Assessment and Analysis of Aircraft Fuel Consumption in a Tropical Environment: The Case Study of the Maya-Maya International Airport, Republic of the Congo

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ABSTRACT

Fuel consumption at tropical airports in developing regions remains poorly documented, creating a significant empirical gap in both academic literature and operational guidance. This paper presents a comprehensive assessment and analysis of aircraft fuel consumption at Maya-Maya International Airport (FCBB), Republic of the Congo, using four years of operational data (2021–2024) covering 22,968 flight movements. Fuel consumption is estimated using the ICAO Carbon Emissions Calculator (ICEC v13.1), and a distance-based allocation approach is introduced to decompose the total fuel consumption into airborne and ground operation components. A reproducible engineering methodology is developed, combining the ICAO calculator with a parametric ground fuel allocation and log-linear regression analysis. Over the study period, the total fuel consumption reached 183,010 tonnes, generating 578,313 tonnes of CO_2. Ground operations account for approximately 7.0% of the total fuel burn (12,780 tonnes). Delay analysis reveals average delays of 19.5 min per flight with a strongly right-skewed distribution — median nine min against a maximum of 521 min — indicating that extreme events disproportionately drive total fuel burn. Regression analysis identifies flight distance, aircraft generation, and operational delays (approximately 15 kg of additional fuel per min of delay) as the primary drivers of fuel consumption. A three-phase strategic framework combining operational improvements, fleet modernization, and integrated decision-support systems projects fuel savings of 15–23% under realistic implementation scenarios. The methodological framework is transparent, replicable, and directly transferable to other data-constrained tropical airports in Sub-Saharan Africa and beyond.

Keywords-aircraft fuel consumption; tropical airports; ICAO methodology; ground operations; operational efficiency; CO_2 emissions; delay analysis; developing regions

I. INTRODUCTION

The global aviation industry faces a dual challenge: accommodating growing demand for air travel while significantly reducing its environmental footprint. Aircraft fuel consumption is both the primary operating cost and the dominant source of aviation greenhouse gas emissions, making its accurate quantification and systematic reduction a priority for airlines, airport operators, and regulators alike. The ICAO 2022 Environmental Report [1] documents that aviation CO_2 emissions represent approximately 1.5% of the total global CO_2 emissions, while the sector's total climate forcing effect, including condensation trails and other non-CO_2 impacts, reaches approximately 3.5% of the total anthropogenic forcing, making fuel consumption the primary lever for emissions reduction. While considerable research has focused on in-flight fuel burn, cruise efficiency, and aircraft design improvements, ground operations at airports represent a significant and often underestimated component of total fuel consumption, particularly at airports in developing regions where operational constraints and aging fleets compound inefficiencies.

Authors in [2] quantified fuel consumption and emissions during taxi operations at Dallas/Fort Worth International Airport using aircraft position data, showing that stop-and-go situations resulting from taxiway congestion account for approximately 18% of the total taxi fuel burn, with constant-speed taxiing as the dominant operational state. Taxi operations represent the largest source of emissions within the standard Landing and Take-Off (LTO) cycle [2], and at operationally constrained airports, fuel burn increases significantly due to extended taxi times and suboptimal routing.

Tropical airports in Sub-Saharan Africa operate under a specific set of physical and institutional conditions that affect fuel consumption. High ambient temperatures reduce air density, increase required thrust, and raise specific fuel consumption. Seasonal weather patterns generate operational uncertainty. Airport infrastructure is increasingly exposed to climate-related risks, including taxiway pavement deterioration, higher fuel consumption under elevated temperatures, and operational disruptions, as documented by the Airports Council International [3], which proposes that airports integrate climate resilience into their master plans. At the same time, systematic data collection and analysis capabilities remain limited at many African airports, creating a crucial empirical gap in the literature. Published studies on aircraft fuel consumption and emissions at airports in tropical developing regions remain scarce, while no study to date has provided a systematic, multi-year quantitative assessment for a Central African airport. Among the few available studies on airports in tropical regions, authors in [4] developed an econometric model to forecast pollutant emissions generated by domestic flights at Salvador Airport (Brazil), providing one of the rare quantitative assessments of aviation emissions in a tropical developing-country context.

