Queuing theory for analysis of aircraft eco-efficiency at a Brazilian international airport

Patrícia Regina da Silva Zaluski (UFSC)
przaluski@gmail.com

Maria José Pereira Dantas (PUC-GO)
mjpdantas@gmail.com

Lucila Maria de Souza Campos (UFSC)
lucila.campos@ufsc.br

Abstract

The objective of this research is to estimate local emissions of CO_2 by aircraft at the Brasília–Presidente Juscelino Kubitschek International Airport. Real data requested and provided by Centro de Gerenciamento de Navegação Aérea (CGNA) were used. Has used a simulation of M/E/k queues and the methodology for calculating emissions from the International Panel of Climate Change (IPCC). The results pointed out the environmental impact generated by the consumption of aviation kerosene - QAv. On average, about 11 tons of CO_2 are emitted per aircraft's movement. In total, some 1937.73 tons of CO_2 emitted during the analyzed period were identified. The average emissions based on the aircraft model, engine, and operating time are also shown. The aircraft analyzed were Airbus, Embraer, and Boeing. This research shows that the use of Erlang distribution is more appropriate for aircraft simulations on the ground. The arrival and departure distribution were approximate to the real observed values in the simulation.

Key-words: Atmospheric emissions; logistics; airport operations

1. Introduction

Despite the pandemic of COVID-19 directly impacting the aviation sector, in the pre-COVID era, rapid economic growth and the consequent increase in demand for air transport contributed significantly to anthropogenic climate changes (HASAN et al., 2021). The sector is responsible for 12% of global emissions of greenhouse gases related to transport.

The aviation sector seeks to reduce greenhouse gases with the use of more efficient engines and alternative fuels. Sometimes it is necessary to renew and replace aircraft in search of better eco-efficiency. The International Air Transport Association (IATA) predicted for 2020 a growth of the low carbon sector for aviation, stipulating a 50% reduction in CO_2 emissions by 2050 (IATA, 2021).

Among the fuels alternative to QAv (aviation kerosene), researchers point the use of biofuels and synthetic fuels as main substitutes. The International Council on Clean Transportation - ITCC reports technical barriers for the transition of aircraft powered by hydrogen or electricity. It is estimated that until 2050 the aeronautical industry will still depend on liquid fuels. The sector must seek alternatives among sustainable fuels to achieve the emission reduction target ITCC (2021).

Current market conditions are at a critical level, where issues of energy scarcity and environmental degradation are widely considered. Sureeyatanapas et al. (2018) pointed out that organizations should consider their social and environmental impacts, as consumers are increasingly demanding environmental awareness. Low-carbon logistics has attracted the attention of organizations and administrative authorities, especially on the tangent of reducing energy consumption and CO_2 emissions, becoming an inevitable trend for the logistics sector (HE et al., 2017).

The objective of this research is to present an estimate of local emissions of CO_2 in aircraft movements. To achieve this objective is used a simulation of M/E/k queues considering real data and use of the methodology for calculating emissions from the International Panel of Climate Change.

Similar to this research, Liu & Ge (2018) evaluated the eco-efficiency of a container terminal, considering CO_2 emissions. The authors used the queuing theory methodology to minimize pollutant emissions. In this research, the central objective is to evaluate the eco-efficient performance of aircraft operations on the ground in Brasilia International Airport.

The modeling and simulation of logistic operations are used to solve complex problems. There are a variety of mathematical models that, in operational research, are designed to aid decisionmaking. The air traffic management system is one of the most complex modern systems, having as its concern the safety of flights with the best possible efficiency in its execution.

2. Computer simulation in the aeronautical sector

The most well-known specific models in aeronautics for queue simulation are LMINET, AND, NASPAC, among others. These models have similarities with each other, are based on the theory of the queues they gather characteristics like the selection of dynamic variables, such as climatic conditions. NASA has developed an aircraft queuing model, known as LMINET. This model estimates delays, cancellations, conditions of operations including climatic. This model was initially based on queuing theory, where the arrivals and intervals of arrivals in the taxi queue receive Poisson distribution and model M/M/1 queues, the landings, and take-off process can receive the M/M/1 model or M/Ek/1 (LONG et al., 1999; LOVELL et al., 2013).

Another model of queues presented by Lovell et al. (2013) for aircraft approximations was developed by MIT, known as DNA, originally proposed by Malone in 1995. This model estimates delays being fed by aircraft arrivals generating a propagation algorithm, the model follows the M/M/1 characteristic. The model used by FAA's - Federal Aviation Administration's, NASPAC was one of the first aeronautical simulation models developed.

Other more developed models involve the microscopic modeling of all airport components, such as airport layout, operation of each aircraft, and total airspace. These models are known as SIMMOD and TAAM, require adaptations and repetitions to generate significant statistics (SIMAIAKIS & BALAKRISHNAN, 2016).

