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AIRPORT COMPLEXITY AND ENVIRONMENTAL EFFICIENCY METRICS FOR AIR TRAFFIC MANAGEMENT EVALUATION

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Abstract. The aviation industry is experiencing significant growth due to the growing global demand for air travel. The International Civil Aviation Organization predicts that air passenger volumes will quadruple by 2040, putting pressure on airport infrastructure and airspace capacity. This growth is causing environmental challenges, particularly concerning emissions from aircraft operations and airport activities. These emissions contribute to local air pollution and global climate change. Airports are complex operational hubs, requiring sophisticated planning and efficient operations management to mitigate emissions and maximize throughput. This thesis investigates how airport complexity and air traffic management strategies influence inefficiencies in fuel use, time, cost, and environmental impact. Traffic scenarios were generated and analysed using MATLAB code, calculating emissions and fuel consumption across all phases of the landing and take-off (LTO) cycle. The results show significant differences in operational efficiency and environmental impact, offering insights into the effectiveness of modern traffic control methods.

Keywords: emissions, airport complexity, inefficiency, air traffic management, fuel consumption, CO_2 emissions, flight phases.

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1. Introduction

The aviation industry is experiencing significant growth due to global air travel demand, with the International Civil Aviation Organization (ICAO) predicting a double-digit increase in flying passengers by 2040. This growth is causing environmental issues, including emissions from airplane operations and airport activities, contributing to local air pollution and global climate change. Surface congestion, ineffective taxiing, and airport delays increase fuel consumption and emissions (Cereijo, 2024). Contemporary airports are becoming sophisticated operating centers with complex interactions among stakeholders, such as air traffic control, airline operators, ground handlers, and regulatory bodies. High-complexity airports face difficulties in managing arrivals and departures, requiring sophisticated scheduling, collaborative decision-making systems, and integrated airport operations management to enhance throughput and minimize emissions. Recent improvements in air traffic control systems aim to improve flight efficiency and mitigate environmental concerns.

2. Airport traffic complexity

Airport traffic complexity is a significant concern due to the increasing demand for worldwide air travel. It involves challenges in managing aviation operations due to traffic density, aircraft interactions, weather unpredictability, airspace configuration, and human constraints (Delahaye et al., 2014). Understanding and measuring this complexity is crucial for improving air traffic control, reducing delays, maintaining safety (Eleimat & Őszi, 2025), and facilitating automation in the future air transportation system.

Airport traffic complexity can be categorized as airside complexity, which pertains to aircraft in the airspace around the airport and runways, and groundside complexity, which relates to aircraft taxiing and gate operations. Factors contributing to traffic congestion at airports include traffic density and interaction (Wang et al., 2023), airport design and runway arrangement (Olive et al., 2025), meteorological conditions (Dalmau & Attia, 2025), aircraft composition and wake turbulence, and various aircraft classifications (Yin et al., 2024).

Metrics to assess air traffic complexity include traffic density, conflict rate, dynamic density (Laudeman et al., 1998), and entropy-based metrics (Moreno et al., 2024a). Recent improvements in machine learning and data-driven approaches have been used to classify traffic complexity using radar data, aircraft trajectories, and air traffic control communications (Moreno et al., 2024b). Ground complexity includes gate assignment disputes, taxiway congestion, pushback time, and runway crossing management. Simulation techniques like the Federal Aviation Administration's

Surface Management System (SMS) and EUROCONTROL's Enhanced METeo Information Translation (EMIT) are used to simulate and forecast the complexity of surface movement (Yin et al., 2024).

The burden of controllers is both a cause and a result of traffic complexity. Research has associated elevated subjective effort with heightened complexity metrics and an increased likelihood of errors (Hilburn, 2004). Cognitive load theory suggests that exceeding a certain threshold of complexity impairs performance, necessitating the implementation of support aids or traffic flow limitations (Delahaye et al., 2014).

Various solutions to alleviate complexity include pre-tactical planning, dynamic re-sectorization, decision support systems, and automation and artificial intelligence (AI) (Moreno et al., 2024a, 2024b). The research in this article focuses on flight control and traffic management at airports and the sustainable development of air traffic.