This paper contributes to filling this gap by presenting a comprehensive assessment of aircraft fuel consumption at Maya-Maya International Airport (FCBB), Brazzaville, Republic of the Congo, using 22,968 flight movements over 2021-2024. It makes three specific contributions, each with a clear engineering focus:

1. Methodological (engineering replicability): It develops and applies a transparent, replicable methodological framework combining the ICAO Carbon Emissions Calculator (ICE v13.1) with an explicit decomposition of ground and airborne fuel, tailored to data-constrained environments. The parametric allocation approach is compared with more detailed models (FAA AEDT, [2]) and justified for use where taxi time records are unavailable.
2. Quantitative (operational engineering): It provides a quantitative assessment of fuel consumption trends, delay distributions, and their influencing factors through multivariate regression analysis, enabling direct quantification of marginal fuel impacts (≈15 kg per delay min) and identification of extreme delay contributions.
3. Strategic (decision support engineering): It derives a phased, implementation-oriented strategic framework with quantified savings ranges (15–23%) and explicit roles for stakeholders, applicable to FCBB and transferable to similar tropical airports.

II. METHODOLOGICAL FRAMEWORK

A. ICAO-Based Fuel Consumption Estimation

This study employs the ICEC methodology, version 13.1, as the primary estimation framework [5]. The fundamental equation is:

$$F_{total} = F(d_{corr}, A) \times f_{load} \times f_{cargo} \tag{1}$$

where F_{total} is the total fuel consumption, d_{corr} is the corrected great-circle distance, A is the aircraft type, f_{load} is the passenger load factor (0.661), and f_{cargo} is the cargo adjustment factor (0.8432), corresponding to the Intra Africa route group ([5], Appendix A).

1) Distance Calculation and Correction

The great-circle distance between airports is calculated on the WGS-84 ellipsoid:

$$D_{GCD} = R * arccos[\sin(\phi_1)\sin(\phi_2) + \cos(\phi_1)\cos(\phi_2)\cos(\lambda_1 - \lambda_2)] \tag{2}$$

where R is the Earth's radius (6371 km), ϕ is the latitude, and λ is the longitude. The following ICAO distance corrections are then applied [5]:

$$d_{corr} = \begin{cases} D_{GCD} + 50 \quad if \; D_{GCD} < 550 \\ D_{GCD} + 100 \; if \; 550 < D_{GCD} < 5500 \\ D_{GCD} + 125 \quad if \; D_{GCD} < 5500 \end{cases} \tag{3}$$

2) Aircraft Type Standardization and Fuel Models

Actual aircraft types are mapped to 336 standardized ICAO equivalents. Fuel consumption F(d) is estimated from the ICAO fuel consumption formula for each equivalent aircraft type [5], with linear interpolation where needed:

$$F(d) = F(d_0) + [F(d_1) - F(d_0)] \times \frac{d - d_0}{d_1 - d_0} \tag{4}$$

where d_0 and d_1 are the tabulated distances bracketing d.

CO_2 emissions are derived using the universal stoichiometric factor:

$$E_{CO2} = 3.16 * F_{total} \tag{5}$$

B. Ground Operation Fuel Estimation

Total trip fuel is decomposed as:

$$F_{total} = F_{ground} + F_{air} \tag{6}$$

where F_{ground} is the fuel consumed during taxi-out and taxi-in, and F_{air} is the airborne component. Ground fuel is estimated using a distance-dependent allocation factor $\alpha(d)$:

$$F_{ground} = F_{total} \times \alpha(d) \tag{7}$$

The allocation factors are informed by detailed taxi fuel studies [2] and the phase-based modeling approach of [6], which analyzed fuel consumption under varying thrust levels and taxiing states at Shanghai Pudong International Airport:

$$\alpha(d) = \begin{cases} 0.09 \ if\ d < 1000, \\ 0.065 \ if\ 1000 < d < 3000 \\ 0.04 \ if\ d > 3000 \end{cases} \tag{8}$$

From an engineering standpoint, the distance-based allocation factor $\alpha(d)$ is a simplified but robust approximation. Compared to the FAA AEDT method, which requires taxi time distributions and engine idle fuel flow rates [7], the proposed approach reduces input requirements to only flight distance and aircraft type. The α values (0.09, 0.065, 0.04) are derived from the empirical taxi fuel fractions observed in [2, 6], and are consistent with the idle thrust fuel flow methodology when average taxi times are assumed proportional to distance. This trade-off between granularity and data availability is appropriate for the present operational context.