The international literature shows studies on the applicability of queuing theory in airports in a dynamic way due to the complexity of the airport system and can be applied mostly in soil and air operations. More recent studies are presented below. Table 1 presents a systemic analysis of the study of queues at airports highlighting the object studied at the airport and the method used.

Table 1: Systematic analysis of queuing studies at Airports

Study object	Methodology	Researchers
Air traffic and ground operations	M/M/1 e M/E*k*/1	Long et al. (1999)
Inspection Queues	M/G/1; M/G/2; M/M/1; M/M/M; virtual queue simulation	Dorton & Liu (2016); Lange et. al (2013); Aniyeri & Nadar (2018)
Aircraft delays	M/E/1; M/M/1; Monte Carlo simulation	Pyrgiotis et al. (2013); Lovell et. al (2013); Jackillat & Odoni (2014); Simaiakis & Balakrishnan (2016)
Arrivals and departures of aircraft	M/E/1; M/D/1	Jacquillat et. al (2016); Caccavale et. al (2014);
passengers in the queue	Poisson hybrid model – Bayesian	Wu et. al (2014)

The authors Dorton & Liu (2016) performed a discrete queuing simulation to investigate the effects of alarm rates and baggage volume on inspection queues and to evaluate their performance. In the study, the proposed model was based on the combination of M/G/1 and M/M/1 queues, the authors assumed that the model is limited in several aspects, since they did not explain non-stationary arrivals and times of non-exponential services. The authors used for validation of the model, lots of 100 replicates, concluded that if each passenger took two items less, about 15 seconds would be saved regardless of the alarming rate. Lange et al. (2013) conducted a similar study to that of Dorton & Liu (2016), the authors analyzed the inspection queues using virtual queue simulation to test cost savings with queue inspectors through redistribution of passengers. Aniyeri & Nadar (2018) analyzed the inspection queue based on the multi-server queuing approach (M/M/M), evaluating the performance of the shipping system.

Pyrgiotis et al. (2013) described a dynamic queuing model that treats each airport studied in the network as M(t)/Ek(t)/1. The authors studied the phenomenon of delay propagation in a network of airports caused due to the congestion of individual airports causing a cascade effect. The data used were individual airport delays, flight schedules, and demand rates at all airports in response to calculated local delays. Demand shifts were observed at certain times of day and on bad weather days, as well as the increase in the total average delay throughout the day. The model cannot identify the actual causes of flight delays, which implied the reproduction of measured delay rates. The authors proposed improvements in airport network management and ground operations as a means of mitigating delays.

Lovell et al. (2013) have modeled the propagation and variance of delay approximations in continuous aircraft queues in airspace using the M/M/1 queue topology, representing an airport, lane, or route with actual data. To validate the model the authors used the Monte Carlo simulation to compare the steady-state obtained in the M/M/1 queue, the queuing model was shown to be faster in obtaining results.

The applicability of queuing theory in airports has a variability of objectives found in the international literature, among them to measure the efficiency of processes such as arrival and departure of aircraft, waiting times at check-in, aircraft approximations, flight delays, baggage, inspection queue, among others. The study of queues at airports is dynamic and can involve different operations and systems with different objectives, which can be applied in risk analysis, forecasting passenger demand, performance analysis, among others.

3. Methodology

3.1. Conceptual model: Restrictions and physical limitations

We requested a reals database from CGNA (Centro de Gerenciamento da Navegação Aérea). The reals data of aircraft arrivals and departures made possible a fidelity representation of reality. The data used in this research are limited to the period before COVID.

The international airport of Brasilia has a runway capacity of 64 movements/hour, representing an average of over 600 flights per day. The average time of occupation of the runway for landings is 65 seconds, and for takeoffs is 55 seconds (DECEA, 2019). The airport has 2 lanes, 29R11L and 29L11R. Currently has homologation operates simultaneously.

The conceptual model was based on the IDEF-SIM methodology (showed in Figure 1) where the aircraft (1) arrive at certain time intervals, (2) use the landing strip, (3) perform taxi-in, (4) wait for a certain time in the system (finger), (5) take a taxi-out and return to the runway to take off (6) and finally, (7) leave the system.

Figure 1: IDFSIM airport

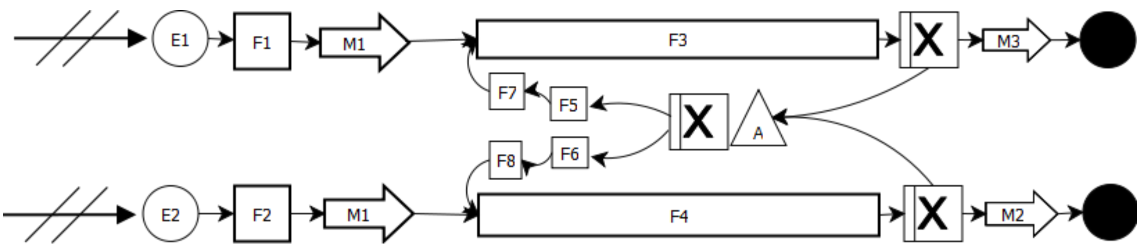


Table 2 contains descriptions and types of commands for each item used in this simulation.