2.1. Flight control and traffic management at airports

Airport air traffic control is divided into tower control, approach/departure control, and en-route control. Tower controllers oversee aircraft on runways and taxiways, while approach/departure controllers manage aircraft entering and departing the terminal manoeuvring area (International Civil Aviation Organization [ICAO], 2025). The airport air traffic control service provides information to pilots, including engine start times, meteorological and airport information, local traffic, unauthorized departures, turbulence dangers, incorrect aircraft configurations, and airport status information (Netjasov & Babić, 2020; Poškuvienė et al., 2022). Airports use various methods to organize and manage traffic, particularly during peak periods. Arrival and departure management (AMAN/DMAN) regulates aircraft entry into optimum time slots to mitigate congestion and fuel use. Time-Based Flow Management (TBFM) is used in the United States (Federal Aviation Administration, 2022), while Extended Arrival Management (XMAN) is used in Europe (Eurocontrol, 2021). Optimal runway use is essential for maximizing throughput (Memarzadeh et al., 2023). Ground controllers monitor taxiway systems using surveillance technologies like ASDE-X or A SMGCS. Airport Collaborative Decision Making (A-CDM) combines airlines, airport operators, ground handlers, and air traffic control to make real-time decisions on turnaround times (Wei et al., 2024), slot utilization, and delays (ICAO, 2015). Automation is used in aviation and airport traffic management, with Decision Support Systems (DSS) (Jung et al., 2016), and machine learning and AI forecasting runway occupancy durations, surface congestion, and conflict zones (Nguyen et al., 2022).

At the strategic level, Airport Collaborative Decision-Making entails collaboration between airlines, airport operators, ground handlers, and air traffic control to make real-time decisions on turnaround times, slot utilization, and delays. The Network Manager Operations Centre (NMOC) in Europe oversees and regulates traffic flow at the network level, allocating Air Traffic Flow Management (ATFM) slots when demand exceeds capacity. Automation is used in aviation and airport traffic management, with Decision Support Systems (DSS) guiding controllers in sequencing, dispute resolution, and ideal taxi routes.

3. Emissions from the aviation sector

The aviation industry is a significant contributor to global climate change, accounting for over 2.5% of global carbon dioxide (CO_2) emissions and contributing approximately 3.5% to global warming when including non-CO_2 impacts such as nitrogen oxides (NO_x), contrails, and cirrus cloud production (Our World in Data, 2020). Despite improvements in aviation fuel efficiency, overall emissions from the industry have persistently increased due to the exponential expansion of air travel. In 2018, commercial aviation produced over 918 million tonnes of CO_2, ranking it as the sixth-largest emitter worldwide (Overton, 2019).

In addition to CO_2, airplane engines release NO_x at high altitudes, facilitating ozone production and diminishing atmospheric methane (Transport & Environment, 2021). Additionally, airplanes' condensation trails may evolve into cirrus clouds, which retain heat in the Earth's atmosphere and exacerbate warming effects. The non-CO_2 impacts may constitute two-thirds of aviation's overall climate impact (Lee et al., 2021).

Subsonic aircraft influence climate through radiative forcing mechanisms, such as CO_2 emissions resulting in positive Radiative Forcing (RF) (warming), NO_x emissions forming tropospheric O_3 via atmospheric chemistry, NO_x emissions destroying ambient methane (CH_4) via atmospheric chemistry, sulphate particles arising from sulphur in the fuel resulting in negative RF (cooling), soot particles resulting in a negative RF (warming), persistent linear contrails forming in the wake of an aircraft, contrail-cirrus cloud formation from spreading contrails, and a sub-component of aviation-induced cirrus initiated by soot particles initiating cirrus clouds (Lee et al., 2009; Bagdi et al., 2023).

Aviation emissions within the European Union (EU) are around 3.8% of total greenhouse gas emissions, making them the second-largest source of transport emissions behind road transport. In the absence of mitigation, forecasts indicate that aviation emissions may quadruple by 2050 relative to 2015 levels, jeopardizing the attainment of global climate objectives (European Commission, 2022). Addressing aviation's environmental impacts requires a synthesis of technological innovation, regulatory structures, and behavioral changes.

The landing and take-off (LTO) cycle, defined by the International Civil Aviation Organization, involves activities below 3000 feet. Airplane engines release pollutants such as carbon monoxide, hydrocarbons, nitrogen oxides, and particulate matter. These emissions are harmful to human health and contribute to the production of ground-level ozone. The emissions vary across flight phases, affecting environmental and health impacts. Analyzing emissions during specific flight phases is crucial for understanding these impacts.

3.1. Emissions from the aviation sector: detailed pollutant analysis

Hydrocarbons, emitted during inefficient combustion, contribute to photochemical smog and respiratory health issues. Engine design improvements have decreased hydrocarbon emissions by 8.7% from 2005 to 2011, thanks to fuel atomization and combustion regulation (Wasiuk et al., 2016).

Carbon monoxide, a colorless gas, is released during idle and taxi operations in aviation. Despite its brief air presence, it poses health hazards. CO emissions decreased by 1.6% between 2005 and 2011 (Wasiuk et al., 2016).