It is important to distinguish this parametric approach from detailed models such as in [2], which use recorded taxi times, phase-dependent engine fuel flow, and aircraft-specific performance parameters not available for FCBB. The present method is well-suited to data-constrained environments such as FCBB, where flight-by-flight engine performance records are unavailable, and provides a transparent and replicable basis for academic analysis and evidence-based policy recommendations.

C. Regression Analysis Framework

To identify and quantify the key drivers of fuel consumption, a log-linear regression model is applied:

$$ln(F_{total}) = \beta_0 + \beta_1 ln(d) + \beta_2 T + \beta_3 D + \beta_4 A + \varepsilon \tag{9}$$

where d is the flight distance, T is an aircraft type-generation factor, D is the delay duration, A is an aircraft age proxy, and ε is the error term. The log-linear specification is consistent with the well-documented non-linear relationship between flight distance and fuel efficiency in commercial aviation [8], and produces directly interpretable elasticity coefficients.

III. DATA ANALYSIS AND RESULTS

A. Operational Data Overview

The analysis covers 22,968 flight movements at FCBB between 2021 and 2024. Operations are dominated by narrow-body aircraft (B737-800, A320-family) with a growing share of modern types in recent years. International flights grew from 65% of movements in 2021 to 72% in 2024, reflecting increasing regional connectivity. Table I summarizes the annual operational profile.

B. Fuel Consumption Patterns

The total fuel consumption at FCBB over the four-year period reached 183,010 tonnes, generating 578,313 tonnes of CO_2. The annual consumption increased from 41,637 tonnes in 2021 to 49,777.1 tonnes in 2024, tracking the recovery of air traffic. Table II presents the evolution of key metrics.

TABLE I. SUMMARY OF OPERATIONAL DATA AT FCBB (2021-2024)

Metric	2021	2022	2023	2024
Total movements	5,141	5,950	5,626	6,251
Departures	2,697	3,043	2,916	3,320
Arrivals	2,444	2,907	2,710	2,931
Average flights/day	14.1	16.3	15.4	17.1
International flights (%)	65	68	70	72
Domestic flights (%)	35	32	30	28

TABLE II. CONSUMPTION AND OPERATIONAL METRICS AT FCBB (2021-2024)

Year	Movements	Total fuel (t)	Avg. cons. (kg/flight)	Avg. delay (min)
2021	5,141	41,636.7	8,099	16.7
2022	5,950	45,225.0	7,601	20.1
2023	5,626	46,371.5	8,242	25.7
2024	6,251	49,777.1	7,963	15.5
Total/Avg.	22,968	183,010.3	7,976	19.5

The year 2023 stands out with both the highest per-flight fuel consumption (8,242 kg) and the highest average delay (25.7 min), consistent with the regression finding that delays increase fuel burn. The year 2024 shows the highest movement count (6,251) with improved per-flight efficiency (7,963 kg), suggesting partial fleet modernization effects.

C. Ground Operation Fuel Estimation

Applying the distance-based allocation framework (Section II-B), ground operations account for an average of 7.0% of the total fuel consumption, representing approximately 12,780 tonnes over 2021-2024 (40,385 tonnes CO_2). Table III details the results by flight distance category.

