CHARACTERISING THE ROLE OF FLEET RENEWAL ON THE PATHWAY TO 2050: A EUROPEAN AIRLINE CASE STUDY

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Abstract

This work developed a simulation tool that incorporates both airline operations and aircraft specific capabilities when investigating the environmental and economic sustainability pathways for short haul aviation. A network of airports, centred around the island of Ireland and its connectivity to Europe, was created using the mathematics of multi-commodity flow networks and solved using mixed-integer linear programming. The model schedules a given fleet of aircraft to flights in the network such that passenger demand is met in the most environmentally and economically sustainable way. Three fleet composition cases are studied to investigate the impact fleet renewal has on the sustainability of an airline. The three cases vary the composition of the fleet with 0%, 25% and 50% of the fleet population being the advanced B737-8200 aircraft with the balance of the population being the current generation B737-800 variant. The scheduling model is capable of completely scheduling an airline's fleet as well as generating solutions that are influenced by the performance of the aircraft comprising the fleet. This important functionality within the model ensures that the solution offered by the optimisation algorithm is intrinsically linked to and dependent upon both the airline's operational attributes and the specific aircraft parameters. This core functionality enables the completion of these case studies investigating the sustainability of current generation and next generation aircraft technology implementation. Airline sustainability was analysed to determine the business case and environmental benefits of substituting B737-8200 aircraft in place of B737-800's for the real world operations of a European airline, to characterise the role of technology improvements on a fleet-wide basis and to help inform and provide insight into the role of fleet renewal on the route to net-zero.

Keywords: Sustainability, airline scheduling, optimisation, aircraft performance, fleet renewal

1. Nomenclature

ASK = Available Seat Kilometres [seat.km]
ATC = Air Traffic Control
ATR = Average Temperature Response
C_D = Coefficient of Drag [-]
$C_{D,0}$ = Zero-Lift Coefficient of Drag [-]
C_L = Coefficient of Lift [-]
CASK = Cost Per Available Seat Kilometre [cent/km]
CI = Cost Index
CO_2 = Carbon Dioxide
D = Aerodynamic Drag [N]
EU = European Union
FAA = Federal Aviation Administration
FLEET = Fleet-Level Environmental Evaluation Tool
IATA = International Air Transport Association
ICAO = International Civil Aviation Organisation
ID = Identification
k = Lift Dependent Constant of Proportionality [-]
KPI = Key Performance Indicator

L = Aerodynamic Lift [N]
LTAG = Long Term Aspirational Goal
MILP = Mixed-Integer Linear Programming
MR = Mission Range [nmi]
NPSS = Numerical Propulsion System Simulation
$\boldsymbol{r}$ = Route Vector
R^2-value = Coefficient of Determination [-]
RASK = Revenue Per Available Seat Kilometre [cent/km]
RPK = Revenue Passenger Kilometres [pax.km]
S = Wetted Area [m^2]
SAF = Sustainable Aviation Fuel
SUAVE = Stanford University Aerospace Vehicle Environment
T = Thrust [N]
TOW = Takeoff Weight [kg]
TSFC = Thrust Specific Fuel Consumption [g/s.kN]
V_∞ = Freestream Velocity / True Airspeed [m/s]
W = Weight of Aircraft [N]
θ = Flight Path Angle [°]
ρ = Air Density [kg/m^3]

2. Introduction

Sustainability has become the contemporary driving force for progress within the aviation sector as many stakeholders from across the industry are encountering and developing solutions to the challenge of decarbonisation [1]. Airbus have committed to developing a hydrogen fuelled commercial aircraft by 2035 with their "ZEROe" project [2]. Rolls-Royce have successfully operated a gas turbine aeroengine on increasing portions of sustainable aviation fuel (SAF) with some recent tests being up to 100% SAF fuelled [3]. As well as this, Rolls-Royce have developed the "Ultrafan" engine which is a technological breakthrough in terms of overall propulsion system efficiency; 10% efficiency improvement versus the "Trent XWB" engine and is capable of running on 100% SAF [4]. Boeing are developing the "most efficient twin-engine aircraft" with 10% more fuel efficiency and a 10% reduction in operating costs for airlines [5]. Other manufacturers and technology suppliers within the sector are also developing and integrating more sustainable methodologies into their products: ZeroAvia's hydrogen fuel cell powered aircraft [6], Spirit AeroSystems using lightweight, high-strength composite materials in aircraft component fabrication to decrease fuel consumption [7], among others. While these are all very interesting and critical advancements within the field, these technologies must earn their way onto an aircraft, and new aircraft must earn their way into an airline's fleet. Characterising the performance of such new technologies within the context of the real world operations of an airline is of pivotal importance. An International Civil Aviation Organisation (ICAO) report on the "Long-Term Aspirational Goal" (LTAG) of reducing CO_2 emissions indicates that airlines are in favour of fleet renewal as this will offer sustainability gains in the form of more fuel efficient aircraft [8]. However, the attainable real world, fleet-wide benefits may not be as pronounced as those which would be expected based on an evaluation of an individual aircraft candidate on the airframer's "design mission". Hence the sentiment of technology proving its worth, for example via fleet-wide adoption simulations, is a critical step towards its deployment within the aviation sector.