Carbon dioxide is the primary greenhouse gas released by aircraft, contributing significantly to global warming due to its prolonged air lifespan and radiative forcing impact. In 2018, commercial aviation released around 918 million tons of CO_2, constituting 2.4% of total worldwide emissions (Lee et al., 2021). CO_2 emissions are the most significant component of aviation's total contribution to climate change, accounting for approximately 2% of all anthropogenic emissions (ICAO, 2025). Improving fuel efficiency is crucial to minimizing environmental impact. Removing CO_2 from the atmosphere requires several processes, with 50% expected to be removed in 30 years and 30% in the next few centuries (EASA Eco., n.d.).

Hydrocarbon fuel combustion produces water vapor, a significant portion of airplane exhaust. This vapor can form condensation trails, cirrus clouds, which retain infrared radiation, causing net warming (Burkhardt & Kärcher, 2011).

Aviation gasoline contains sulfur compounds that produce sulfur dioxide (SO_2), which can oxidize into sulfate aerosols, affecting air quality and human health. Although the aviation sector contributes less to SO_x than ground transportation or industrial activities, its high-altitude emissions are significant.

4. Experiment

4.1. Methodology

The methodology involves understanding airport maneuvering surfaces, airspace configuration, traffic volume, aircraft paths, departure and landing distribution, aircraft share ratio, fuel consumption, emissions, and costs of emissions and noise. It also considers traffic volume, aircraft types, fuel consumption, and emissions during flight phases.

This study evaluates traffic complexity within an airport system, considering all aircraft in the system, from landing to take-off, and analyzing the airport's maneuvering regions and surrounding airspace, varying based on aircraft type.

ATM can mitigate the environmental impacts of air transportation by measuring performance using flight inefficiency measures, which refer to deviations from optimal 4D flight trajectory during any phase.

The Inefficiency Metric (IM) quantifies the disparity between actual and optimum values of the examined parameters, represented in a generic form as follows (Reynolds, 2009):

$$IM(\%) = \frac{Actual\ value - Optimal\ value}{Optimal\ value} \times 100. \quad (1)$$

The study examines the time, fuel, and gas emissions of airplanes, focusing on Inefficiency Metrics. Actual and optimal values represent actual and optimal duration, fuel use, and emissions, while optimal values represent unobstructed flight and taxiing.

Inefficiency measurements are crucial for sustainability, and analyzing performance indicators and metrics related to economic, social, and environmental concerns at an airport can be valuable for all parties involved.

The Time Inefficiency (TI) of a flight is determined by the Equation (Simić & Babić, 2015):

$$TIi = \frac{\sum_j Tij - \sum_j Toptij}{\sum_h Toptij} \times 100 \qquad j = 1, \dots mi, \quad (2)$$

where: T_{ij} – the time that the observed flight i spends in flight phase j; T_{optij} – optimal time – the time flight i would spend in flight phase j if it were alone in the system (without delay); m_i – the total number of observed flight phases for flight i (each flight in the observed system goes through certain phases depending on the type of operation: landing or take-off).

T_{ij} and T_{optij} are used to determine aircraft delays, indicating weather inefficiency and operational performance at the airport.

Fuel consumption values and emissions of gases during flight phases are sourced from the ICAO database (ICAO, 2025) and EUROCONTROL's database, using the Advanced Emission Model based on the BADA database (EUROCONTROL, 2022).

Fuel consumption (*FBij*) during a certain phase j of flight i (in kilograms) is calculated by the equation (Simić & Babić, 2015):

$$FBij = Tij \times Ni \times FBIij, \quad (3)$$

where: T_{ij} – the time flight i spends in flight phase j (in seconds); N_i – engine number of the aircraft performing the flight i; FBI_{ij} – fuel consumption index of one engine in flight phase j for a specific type of aircraft engine in flight i (in kg/s).

The total fuel consumed on the flight and during the observed phases of the flight j is (Simić & Babić, 2015):

$$TFi = \sum_j FBij = \sum_j \left(Tij \times Ni \times FBIij\right) \quad j = 1, \dots mi. \quad (4)$$

Total spent fuel (*TFa*) of all observed flights *i* (for observed phases of flight *j*) is (Simić & Babić, 2014):

$$TFa = \sum_i TFi \qquad i = 1, \ldots n, \tag{5}$$

where: *n* – total number of observed flights *i*.

The emission of gas *k* during phase *j* of the observed flight *i* is determined, depending on the gas, in one of the following ways:

1) For the determination of HC, CO, and NOx emissions

$$Eijk = Tij \times Ni \times EIijk, \tag{6}$$

where: *Tij* – the time flight *i* spends in flight phase *j* (in seconds); *Ni* – engine number of the aircraft performing the flight *i*; *EIijk* – gas emission *k* by one engine during flight phase *j* for a specific aircraft engine type in flight *i* (in kg/s).