TABLE III. ESTIMATED GROUND OPERATION FUEL CONSUMPTION BY FLIGHT CATEGORY

Flight category	Avg. distance (km)	Ground fuel share (%)	Avg. ground fuel (kg/flight)
Short-haul (< 1,000 km)	650	9.0	692
Medium-haul (1,000-3,000 km)	1,800	6.5	460
Long-haul (> 3,000 km)	4,200	4.0	288
Weighted average	1,152	7.0	558

D. Environmental Impact Assessment

Table IV presents the annual environmental footprint of operations at FCBB. The CO_2 intensity per movement remained stable (24.0-26.0 t CO_2/movement), reflecting limited fleet renewal during 2021-2024. Ground operations generated 40,385 tonnes of CO_2 cumulatively (6.98% of total). Beyond

CO_2, aircraft operations at airports contribute to gaseous pollutant emissions, including NOx, SO_2, and CO. As demonstrated in [9] at Bucharest Henri Coanda Airport, pollutant concentrations are jointly driven by aircraft movements and meteorological conditions, particularly wind speed and direction, which govern dispersion patterns. Similar dynamics are expected at FCBB, though no ground-level air quality measurements were conducted in the present study.

TABLE IV. ENVIRONMENTAL IMPACT ASSESSMENT AT FCBB (2021-2024)

Year	Fuel cons. (t)	Total CO_2 (t)	Ground ops CO_2 (t)	CO_2/movement (t)
2021	41,636.7	131,572	9,185	25.6
2022	45,225.0	142,911	10,158	24.0
2023	46,371.5	146,534	10,145	26.0
2024	49,777.1	157,296	10,896	25.2
Total	183,010.3	578,313	40,385	25.2 (avg.)

E. Delay Analysis

Operational delays are a significant fuel efficiency factor at FCBB. Table V presents the delay statistics for each year of the study period.

TABLE V. DELAY STATISTICS BY YEAR AT FCBB (2021-2024)

Year	Mean (min)	Median (min)	Std. dev. (min)	Max (min)
2021	16.7	8.0	21.5	521
2022	20.1	9.0	24.8	498
2023	25.7	12.0	28.4	512
2024	15.5	7.0	19.2	487
Overall	19.5	9.0	23.5	521

The consistently large gap between mean and median (e.g., 25.7 vs. 12.0 min in 2023) reveals a strongly right-skewed distribution, characteristic of a mixture of on-time operations and occasional severe disruptions. Extreme events of 487-521 min are observed in all years. This distributional pattern has an important operational implication: interventions targeting the tail of the distribution (e.g., eliminating root causes of multi-hour delays) yield higher fuel savings per unit of effort than uniform average delay reduction programs.

The regression model quantifies the marginal fuel impact: each additional min of departure delay is associated with an average increase of approximately 15 kg in fuel consumption (β_3 > 0, p < 0.001). Over 22,968 flight movements, the cumulative fuel penalty attributable to delays is estimated at approximately 7,300 tonnes — 4.0% of the total fuel consumption over the study period.

This marginal value is obtained as $\beta_3 \times \bar{F}$, where $\beta_3 = 0.00192$ (coefficient of delay in the log-linear model) and $\bar{F} = 7{,}947$ kg (mean fuel consumption per flight). The calculation yields $0.00192 \times 7{,}947 \approx 15.3$ kg per delay-min. This is a practical engineering parameter that can be used by airport operators to estimate fuel savings from delay reduction programs or to set performance targets for ground handling.

F. Regression Analysis Results

The log-linear regression model is estimated on fuel consumption per km ($\ln(F/d)$) as the dependent variable, which captures operational efficiency independently of route length. The model achieves an adjusted R^2 of 0.664 (F-statistic = 11,221; $p < 0.001$; $n = 22{,}738$), indicating that the four predictors jointly explain approximately 66% of the variance in fuel efficiency across flight movements. The results, listed by decreasing contribution, are:

- Flight distance ($\ln d$): The dominant predictor ($\beta_1 = -0.861$, $p < 0.001$). A 1% increase in corrected distance is associated with a 0.86% decrease in fuel consumption per km, reflecting well-documented scale economies on longer routes.
- Engine technology (A): More recent engine technology is associated with a 10.3% reduction in fuel per km per technology level ($\beta_4 = -0.103$, $p < 0.001$), consistent with efficiency gains from high-bypass turbofan engines.
- Operational delays (D): Each additional min of departure delay increases the total fuel consumption by approximately 15 kg on average ($\beta_3 > 0$, $p < 0.001$). Over 22,968 flight movements, the cumulative delay-attributable fuel penalty is estimated at approximately 7,300 tonnes.
- Aircraft generation (T): The generation coefficient is positive ($\beta_2 > 0$, $p < 0.001$), reflecting the strong collinearity between aircraft generation and route length at FCBB — newer-generation aircraft (A350, B787) operate predominantly on longer international routes. The net efficiency gain of newer airframes is captured through the engine technology variable (A).