Table 2: IDFSIM symbols

Item	Type	Description
	System start	Aircraft entry on runways 29R11L / 29L11R
E1/E2	Entity	Aircraft
F1/F2	Occupation	Queue
M1/M2	Movement	Input flow
F3/F4	Occupation	Runways 29R11L / 29L11R
X	Decision	Decision point
A	Unity	Amalgamation points between the aircraft from the two runways.
F5/F6	Occupation	Taxy-out and position 2
F7/F8	Occupation	Queue - position 3
M3/M4	Movement	Outflow
	End of the system	Aircraft departure

The symbology represented in Figure 1 and described in Table 2, indicates the arrival flow of entities - aircraft (E1); (E2) in the system, where they line up (F1) and (F2) with non-preemptive priority. Item (A) is the point of union between the two entrances, where the aircraft waits for a period of permanence. Then it is directed to the functions (F5) or (F6) that represent the taxi-out time and wait again in lines (F7) and (F8) to return to the processes (F3) and (F4).

For the construction of the model, two landing rates were considered, since runway 29L11R is more used for takeoff while runway 29R11L operates a larger number of landings, due to the route of the arrival of aircraft being predominant in the south and southeast regions. Adopting the formula proposed by DECEA (2015), we obtain the following lane service fee for medium-sized aircraft:

$$MATOP_A = \frac{TOPD_A + TOPP_A}{2} = \frac{55 + 65}{2} = 60\ seconds \quad (1)$$

Only medium-sized aircraft were considered for the simulation. Considering the 120-second safety interval rate proposed by CONAR, the total service value of 180 seconds is given between landings and take-offs.

3.1. Development of the model

The aircraft take-off process can be seen as a type of service. In this case, the runways 29R11L and 29L11R are servers and the aircraft are the customers. The aircraft is assumed to arrive at the runway ($i \in \{1, 2 \ldots n\}$) with an expected arrival rate λ_i (aircraft/hour). There is no wait on the arrival of the aircraft if the system is empty; it occupies the server immediately leaving the system after the operation. If the system is busy, the aircraft waits in a queue. The average queue service rate of aircraft at position 2 is μ_i (aircraft/hour), the queue of aircraft at position 2 is designated as L_i (aircraft). The expected service time is defined as $E(t_i)(1/\mu_i,)$ - measured in hours per aircraft. The expected occupancy rate for the runway is $\rho_i = (\lambda/\mu)$.

For the exponential distribution (M/M/1), the queue compliance value is expressed by the equation:

$$L_i = \frac{\lambda}{\mu - \lambda} \qquad (2)$$

If the service time has a low variation, a D-degenerate distribution is assumed, with $Var[t_i] = 0$:

$$L_i = \rho_i + \frac{\rho_i^2}{2(1-\rho_i)}, \qquad \forall i \in \{1,2,\dots,n\} \qquad (3)$$

If the time variation followed is Erlang-*k*-E*k* distribution, it is assumed that aircraft arrivals on the runway follow distribution Ek with variance $\rho_i^2/k\lambda_i^2$. Substituting the values of equation 4, we have:

$$L_i = \rho_i + \frac{(1+k)\rho_i^2}{2k(1-\rho_i)}, \qquad \forall i \in \{1,2,\dots,n\} \qquad (4)$$

In the case of the E*k* distribution, if the value of *k* is assumed to be *k* = 1, the distribution becomes M - negative exponential distribution (Markovian), assuming the value of k ≥30, the Erlang-*k* distribution becomes an approximation to normal (LIU & GE 2018).

3.2. Estimation of CO_2 emissions

According to IPCC 2006 guidelines for national greenhouse gas inventories (2018), the pollutant emission values can be calculated by the equation:

$$E_{CO_2} = Cons \times \rho_{energia} \times Fe_C \times \%oxidação \times \frac{44}{12} \qquad (5)$$

- E_{CO_2}: Total CO_2 emissions in tones
- $Cons$: Kerosene Aviation Consumption - QAv (m^3)
- $\rho_{energia}$: Energetic density of fuel QAv (tep/m^3)
- Fe_C: Elementary carbon emission factor per unit of energy contained in QAv (tCTJ)
- $\%oxidação$: Oxidized fraction of elemental carbon in combustion
- $\frac{44}{12}$: Ratio between the molecular masses of CO_2 and elemental carbon (gCO_2 / gC)