2) To determine CO_2, H_2O and SO_x emissions

$$Eijk = wk \times FBij, \tag{7}$$

wk – multiplying factor of fuel consumed in a given flight phase *j* on flight; *i* for specific gas *k* (w_{CO2} = 3.149; w_{H2O} = 1.23; w_{SOx} = 0.00084); *FBij* – fuel consumed on flight *i* during a certain flight phase *j* (in kg).

The different inefficiencies during phase *j* of the observed flight *i* are determined in the following ways:

1. Inefficiency of fuel consumption

Following the establishment of the methodology for assessing fuel consumption and gas emissions during specific and all recorded flight phases, the flight's fuel inefficiency (*FI*) may be calculated using the equation below:

$$FIi = \frac{TFI - TFopti}{TFopti} \times 100, \tag{8}$$

where is: *TFi* – total fuel consumed during the flight and during the observed flight phases *j*; *TFopti* – the amount of fuel that would be consumed on flight *i* (during the observed phases of flight *j*) when the aircraft would be alone in the system (without delay).

2. Inefficiency of gas emissions

Similarly, the inefficiency of gas emissions EI (Emission Inefficiency) of the flight can be determined by the equation:

$$EIi = \frac{tEI - TEopti}{TEopti} \times 100, \tag{9}$$

where is: *TEi* – total gas emission for all observed gases *k* during flight phases *j* on flight *i*; *TEopti* – the amount of observed gases *k* that would be emitted on flight *i* (during the observed phases of flight *j*) if the aircraft were alone in the system (without delay).

The inefficiencies of fuel consumption and gas emissions are indicators of the airport's environmental performance.

3. Cost inefficiency

When determining the so-called cost inefficiencies, CI cost values related to the emission of certain gases and noise were considered.

The costs of gas emissions are calculated as follows:

- The cost of gas emissions *k* during phase *j* of observed flight *i* is determined using the following Equation (10):

$$CEijk = cek \times EIijk, \tag{10}$$

where is: *cek* – cost of emission of a certain gas (in Euro/kg; ce_{CO} = 0.154762, ce_{CO2} = 0.04127, ce_{HC} = 6.190476, ce_{Nox} = 7.050265, ce_{Sox} = 6.706349); *EIijk* – emission of gas *k* by one engine during flight phase *j* for a specific type of aircraft engine on flight *i* (in kg/s).

4.2. Application of methodology

The proposed methodology aims to evaluate the impact of air traffic control management on airport sustainability by analyzing traffic complexity and system inefficiency indicators. An experiment will be conducted using a hypothetical airport to demonstrate the implementation of this approach, considering medium-term traffic forecasts predicting congestion and delays.

The system under consideration includes landing and departing aircraft, airport manoeuvring surfaces and platforms, traffic volume, fuel consumption, gas emissions, and noise produced by specific aircraft types. The methodology assumes predetermined values for aircraft speeds, separation distances, and separation on the runway and during taxiing. The system uses taxiways and intersections based on the "First come – first served" (FCFS) principle, and aircraft movement is not monitored. The system is initially devoid of traffic at the beginning of the observed period.

The experiment examined two air traffic management strategies to optimize infrastructure: implementing a sequencing strategy where landings take precedence (Arrivals Priority – A/P) and departing aircraft order is determined by arrival and departure times (FCFS sequence). This strategy allows take-offs to escape the runway if sufficient time exists between landings or after the preceding take-off. However, supplementary delays may be imposed on landings, but overall aircraft take-off delays may be reduced compared to the prior sequencing strategy.

The study assumes random aircraft entry into a system with uniform inter-arrival times for low-intensity R (60s, 180s) and high-intensity traffic R (30s, 90s). This aligns with medium-term traffic predictions, demonstrating the level of traffic that results in system congestion and severe aircraft delays. The observed time frame was one hour.

The experiment randomly assigned landing and take-off operations to previously generated aircraft, with an equally distributed 50/50% ratio. Two aircraft types were observed: heavy and large, with a 25/75% ratio. Heavy aircraft included B747s and A310s, while large aircraft included B737-700s and F100s. Each type had a 50/50% distribution. Heavy aircraft landing speeds are 150 kt, large aircraft 130 kt, with taxiing speed on taxiways 25 kt and 15 kt at apron exit. Take-off is permitted when aircraft are over 2 NM from landing threshold, previous aircraft left PSS, and distance from previous take-off is sufficient, with separation between aircraft being 120s or 90s.