G. Aircraft Generation and Fuel Efficiency

The analysis of fuel consumption by aircraft generation reveals substantial efficiency differences across the fleet operating at FCBB. Table VI summarizes these findings, which provide a direct empirical basis for fleet modernization recommendations.

IV. DISCUSSION: EFFICIENCY IMPROVEMENT OPPORTUNITIES

A. Operational Improvements

The delay distribution analysis reveals that a small proportion of flights with very long delays (> 120 min) account for a disproportionate share of delay-attributable fuel consumption. Implementing Airport Collaborative Decision Making (A-CDM) [10] could reduce the average taxi-out time by 1-3 min per departure, with network-level ATFM delay reductions of 20-25%, potentially saving 0.15-0.20% of the total fuel. Single-engine taxiing, combined with optimized taxiway routing, offers additional savings of 20-30% of the ground fuel, consistent with the 0.6-0.9% total fuel savings shown in Table VII for Phase 1 combined measures. Better integration of delay forecasts into flight planning could reduce fuel reserves by 5-10%.

TABLE VI. FUEL EFFICIENCY BY AIRCRAFT GENERATION AT FCBB

Generation	Example types	Avg. fuel efficiency (kg/km)	Relative efficiency
Old (pre-1990)	MD-83, B737-300	5.40	100% (baseline)
Classic (1990-2000)	B737-700, A320ceo	4.80	112%
Modern (2000-2015)	B737-800, A320ceo (newer)	4.35	124%
New generation (2015+)	B737 MAX, A320neo	3.95	137%

B. *Fleet Modernization*

The efficiency gap between aircraft generations at FCBB is substantial: a transition from the pre-1990 baseline to the current new-generation aircraft represents a 27% reduction in fuel consumption per km (from 5.40 to 3.95 kg/km, i.e., a 37% relative efficiency gain). Complete fleet modernization could reduce the total fuel consumption by 20-25%, consistent with the findings in the wider literature [11]. Recent studies on electric taxiing systems further reinforce the potential for airport-level fuel efficiency improvements [12].

C. *Transferability to Other Tropical Airports*

Several elements of the methodology are directly transferable. The ICEC, the distance-based ground fuel allocation, and the regression framework can be replicated wherever basic flight and schedule data are available. The operational levers identified — delay management, taxiing optimization, and flight planning efficiency — are consistent with the wider literature on airport ground and terminal area operations [13, 14]. Context-specific factors, such as traffic mix, institutional configuration (ASECNA, national civil aviation authorities), and local resource constraints, should be considered when extrapolating quantitative estimates to other airports.

D. *Engineering Implications for Airport Operations*

The regression results and delay distribution analysis lead directly to actionable engineering recommendations for FCBB and similar airports:

- Delay threshold targeting: The strongly right-skewed delay distribution (median 9 min, maximum 521 min) implies that interventions focusing on extreme delays (>75 min) yield higher fuel savings per unit effort than reducing the average delays across all flights. For FCBB, eliminating the top 5% of the delayed flights (those exceeding 75 min) would reduce delay-attributable fuel consumption by an estimated 34% (≈2,750 tonnes over four years).

- Taxiway routing optimization: Using the ground fuel allocation factors ($\alpha(d)$), a reduction of the average taxi distance from 2.5 km to 1.8 km for short-haul flights would lower ground fuel by approximately 23 kg per movement, equivalent to 0.18% of the total fuel. This can be achieved through gate assignment strategies and dedicated rapid exit taxiways.

- Single engine taxiing: Based on the idle thrust fuel flow rates, adopting single engine taxiing for all departures would reduce ground fuel by 20–30%, i.e., 0.6–0.9% of the total fuel at FCBB.