To determine the amount of fuel consumed per aircraft, one can use the expression given by:

$$C_{af} = \sum nM_a \times Fc_{af} \times t_{af} \qquad (6)$$

In expression we have that:

- C_{af}: Consumption of QAv (kg) of aircraft *a* in phase *f*
- nM_a: Number of aircraft engines *a*
- Fc_a: Aircraft fuel flow *a* in phase *f*
- t_{af}: Remaining time in aircraft seconds *a* in phase *f*

For a microscopic evaluation of the model, the study considers the characteristics of each aircraft, such as the type of engine used and fuel flow in each LTO phase. The time spent on aircraft ground, extracted from the CGNA database, allowed a detailed analysis of emissions per aircraft. The properties of the QAv and fuel flow of aircraft engines are described in Table 3 and 4:

Table 3: Physical and chemical properties of QAv

Property	**Unit**
Volume in m³	790 kg/m³
Emission Factor	19,5 (tC/TJ)
Fraction of oxidized carbon	100%
Density (tep/m³)	0,822

Source: 2006 IPCC Guidelines for National Greenhouse Gas Inventories (2018)

Table 4: Characteristics of aircraft engines considered in the study

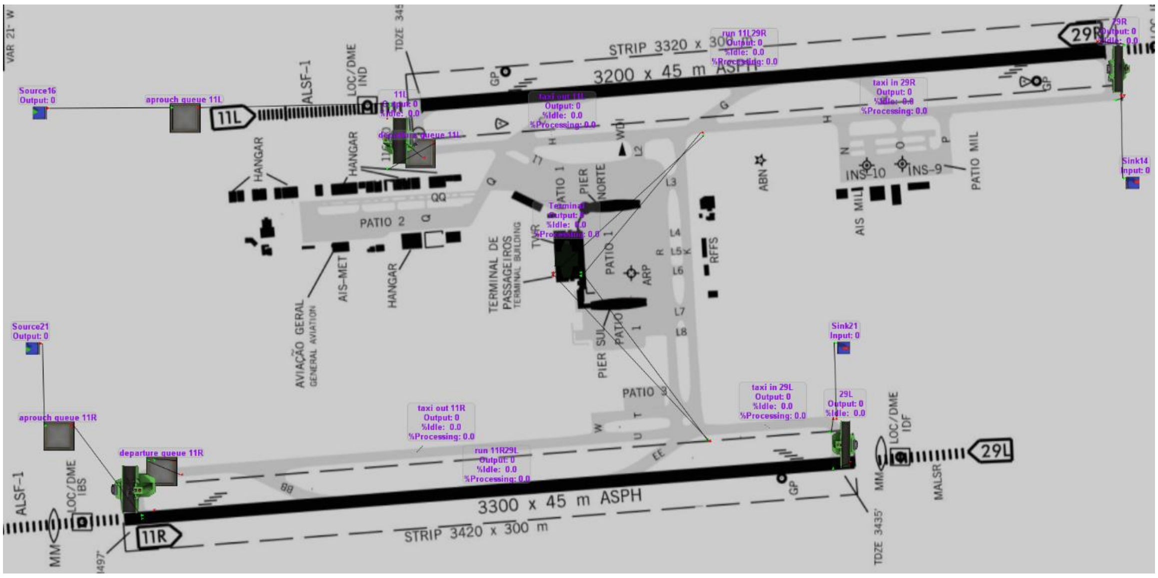
Aircraft	**Model considered**	**Engine**	**Fuel flow phase idle (taxi-in; taxi-out)**	**Fuel flow phase take-off (takeoff)**
Airbus	A320; A319; A321	V2527-A5	0,128 kg/s	1,053 kg/s
Boeing	B727	CFM56-7B26	0,108 kg/s	1,21kg/s
Embraer	E190	CF34-10E2A1	0,084 kg/s	0,769 kg/s

Source: ICAO Engine Exhaust Emissions Data Bank Subsonic Engines (2018)

4. Discussions

For the development of the computational model, the logic specified in the conceptual model IDEF-SIM was considered. The program's construction was carried out with the help of the airport's floor plan, facilitating the location and fixation of processors and queues in the system. Figure 2 contains a representation of the Flexsim® structure of the model used.

Figure 2: Brazilian airport's flexsim® model



After calibrating the model with *k*-Erlang distribution, it was possible to obtain approximate results for the real system. With this it is possible to present the main statistical characteristics of the analyzed airport, considering its emissions from aircraft movements, average fuel consumption, among others.

Table 5 contains the average values obtained from the service time (*Wq*) in minutes, and respective data of idle time, emissions in tons, and consumption of aviation kerosene QAv in kilograms per aircraft.