5. Results and discussion

The experiment examined Scenario 1 and Scenario 2, assessing the impact of tactical forecast management strategies on inefficiency solutions, using MATLAB codes to generate aircraft operations with all traffic composition and attribute requests (see Appendix).

The next figures will compare computations and results, analyze scenarios and traffic intensities to identify system inefficiencies and determine effective techniques for each situation.

Figure 1 shows average inefficiency values under low-intensity traffic conditions, comparing Arrivals have priority (A/P) and Arrivals/Departure (A/D). Time inefficiency is moderate, with A/D showing slightly higher values. Fuel and cost inefficiencies remain close to zero or slightly negative, while emissions of CO_2, H_2O, SO_x, and NO_x remain close to zero. Emission inefficiencies for hydrocarbons and CO are significantly elevated, suggesting incomplete combustion emissions are disproportionately affected.

Figure 2 shows high inefficiency values for various parameters under high-intensity traffic conditions, comparing A/P and A/D traffic scenarios. Time inefficiency is high, with A/D reaching over 200%, indicating significant delays. Fuel inefficiency and emissions of CO_2, H_2O, and SO_x show negative values, while emission inefficiencies for hydrocarbons and CO are significantly elevated, especially in the A/D scenario. NO_x inefficiency also increases, and cost inefficiency rises moderately.

In Figure 2, negative values of fuel and CO_2 inefficiency can be observed for high-intensity traffic. While this may appear counterintuitive at first, it results from the way inefficiency is defined relative to the theoretical "optimal" no-delay baseline. In real-world conditions under very high traffic intensities, airplanes may operate at speeds and engine loads that occasionally place them in a more favorable efficiency range (e.g., closer to optimal fuel consumption per distance traveled). This can cause the calculated real-world scenario to appear "more efficient" than the baseline reference. Thus, negative values do not indicate a methodological error but rather highlight that, under certain operating regimes, actual driving conditions can exceed the assumed optimal benchmark in terms of fuel use and CO_2 emissions.

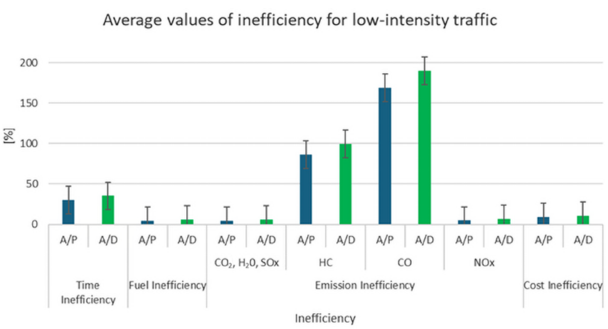

Figure 1. Average values of inefficiency for low-intensity traffic (source: own edition)

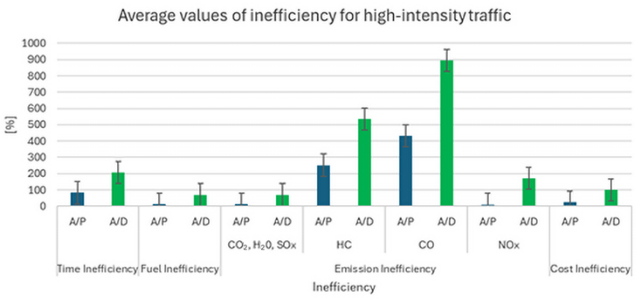

Figure 2. Average values of inefficiency for high-intensity traffic (source: own edition)

Figure 3 shows fuel consumption and emissions under low traffic intensity conditions across different operational scenarios. CO_2 emissions are highest, ranging from 21 000 to 22 000 units, indicating a strong correlation with total fuel usage. Fuel consumption values are lowest in the baseline scenario and highest in the A/D scenario, indicating delay-related inefficiencies. H_2O emissions follow a similar pattern to fuel use, slightly elevated under A/D conditions. Take-off at the gate configurations show reduced fuel and emission levels, suggesting potential efficiency benefits.

Figure 4 shows the average hourly emission values of key pollutants, including hydrocarbons (HC), carbon monoxide (CO), nitrogen oxides (NO_x), and sulfur oxides (SO_x), under low traffic intensity scenarios. NO_x emissions are the most prominent, consistently exceeding 110 kg/h. CO emissions show greater variability, with the highest values in the A/D scenario and lowest in the no-delay configuration. Delays increase CO and HC emissions, while NO_x remains consistently high.