- Decision support heuristic: A simple heuristic derived from the regression model is: for any flight, the fuel penalty per min of delay is ≈ 15 kg, independent of the aircraft type (because the delay coefficient was stable across generations). This allows real-time cost benefit analysis for delaying a flight versus holding passengers or reallocating gates.

These recommendations are not speculative. They are directly quantified from the empirical model and can be implemented using existing airport management systems.

V. STRATEGIC FRAMEWORK FOR FUEL EFFICIENCY IMPROVEMENT

Based on the empirical findings, a three-phase implementation framework is proposed. Table VII summarizes the phases, key strategies, expected fuel savings, and implementation timelines.

TABLE VII. PHASED IMPLEMENTATION FRAMEWORK FOR FUEL EFFICIENCY IMPROVEMENT AT FCBB

Phase	Key strategies	Expected fuel savings	Timeline
Phase 1: operational improvements	A-CDM implementation; single-engine taxiing; delay reduction; optimized flight planning	8-12% of ground fuel (0.6-0.9% of total)	0-2 years
Phase 2: technological upgrades	Fleet renewal (priority: pre-1990 aircraft); advanced flight planning systems; ground support equipment modernization	10-15% of total fuel	2-5 years
Phase 3: integrated systems	Integrated airport management system; predictive analytics; sustainable aviation fuel integration	5-8% additional (15-23% cumulative)	5+ years

Cumulative fuel savings of 15-23% correspond to 6,863-10,523 tonnes per year, equivalent to 21,687-33,252 tonnes of CO2 avoided annually and economic benefits of approximately $6.9-10.5 million per year at the current jet fuel prices. These projections are consistent with quantitative findings from operational studies at other airports [14, 15].

VI. CONCLUSION

This paper presents the first comprehensive, multi-year quantitative assessment of aircraft fuel consumption at a tropical Central African airport and makes three specific engineering contributions. First, it develops a reproducible fuel estimation pipeline combining the ICAO Carbon Emissions Calculator (ICEC) with a distance-based ground allocation and log-linear regression, specifically designed for data-constrained environments where detailed engine performance records are unavailable. Second, it provides a quantitative model of the marginal fuel cost of delay, approximately 15 kg per min, and demonstrates that extreme delays (the strongly right-skewed tail of the distribution) drive the majority of the delay-attributable consumption. Third, it proposes a phased strategic framework with quantified fuel savings (15–23%) and implementation timelines, derived directly from the regression coefficients and fleet efficiency gaps measured at FCBB.

Applying the ICEC (v13.1) to 22,968 flight movements at Maya-Maya International Airport (FCBB) over 2021–2024, the total fuel consumption reached 183,010 tonnes, generating 578,313 tonnes of CO_2. Ground operations account for approximately 7.0% of the total fuel burn (12,780 tonnes), and the regression model identifies the flight distance, aircraft generation, and operational delays as the dominant drivers.

The delay distribution analysis reveals a strongly right-skewed pattern (median 9 min, maximum 521 min), indicating that extreme events disproportionately drive fuel burn. Each delay-min increases the fuel consumption by approximately 15 kg; the cumulative delay-attributable fuel penalty over the study period is estimated at approximately 7,300 tonnes (4.0% of the total). This finding has direct operational implications: targeted interventions on the tail of the delay distribution yield higher fuel savings than uniform mean delay reduction programs.

The proposed three-phase strategic framework demonstrates that fuel savings of 15–23% are achievable through a combination of A-CDM implementation, fleet modernization, and integrated management systems. The methodological framework, based on the publicly available ICEC and standard operational data, is transparent, replicable, and directly applicable to other data-constrained tropical airports in developing regions.

Future research should incorporate actual taxi time records, aircraft-specific engine performance data, and meteorological measurements to refine ground fuel estimates. Comparative studies across multiple tropical African airports would further strengthen the generalizability of these findings and support the development of regional fuel efficiency benchmarks.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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DATA AVAILABILITY

The flight operational data used in this study were obtained from FCBB operational records and are not publicly available due to institutional restrictions. The ICAO Carbon Emissions Calculator methodology (v13.1) is publicly available in [16]. The Python implementation of the fuel estimation algorithm is described in Appendix A.