Table 5: average time *Wq*

28R11L	**Wq real**	**Wq simulated**	**%idle**	**Fe(tCO2)/ aircraft**	**QAv kg/aircraft**
taxi-out	11,52	11,3	65,4	12,3222	209,664
taxi-in	1,74	1,67	91,4	1,57079	26,7264
28L11R	**Wq real**	**Wq simulated**	**%idle**	**Fe(tCO2)/ aircraft**	**QAv kg/aircraft**
taxi-out	13,73	13,43	33,1	12,12397	206,2848
taxi-in	2,76	2,79	75,1	2,518681	42,8544

The highest values of emissions belong to the taxi-out processes, with 12 tons of CO_2 per aircraft in taxi-in the analyzed period. Fuel consumption is also auto during taxi-in, due to the longer time spent during movement. On average the time for taxi-out is 11.52 minutes for runway 29R11L and 13.73 minutes for runway 28L11R. The biggest idle times belong to the taxi-in lanes.

Table 6 shows the number of aircraft expected per hour (*Lq*) real and simulated, allowing comparison and validation of the model. An average of 3.25 aircraft per hour on runway 29R11L and 6.15 aircraft on runway 29L11R were expected.

Table 6: Aircraft expected per hour (*Lq*)

runway	Lq real	Lq simulated
29R11L	3,25	3,5
29L11R	6,15	6,45

Figure 3 shows the number of aircraft waiting for takeoff and approach for landing, for the respective headlands 11L and 11R. A greater number of aircraft waiting for landing at the 11R headland is seen. As shown in table 4, a higher number of landings per hour on runway 29L11R was expected. There is also a small occurrence of a queue for landing for runway 29R11L, close to 3 pm.

Figure 3: aircrafts waiting in the queue

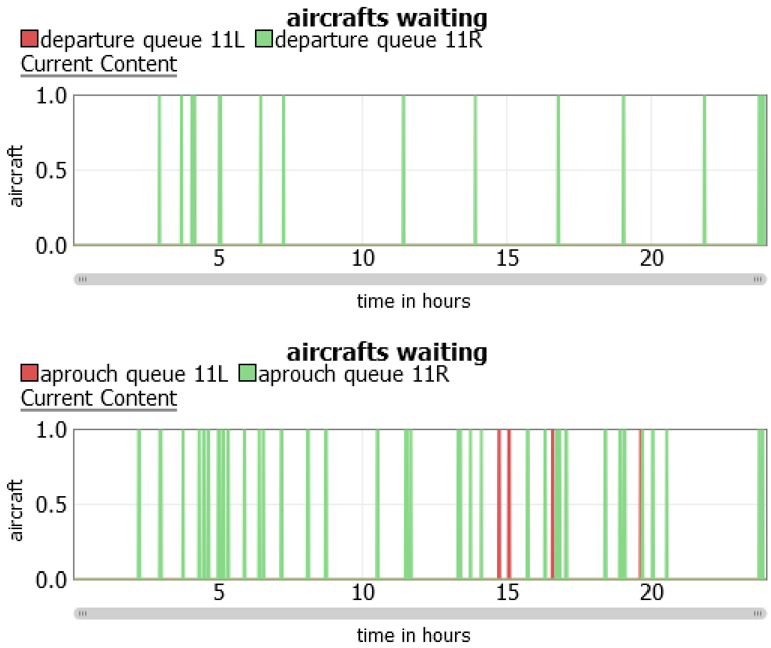
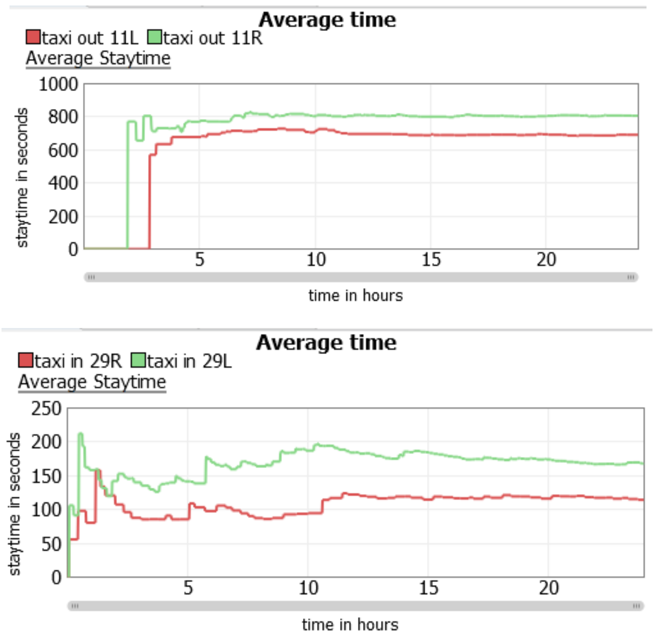


Figure 4 shows the average time spent on taxi movements. The time spent for taxi-out is longer in both lanes, with the value stabilizing at approximately 800 seconds (13 minutes) for the 11L headland and 600 (10 minutes) seconds for the 11R headland. Taxi-in values are lower, with an average stabilizing at 150 seconds (2.5 minutes) for the 29L headland and 100 seconds (1.6 minutes) for the 29R headland.