Figure 5 shows fuel consumption and emissions in different operational scenarios under high traffic intensity. The A/D scenario has the highest emissions, with CO_2 emissions approaching 60 000 kg/h and fuel consumption exceeding 20 000 kg/h. The A/D scenario with take-off at the gate yields lower values, suggesting operational benefits in emission reduction. The no-delay scenario also performs favorably, with lower fuel and CO_2 values. CO_2 remains the dominant emission type.

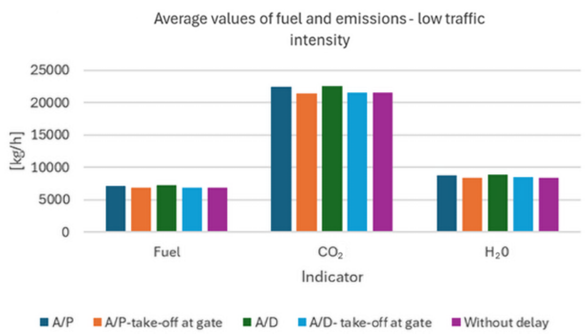

Figure 3. Average values of fuel and emissions – low traffic intensity (source: own edition)

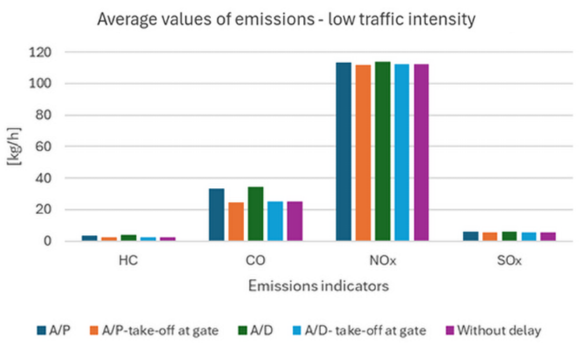

Figure 4. Average values of emissions – low traffic intensity (source: own edition)

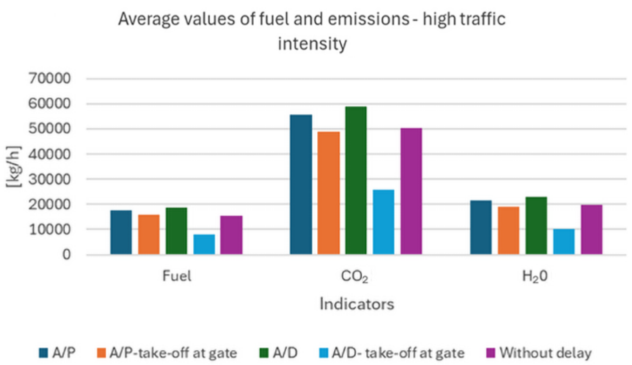

Figure 5. Average values of fuel and emissions – high traffic intensity (source: own edition)

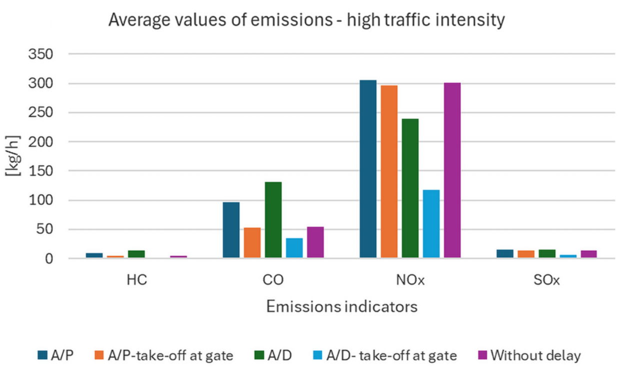

Figure 6. Average values of emissions – high traffic intensity (source: own edition)

Figure 6 shows the average hourly emission values of key pollutants under low traffic intensity. NO_x emissions dominate, exceeding 250 kg/h in most cases. CO emissions vary, with the highest values in the A/D scenario. HC and SO_x emissions remain low, with slight increases in A/D and A/P. Scenarios involving take-off at the gate significantly reduce all emission types, especially CO and NO_x. The no-delay scenario also performs favorably for CO and HC emissions.

6. Conclusions

The increasing complexity of airport traffic poses significant challenges to effective airspace management and ecological sustainability. With the expansion of global air travel, airports face increased demands on ground operations, air traffic management, and runway capacity, leading to prolonged taxiing durations, delays, and elevated fuel consumption. This operational inefficiency leads to increased emissions of greenhouse gases (GHGs) and air pollutants. Aviation fuel usage is linked to traffic density and airport congestion, with idle time on taxiways, holding patterns upon landing, and inefficient aircraft routing contributing to excessive fuel use. Consequently, CO_2 emissions and other harmful pollutants escalate, intensifying the aviation industry's environmental impact.