REFERENCES

[1] International Civil Aviation Organization (ICAO), *ICAO Environmental Report 2022*, (2022), https://www.icao.int/icao-environmental-report-2022.

[2] T. Nikoleris, G. Gupta, and M. Kistler, "Detailed estimation of fuel consumption and emissions during aircraft taxi operations at Dallas/Fort Worth International Airport," *Transportation Research Part D: Transport and Environment*, vol. 16, no. 4, pp. 302–308, June 2011, https://doi.org/10.1016/j.trd.2011.01.007.

[3] "Airports' Resilience and Adaptation to a Changing Climate." Airports Council International. https://store.aci.aero/wp-content/uploads/2018/10/Policy_brief_airports_adaption_climate_change_V6_WEB.pdf.

[4] D. A. Pamplona and C. J. Pinto Alves, "Civil Aircraft Emissions Study and Pollutant Forecasting at a Brazilian Airport.," *Engineering, Technology & Applied Science Research*, vol. 10, no. 1, Feb. 2020, Art. no. 5217, https://doi.org/10.48084/etasr.3227.

[5] International Civil Aviation Organization (ICAO), ICAO Carbon Emissions Calculator Methodology (Version 13.1), https://icec.icao.int/Documents/Methodology%20ICAO%20Carbon%20Emissions%20Calculator_v13_Final.pdf.

[6] M. Zhang, Q. Huang, S. Liu, and H. Li, "Assessment Method of Fuel Consumption and Emissions of Aircraft during Taxiing on Airport Surface under Given Meteorological Conditions," *Sustainability*, vol. 11, no. 21, 2019, Art. no. 6110, https://doi.org/10.3390/su11216110.

[7] Federal Aviation Administration, *Aviation Environmental Design Tool (AEDT): Technical Manual*, (2021), https://aedt.faa.gov/4a_information.aspx.

[8] A. Rudolph and Q. Wang, "Economies of Distance in Commercial Aviation: Emissions Intensity and Marginal Abatement Costs," *Proceedings of the West Virginia Academy of Science*, vol. 98, no. 1, 2026, https://doi.org/10.55632/pwvas.v98i1.1252.

[9] R. Mirea, G. Cican, and M. Cretu, "Evaluation of Aircraft Emissions at Bucharest Henri Coanda Airport," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11829–11836, Oct. 2023, https://doi.org/10.48084/etasr.6242.

[10] EUROCONTROL, *Airport Collaborative Decision-Making (A-CDM) Implementation Manual*, (2017), https://www.eurocontrol.int/publication/airport-collaborative-decision-making-cdm-implementation-manual.

[11] A. Kharina, D. Rutherford, and M. Zeinali, *Cost Assessment of Near- and Mid-Term Technologies to Improve New Aircraft Fuel Efficiency*, (2016), https://theicct.org/publication/cost-assessment-of-near-and-mid-term-technologies-to-improve-new-aircraft-fuel-efficiency/.

[12] M. Lukic, P. Giangrande, A. Hebala, S. Nuzzo, and M. Galea, "Review, Challenges, and Future Developments of Electric Taxiing Systems," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 4, pp. 1441–1457, Dec. 2019, https://doi.org/10.1109/TTE.2019.2956862.

[13] S. Ravizza, J. A. D. Atkin, and E. K. Burke, "A more realistic approach for airport ground movement optimisation with stand holding," *Journal of Scheduling*, vol. 17, no. 5, pp. 507–520, 2014, https://doi.org/10.1007/s10951-013-0323-3.

[14] Y. Tian, L. Wan, K. Han, and B. Ye, "Optimization of terminal airspace operation with environmental considerations," *Transportation Research Part D: Transport and Environment*, vol. 63, pp. 872–889, Aug. 2018, https://doi.org/10.1016/j.trd.2018.06.018.

[15] G. S. Koudis, S. J. Hu, A. Majumdar, R. Jones, and M. E. J. Stettler, "Airport emissions reductions from reduced thrust takeoff operations," *Transportation Research Part D: Transport and Environment*, vol. 52, pp. 15–28, May 2017, https://doi.org/10.1016/j.trd.2017.02.004.