The focus of this study is the impact improved technology may have on decarbonising the aviation sector. Fleet renewal is one such method that can improve the sustainability of an airline's fleet. Ryanair's current fleet comprises of approximately 25% "Gamechanger" aircraft which are the B737-8200 MAX aircraft that offer a 16% reduction in fuel burn for a 4% increase in passenger capacity compared to the B737-800 "Next Generation" aircraft thereby significantly improving emissions per passenger [9]. Ryanair plan to further renew their fleet with the adoption of 300 B737-MAX 10 aircraft by 2034 [9]. These aircraft further improve upon the B737-8200 MAX's benefits with a 20% reduction in fuel burn and 21% increase in passenger capacity compared to the "Next Generation" aircraft [10]. Ryanair are seeing the need to renew their fleet as more advanced technology offering higher fuel efficiency through propulsion and airframe improvements as a direct way of improving their economic and environmental sustainability. The ICAO's LTAG encourages member states to work with manufacturers and other stakeholders within the industry to introduce increasingly more fuel efficient technology into the market [8]. Destination 2050's report on the role of different sustainability drivers within the aviation industry asserts that a 37% reduction in the 2050 projected CO_2 emissions can be achieved through technology improvements alone, 17% of which is solely due to kerosene-based technology advancements [11]. Similarly, the European Commission's "Flightpath 2050" discusses the goals for aviation within Europe with some focus on the development and adoption of a "new generation of air vehicles and ever more efficient, environmentally friendly and quiet engines" [12]. This drive to pursue the utilisation of the best technology makes sense from an environmental perspective as reduced emissions are achieved. However, perhaps more pertinent to airlines, the economic benefits via fuel savings offer a potentially more competitive advantage in an increasingly decarbonising sector. The profit margins of airlines leave little capacity to absorb financial penalties without bankruptcy hence complying and pro-actively seeking to stay ahead of the curve when it comes to new technology and policy is a must for survival. A "chart of the week" published by the International Air Transport Association (IATA) in June 2019 demonstrates how costly operating an airline is, with an average net profit per passenger of $6.12, after a revenue and cost per passenger of $188.98 and $182.86, respectively [13].

System-wide integration analyses, technology utilisation assessments, market and policy understanding, and holistic optimisation approaches are therefore critical steps in taking technological advancements to application, as seen by Roy et al. [14] who investigated a novel methodology for designing an aircraft based on three core subspaces: "Aircraft Design Formulation", "Airline Allocation Formulation" and "Revenue Management Formulation". Roy et al. captured the operational strategy using a fleet allocation model and the economic performance of the airline with a revenue management model. The three subspaces are sought to be optimised in tandem with one-another such that the local optima for individual subspaces do not detract from the global optimal configuration across all subspaces. The key result was that the aircraft designed, fleet allocated, and revenue acquired via the simultaneous optimisation of the design subspaces rather than a decoupled, sequential analysis yielded a more profitable airline.

This type of analysis has become more popular in the literature, Atanasov et al. [15] designed a turboprop aircraft to compete as a cost-efficient, less climate impactful aircraft for airlines to introduce to their fleet. The research forecasted what type of aircraft may be necessary in the future to meet the increasing demand for aviation to decarbonise. An economic assessment comprising of the costs associated with designing and manufacturing an aircraft and projected fuel costs, along with a forecasted network of airports and passenger demand was utilised to inform and alter the design of an aircraft within iterative and simultaneous optimisation studies. It was found that the turboprop aircraft could offer significant reductions in climate impact potential, between 20-30% more fuel efficient compared to traditional turbofan architectures and remain economically competitive under the "pursuit of sustainability". This study demonstrates the necessity for future aircraft design analyses to undertake a more multi-disciplinary and operations focused pathway. While individual technologies can boast relatively major improvements in terms of engineering metrics such as fuel consumption; airlines, lessors and passengers inevitably use and pay for the technology. Therefore, metrics such as operational economic viability and environmental sustainability under climate regulations may hold more sway over a technology's implementation and adoption rather than superior performance alone.