Figure 4: Average time in taxi operations



The total occupation of the terminal over the analyzed period is shown in Figure 5. The analyzed terminal did not reach its maximum operating capacity. The average number of aircraft per hour was 14 finger aircraft. The maximum occupancy point was 20 aircraft per hour.

Figure 5: Terminal occupation along the time

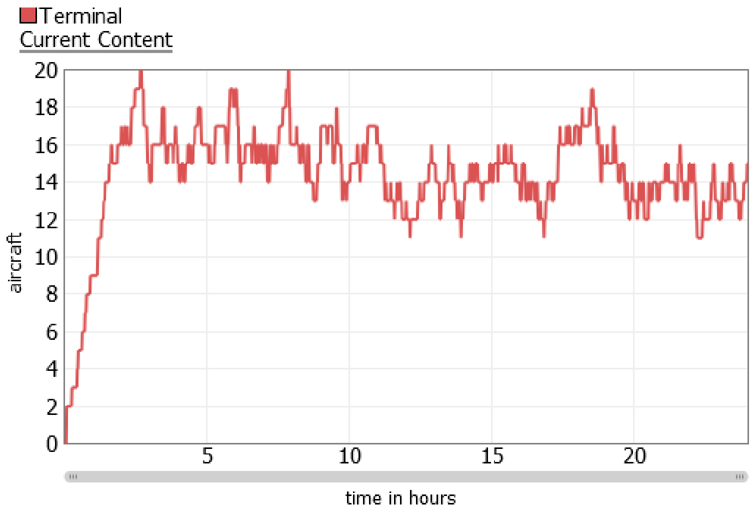
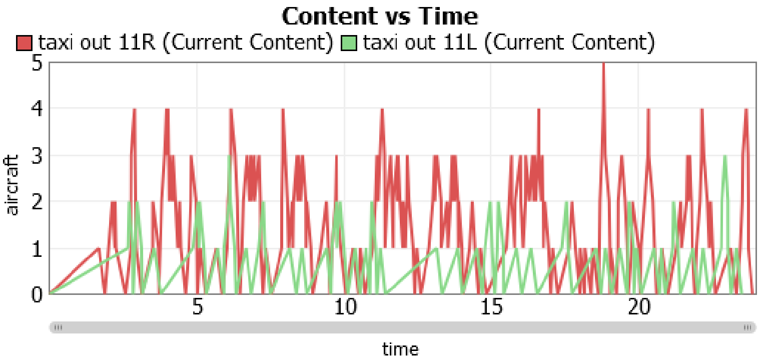


Figure 6 shows the number of aircraft queued for taxi-out on both runways. It is possible to see the occurrence of peaks of 4 aircraft in the process of taxi-out simultaneously to the 11R headland. The highest occurrence is of 5 aircraft at 6 pm. The occurrence of queues in taxi-out to the 11L headland is on average of 2 simultaneous aircraft it is also possible to observe a peak of 3 aircraft at 11 pm.

Figure 6: number of aircrafts in queue to taxi-out

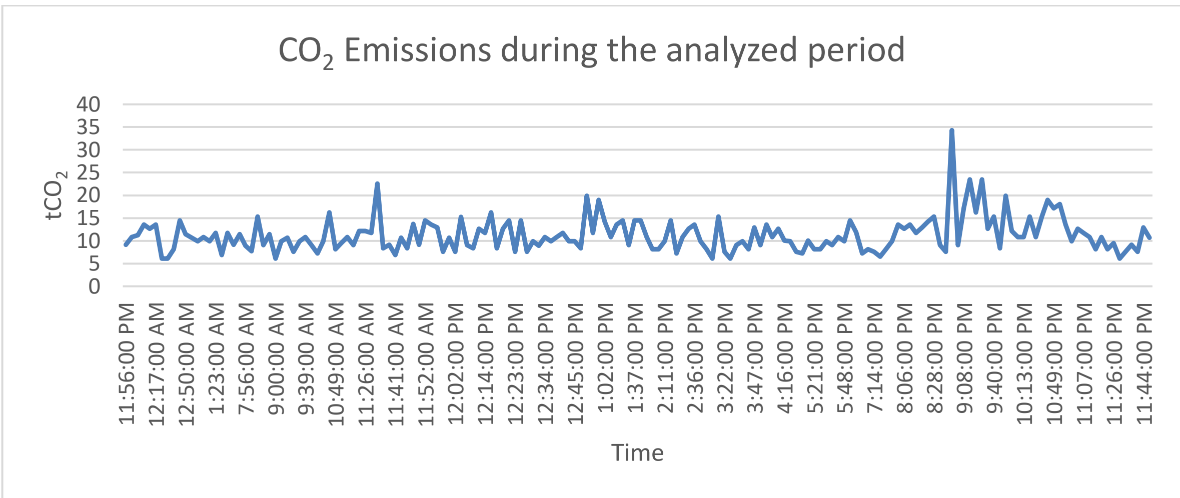


The first part of this article dealt with the statistical aspects of the airport simulation considering the movements, it was possible to observe the average number of CO_2 emissions per movement. In the next subsection, detailed data on emissions are presented based on the aircraft model, engine type, and airline operated at the airport during the analyzed period.