[16] "Carbon Emissions Calculator." ICAO. https://icec.icao.int/.

APPENDIX A: ENGINEERING IMPLEMENTATION OF THE FUEL ESTIMATION AND REGRESSION FRAMEWORK

The data processing pipeline comprises three sequential stages. Stage 1 (upstream pre-processing) was carried out using the ICAO Carbon Emissions Calculator (ICEC v13.1) applied flight by flight to the raw FCBB operational records; this stage produced the corrected great circle distances, fuel estimates per flight, and CO_2 emissions stored in the input CSV files. Stage 2 (Scilab analysis script, AnalyseData.sce) reads these pre-processed CSV files and performs ground fuel allocation, annual aggregation, delay analysis, and statistical summaries. Stage 3 (Python regression script, regression_FCBB.py) estimates the log-linear model of fuel efficiency from the same CSV files. The logic of each stage is described below.

- STAGE 1: Upstream pre-processing (ICAO Carbon Emissions Calculator v13.1)

Input: Raw FCBB operational records (origin, destination, aircraft type, date).

Output: CSV files per year (columns: DISTANCE_KM, FUEL_KG, CO2_KG, AIRCRAFT_TYPE, RETARD_MIN, TYPE_DE_VOL).

For each flight record:

1. Map actual aircraft type to ICAO standard equivalent (336 types).
2. Calculate great circle distance D_GCD on WGS 84 ellipsoid.
3. Apply ICAO distance correction: D_corr = D_GCD + 50/100/125 km.
4. Look up F(D_corr) from ICAO fuel table; apply linear interpolation if needed.
5. Apply load factor (0.661) and cargo adjustment (0.8432) per ICEC v13.1.
6. Compute CO_2 = F_total × 3.16 (ICAO stoichiometric factor).
7. Store D_corr, F_total, CO_2 in output CSV.

- STAGE 2: Scilab analysis script (AnalyseData.sce)

Input: Pre processed CSV files from Stage 1 (departures and arrivals per year).

Output: Annual aggregated statistics; text summary (resultats_final_article.txt).

For each flight record:

1. Read DISTANCE_KM, FUEL_KG, RETARD_MIN from CSV.
2. Filter invalid records (NaN, zero fuel or distance).
3. Compute ground fuel allocation:

$\alpha = 0.09$ if $D < 1000$ km

$\alpha = 0.065$ if $1000 \leq D < 3000$ km

$\alpha = 0.04$ if $D \geq 3000$ km

F_ground = F_total × α

4. Aggregate per year: total fuel, mean delay, ground fuel share, total CO_2.
5. Export annual summary table to resultats_final_article.txt.

- STAGE 3: Regression analysis (Python / statsmodels)

Input: Pre processed CSV files (same as Stage 2).

Output: Regression coefficients, R^2, marginal delay penalty.

The dependent variable is $\ln(F/d)$, where F is total fuel (kg) and d is corrected distance (km). Predictors:

- ln(d) (log of distance)
- T (ordinal aircraft generation: 0 = pre-1990, 1 = 1990-2000, 2 = 2000-2015, 3 = post-2015)
- D (delay in minutes)
- A (ordinal engine technology: 0 = JT8D, 1 = CFM56 classic, 2 = high bypass, 3 = LEAP/PW1100G). Observations with fuel = 0, distance = 0, or delay exceeding the 99th percentile (134 min) are excluded ($n = 22{,}738$). The estimated model is: $\ln(F/d) = 7.620 - 0.861 \cdot \ln(d) + 0.356 \cdot T + 0.00192 \cdot D - 0.103 \cdot A + \varepsilon$. Adjusted $R^2 = 0.664$; F statistic = 11,221 ($p < 0.001$). The marginal fuel cost of delay is derived as $\beta_3 \times \bar{F} = 0.00192 \times 7{,}947$ kg $\approx$ 15 kg per delay minute. The Python script (regression_FCBB.py) is available from the corresponding author upon request.