Aviation emissions account for around 2–3% of worldwide CO_2 emissions, with the potential for significant escalation without mitigating efforts. In addition to carbon dioxide, aircraft release non-CO_2 pollutants at elevated altitudes, contributing to further warming impacts. Enhancing airport traffic management, advancing aircraft technology, and implementing sustainable aviation fuels are crucial measures for mitigating the environmental effects of air travel.

This research assesses the inefficiencies and environmental effects linked to airport ground operations across different traffic levels and procedural arrangements. It finds that the A/D scenario consistently yields the greatest inefficiency across all categories, especially under heavy traffic situations. Take-off operations exhibit much greater inefficiencies in relative and absolute metrics, with significant disparities in CO and HC emissions. Delay mitigation strategies, such as gate-based takeoff protocols and improved scheduling, are essential for airports seeking to reconcile operational needs with environmental accountability, especially under rising air traffic pressures.

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Appendix

A1: MATLAB code for the input - low-intensity traffic scenario

```
% Define constants num_landings = 50;
num_takeoffs = 50; total_aircraft =
num_landings + num_takeoffs;
% Aircraft types and probabilities
aircraft_types = {
'B747 (3GE077)', 'Heavy', 150, 0.25 * 0.5;
'A310 (1GE015)', 'Heavy', 150, 0.25 * 0.5;
'B737-700 (3CM031)', 'Large', 130, 0.75 * 0.5;
'F100 (3RR031)', 'Large', 130, 0.75 * 0.5
```

```
};
% Generate operations ensuring a 50% landing/takeoff ratio operations =
[repmat({'Landing'}, num_landings, 1); repmat({'Take-off'}, num_takeoffs,
1)];
operations = operations(randperm(total_aircraft)); % Shuffle operations
% Generate aircraft types based on probabilities
aircraft_choices = cell(total_aircraft, 1);
aircraft_probabilities =
cumsum(cell2mat(aircraft_types(:,4))); for i =
1:total_aircraft      r = rand;idx = find(r <=
aircraft_probabilities, 1);     aircraft_choices{i} =
aircraft_types{idx, 1}; end
% Generate inter-arrival times and occurrence times
inter_arrival_times = randi([60, 180], total_aircraft, 1);
occurrence_times = cumsum(inter_arrival_times);
% Initialize start of service times
start_service_times = occurrence_times;
%
Separation
parameters
previous_time = 0; previous_type =
'';
for i = 1:total_aircraft         current_aircraft =
aircraft_choices{i};
row_idx =
122
123
strcmp(aircraft_types(:,1), current_aircraft);
current_type = aircraft_types{row_idx, 2};

     if strcmp(operations{i}, 'Landing')       if
~isempty(previous_type)
if strcmp(previous_type, 'Heavy') && strcmp(current_type, 'Heavy')
separation_time = 4 * 10; % 4 NM * 10s per NM        elseif
strcmp(previous_type, 'Heavy') && strcmp(current_type, 'Large')
separation_time = 5 * 10;  elseif  strcmp(previous_type, 'Large') &&
strcmp(current_type, 'Heavy')          separation_time = 3 * 10;
elseif strcmp(previous_type, 'Large') && strcmp(current_type, 'Large')
separation_time = 3 * 10;  else       separation_time = 0;
end

     start_service_times(i) = max(start_service_times(i), previous_time +
separation_time);
     end

     previous_time = start_service_times(i) + (60 *
strcmp(current_type, 'Heavy') +
50 * strcmp(current_type, 'Large'));  previous_type = current_type;

     elseif strcmp(operations{i}, 'Take-off')       start_service_times(i) =
max(start_service_times(i), previous_time + (120 *
strcmp(previous_type, 'Heavy')
+ 90 * strcmp(previous_type, 'Large')));   previous_time =
start_service_times(i); previous_type = '';       end end

% Compute delays delays =
start_service_times - occurrence_times;

% Prepare data for Excel
IAS_approach =
cell(total_aircraft, 1); for i =
1:total_aircraft      if
strcmp(operations{i}, 'Landing')
     row_idx = strcmp(aircraft_types(:,1),
aircraft_choices{i});            IAS_approach{i} =
aircraft_types{row_idx, 3};   else
     IAS_approach{i} =
NaN; end end

% Create table
T = table((1:total_aircraft)', operations, aircraft_choices, IAS_approach, ...
     occurrence_times, start_service_times, delays, ...
     'VariableNames', {'Number_of_Aircraft', 'Operation', 'Type_of_Aircraft', ...
'IAS_Approach', 'Occurrence_in_System', 'Start_of_Service', 'Delay'});
% Save to Excel filename =
'Aircraft_Schedule_MATLAB.xlsx';
writetable(T, filename);
disp(['Excel file saved: ' filename]);
```