4.1. Aircraft model emissions

Figure 7 shows the actual value of emissions by aircraft during the period considered in the simulation. It is possible to verify the presence of emission peaks at different times, whose values are validated due to the occurrence of aircraft queues on the ground at the airport. The average value of CO_2 emissions is approximately 11 tones during the period and a total of 1937.73 CO_2 tones.

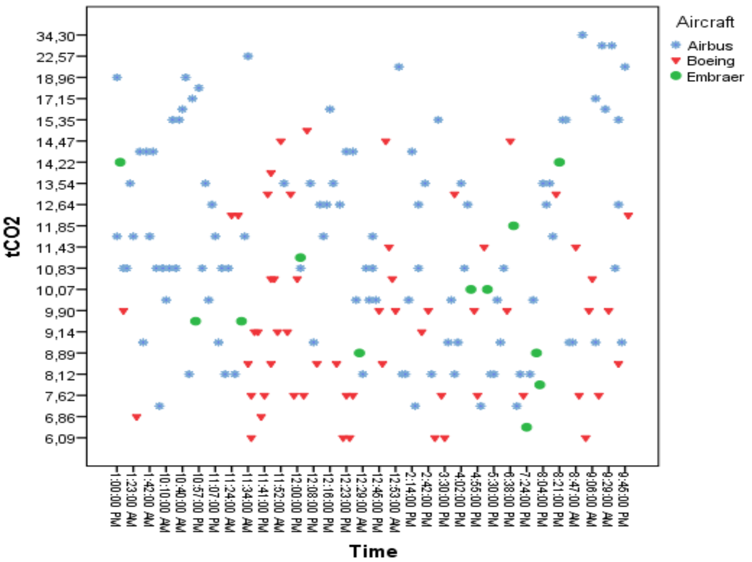
Figure 7: Real CO_2 Emissions during the analyzed period



The graph Generated in figure 8 shows the dispersion of emission values per aircraft model during the analyzed period. Notably, Airbus model aircraft have a greater dispersion of values;

the aircraft model is also responsible for the emission peaks portrayed in the line chart of figure 7.

Figure 8: Dispersion chart of CO2 emissions by aircraft model during the analyzed period



Despite the small number of flights evaluated by Embraer, it is notable that this aircraft has lower emissions rates during the analyzed period. The fact can be proven due to its consumed fuel flow per second being lower than the other models. Despite this, the total capacity of tons carried by aircraft models must be considered. Boeing aircraft, for example, have a greater capacity of passenger allocation than Embraer aircraft.

Table 7 presents the average CO_2 emissions in tons per aircraft model, considering the simulated values for the three types of distribution.

Table 7: Take-off - runway 29L11R, simulation CO_2 ton/aircraft model

	Airbus	Boeing	Embraer	Average ton
Exponential Distribution	17,2	14,4	11,2	14,26
Erlang-*k* Distribution	12,6	10,4	8,29	10,5
Degenerate Distribution	8,12	6,8	5,3	6,7

When estimating the emission values in tones per aircraft model during the take-off phase, the Erlang-k distribution was the one that most approached the actual emission average, which corresponded to 10.5 tons. It can be concluded that the Erlang distribution is the most appropriate for the use of simulation of aircraft queues, a fact that Long et al. (1999) described in his report.

5. Final considerations

In this study it was possible to present the polluting potential of aircraft in the international airport of Brasilia, using real data. The actual and simulated values were compared considering three types of distribution (exponential distribution, Erlang-k, degenerate). The CO2 estimation formulas considered were taken from the IPCC report. The delimitations of the model followed the rules proposed by ICAO, CGNA, and DECEA.

The research is limited to the analysis of operations on the ground. The data used in this research are limited to the period before COVID.

It is noteworthy that only the side operations were evaluated in greater detail (takeoff and landing). Approximation data are presented, however macroscopically, we suggest to future research, an extension of this study to evaluate and verify the emissions of these data. The efficiency of aircraft can be estimated by assessing the passenger allocation capacity per aircraft, the capacity of tons of cargo transported, and the fuel consumption per second. In this way the study would treat the subject microscopically, being able to inform the carbon footprint per passenger/aircraft.

Among the aircraft studied, Embraer had lower fuel consumption per second, resulting in lower emissions. It must be emphasized that the aircraft model considered for the study has a smaller number of passengers than the other models of aircraft studied.

