve accuracy and applicability.

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