A2: MATLAB code for the input - high-intensity traffic scenario

```
% Set random seed for reproducibility
rng(42);
% Number of aircraft
num_landings = 60;
num_takeoffs = 40;
total_aircraft = num_landings + num_takeoffs;
% Aircraft types and classifications
aircraft_types = {'B747', 'A310', 'B737-700', 'F100'};
engine_types
=
containers.Map({'B747','A310','B737-700','F100'},
{'3GE077','1GE015','3CM031','3RR031'});
aircraft_class = containers.Map({'B747','A310'},
{'heavy','heavy'});
aircraft_class('B737-700') = 'large';
aircraft_class('F100') = 'large';
IAS_map = containers.Map({'heavy', 'large'}, [150, 130]); % knots
% Generate operations
```

```
ops = [repmat({‘Landing’}, 1, num_landings), repmat({‘Take-
off’}, 1, num_takeoffs)];
ops = ops(randperm(total_aircraft)); % shuffle
% Generate inter-arrival times and occurrence times
occ_landings = cumsum(60 + (180 - 60).*rand(1, num_
landings));
occ_takeoffs = cumsum(60 + (180 - 60).*rand(1, num_take-
offs));
% Merge occurrence times based on operation
occ_idx_l = 1;
occ_idx_t = 1;
occ_times = zeros(1, total_aircraft);
for i = 1:total_aircraft
if strcmp(ops{i}, ‘Landing’)
occ_times(i) = occ_landings(occ_idx_l);
occ_idx_l = occ_idx_l + 1;
128
129
    else
        occ_times(i) = occ_takeoffs(occ_idx_t);
        occ_idx_t = occ_idx_t + 1;
    end
end

% Generate aircraft types
aircraft_list = cell(1, total_aircraft);
class_list = cell(1, total_aircraft);
engine_list = cell(1, total_aircraft);
IAS_list = zeros(1, total_aircraft);

for i = 1:total_aircraft
    if rand < 0.25 % heavy
        type = randsample({‘B747’,’A310’},1);
    else % large
        type = randsample({‘B737-700’,’F100’},1);
    end
    aircraft_list{i} = type{1};
    class_list{i} = aircraft_class(type{1});
    engine_list{i} = engine_types(type{1});
    IAS_list(i) = IAS_map(class_list{i});
end

% Initialize service times
start_service = zeros(1, total_aircraft);
delays = zeros(1, total_aircraft);
last_service = 0;
last_class = ‘’;
last_op = ‘’;

for i = 1:total_aircraft
    occ = occ_times(i);
    op = ops{i};
130
cls = class_list{i};
    if strcmp(op, ‘Landing’)
        sep = 0;
        if strcmp(last_op, ‘Landing’)
            % Separation in NM to time (s) = NM / speed
(NM/h) * 3600
            switch [last_class ‘-’ cls]
                case ‘heavy-heavy’
                    sep = (4 / IAS_map(cls)) * 3600;
                case ‘heavy-large’
                    sep = (5 / IAS_map(cls)) * 3600;
                case ‘large-heavy’
                    sep = (3 / IAS_map(cls)) * 3600;
                case ‘large-large’
                    sep = (3 / IAS_map(cls)) * 3600;
            end
        end
        occ_time = 60 * strcmp(cls, ‘heavy’) + 50 *
strcmp(cls, ‘large’);
        min_start = max([occ, last_service + sep + occ_
time]);
    else % Take-off
        if strcmp(last_class, ‘heavy’)
            sep = 120;
        elseif strcmp(last_class, ‘large’)
            sep = 90;
        else
            sep = 0;
        end
        min_start = max([occ, last_service + sep]);
    end
    start_service(i) = min_start;
    delays(i) = start_service(i) - occ;
    last_service = start_service(i);
    last_class = cls;
    last_op = op;
end
% Create a table and save to Excel
T = table((1:total_aircraft)’, ops’, aircraft_list’, engine_list’,
IAS_list’, occ_times’,
start_service’, delays’, ...
‘VariableNames’,
{‘Aircraft_ID’,
‘Operation’,
‘Aircraft_Type’,
‘IAS_Approach’, ‘Occurrence_Time’, ‘Start_of_Service’, ‘De-
lay’});
‘Engine_Type’,
writetable(T, ‘Aircraft_Operations_Simulation_MATLAB.
xlsx’);
disp(‘Excel file generated: Aircraft_Operations_Simulation_
MATLAB.xlsx’);
```