The study proved that the use of the Erlang-k distribution has a better approximation to actual landing and takeoff data. The results of this distribution were compared between exponential, degenerate, and actual observed values. Therefore, the use of this distribution model for operations involving aircraft on the ground is favorable.

Acknowledgments

This work has been supported by Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES) and National Council for Scientific and Technological Development (CNPq).

REFERENCES

Aniyeri, R & Nadar, R., (2018). Passengers queue analysis in international airports terminals in Kerala using multiphase queuing system. International Journal of Mathematics in Operational Research, 12(1) 1-30.

Caccavale, M. V; Iovanella, A; Lancia C; Lulli, G & Scoppola B. (2014). A model of inbound air traffic: The application to Heathrow airport. Journal of Air Transport Management (34) 116-122.

DECEA - Departamento de Controle do Espaço Aéreo. (2015). Capacidade do Sistema de Pistas, MCA 100-14/2015, Brasília. https://publicacoes.decea.mil.br/api/storage/uploads/files/f21ab094-351a-4356-879b03e50b4e39d4.pdf

DECEA - Departamento de Controle do Espaço Aéreo. (2019). Relatório de desempenho operacional da terminal Brasília e do aeroporto internacional de Brasília http://especiais.decea.gov.br/performance/wp-content/uploads/2020/04/APP-Bras%C3%ADlia-TWR-BR-Relat%C3%B3rio-ANO-2018.pdf

Dorton, S. L & Liu, D. (2016). Effects of Baggage Volume and Alarm Rate on Airport Security Screening Checkpoint Efficiency using Queuing Networks and Discrete Event Simulation. Human Factors and Ergonomics in Manufacturing & Service Industries 26 (1) 95–109

Hasan, M.A.; Mamun, A.A.; Rahman, S.M.; Malik, K.; Al Amran, M.I.U.; Khondaker, A.N.; Reshi, O.; Tiwari, S.P. & Alismail, F.S. (2021). Climate Change Mitigation Pathways for the Aviation Sector. Sustainability, 13, 3656.

He, Z.; Chen, P; Liu, H; & Guo, Z. (2017). Performance measurement system and strategies for developing low-carbon logistics: A case study in China. Journal of Cleaner Production. 156 395-405.

IATA, (2021). Halving Emissions by 2050 - Aviation Brings its Targets to Copenhagen. Retrieved from http https://www.iata.org/en/pressroom/pr/2009-12-08-01

ICAO – International Civil Aviation Organization, (2018). Engine Exhaust Emissions Data Bank Subsonic Engines http://www.easa.europa.eu/easa-and-you/environment/icao-aircraft-engine-emissions-databank.

IPCC. (2018). 2006 IPCC Guidelines for National Greenhouse Gas Inventories, v.2, Energy. Retrieved from https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol2.html

ITCC. (2021). Assessing the sustainability implications of alternative aviation fuels, Working paper 2021-11

Jacquillat, A; Odoni, A & Webster, M. (2016). Dynamic Control of Runway Configurations and of Arrival and Departure Service Rates at JFK Airport under Stochastic Queue Conditions, Transportation Science, 51(1) 155-176.

Lange, R; Samoilovich, I & Rhee, B. V. D. (2013). Virtual queuing at airport security lanes. European Journal of Operational Research, 225, 153–165.

Liu, D & Ge, Y.E. (2018). Modeling assignment of quay cranes using queueing theory for minimizing CO2 emission at a container terminal. Transportation Research Part D: Transport Environ., 61, 140-151.

Long, D; Lee, D; Johnson, J; Gaier, E & Kostiuk, P. (1999). Modeling Air Traffic Management Technologies with a Queuing Network Model of the National Airspace System. NASA - National Aeronautics and Space Administration Langley Research Center Hampton, Virginia 23681-2199.

Lovell, D. J; Vlachou, K; Rabbani T & Bayen A. (2013). A diffusion approximation to a single airport queue Transportation Research Part C 33 227–237.

Pyrgiotis, N; Malone, K. M & Odoni, (2013). A. Modelling delay propagation within an airport network Transportation Research Part C, 27 60–75.

Sureeyatanapas, P; Poophiukhok, P; & Pathumnakul, S. (2018) Green initiatives for logistics service providers: An investigation of antecedent factors and the contributions to corporate goals, Journal of Cleaner Production, 191, 1-14.

Simaiakis, I & Balakrishnan, H. (2016) A Queuing Model of the Airport Departure Process Transportation Science Massachusetts Institute of Technology – MIT, 50(1) 94-109

Wu, P. P-Y; Pitchforth, J & Mengersen; K. A (2014) Hybrid Queue-based Bayesian Network framework for passenger facilitation modelling Transportation Research Part C, (46), 247–260.