Similar research was undertaken by Hoogreef et al. [16] wherein a "strategic airline planning model" was constructed that assessed and minimised an airline's climate impact based on the fleet planning and design of hybrid electric aircraft. This study conducted sensitivity analyses on the relationships between fleet composition and network planning with hybrid electric aircraft incorporated into the fleet and found that significant emissions reductions (11%) may be achieved when compared to the kerosene fleet, but at the cost of 13% profit loss for the airline of the chosen design case. Other cases were also investigated and found to have a reduced impact on profit while also still contributing to lower emissions, albeit with diminished levels of environmental impact reduction. The study alludes to the imperative need to strategically implement specifically designed technology that has been informed by the operational nuances in which it shall be used, such that a breakeven or optimal point can emerge where the benefits of maintaining or improving airline profitability can be achieved while improving environmental sustainability.

Proesmans et al. [17] investigate what influence a kerosene fleet optimised for minimal climate impact might have on an airline's operations. As well as this, SAF and liquid hydrogen aircraft were studied in a similar vein to determine the consequences of such design and fuel choices from an operational point of view. The climate optimal kerosene aircraft cruises lower and slower than its traditional, profit optimal counterpart. This results in an impressive average temperature response (ATR – a climate impact assessment metric) reduction of 61% but with a profit loss of 21% for the hypothetical airline. When the SAF or liquid hydrogen fuelled aircraft were used, the ATR can be decreased by up to 99% but with an associated profit loss of 45%. It was identified that operating long-range flights using liquid hydrogen severely impacted the profitability of the airline's network due to increased operating costs and flight times. When considering medium-range flights, liquid hydrogen offered significant climate impact reductions with comparatively better profits (degraded by only 5-27% compared to the baseline case). In this study, there was no feedback loop between operational assessments for climate impact and aircraft design. The authors indicate this to be an area for future work as it will enable the refining of an aircraft's design to more optimally tune the payload-range requirements and therefore achieve better climate impacts on a network level that can be adopted by airlines with minimal economic disruption. This re-emphasises the need for aircraft designs to be multi-disciplinary in nature and incorporate technology that will offer an optimal design across all subspaces within the aviation value chain.

Moolchandani et al. [18] discuss the creation of the Fleet-Level Environmental Evaluation Tool (FLEET) to assess the operations, economics and sustainability of an airline with the goal of tracking technologies' influence on aviation's pathway to decarbonisation. The study investigates the relationship between technology and the CO_2 emissions of the aviation sector but delves into influencing factors outside of the technology itself. It was found that, given the expected advancements of technology in the future to render aircraft more fuel efficient by 2050, emissions will not reduce to the necessary levels without careful consideration of how airlines operate their aircraft within their networks, what fuel they rely upon, as well as how these may affect passenger demand and therefore the profitability of the sector. Again, the coupling of aircraft's performance and application were touched on when assessing the optimal pathway to decarbonising the aviation sector. Tetzloff and Crossley [19] also investigate fleet composition and assignment methodologies and their environmental and economic impact for an airline. The study assessed the change in performance for an airline when new aircraft technologies are implemented by formulating an airline's profit-driven, decision-making model such that the technologies introduced are best utilised. This model takes the form of an allocation problem that can be solved, and its performance assessed, using an integer programming, multi-commodity flow architecture with constraints and design variables to enforce logical and practical decision-making. This paper again demonstrates the interest shown within the literature for investigating and developing models to accurately predict the ways in which the end user (airlines) will operate the technologies developed for the aviation sector. A combined application of more accurate models, coupled design analyses and the resulting novel aircraft designs offer a more realisable pathway to decarbonisation than independent development alone could ever endeavour to achieve.

The current study will introduce and discuss the work to date and development of a fleet scheduling model created as part of an overall research interest in sustainable aviation. Prior to this work, Gallagher et al. [20, 21] developed and calibrated a preliminary design tool using real world flight data from Europe's largest airline, Ryanair. This design tool now acts as a baseline model for the ensuing study due to its faithful prediction of aircraft performance with respect to real flight data, having achieved model fuel-flows within 5% error of the real world data [20]. In addition, the model has been used to assess the grid scale energy demand resulting from an aircraft fuelled by green liquid hydrogen and SAF. This analysis was able to accurately predict the energy consumptions of the different conceptual aircraft using the calibrated model [21].

At this point, a predictive tool that accurately determines the performance of an aircraft design has been established and validated, hence the next steps are to incorporate the learnings and key performance predictors from this model into a surrogate that can then be scaled up to and inform the fleet-level model that is able to determine what the environmental and economic impact such an aircraft design may have for airlines. The fleet scheduling model takes the form of a mixed-integer linear programming model (MILP) that seeks to generate an airline's schedule by solving the problem such that the airline maximises its economic and environmental sustainability. The airline's fleet of aircraft, airport network and passenger demand are all set as inputs to the scheduling algorithm and are informed by the industry collaborator, Ryanair. Given these inputs, the scheduling algorithm is tasked with optimisation while considering a simplified set of the operational costs associated with operating flights as well as contending with the level of emissions generated. The fleet scheduling model's setup is discussed in Section 3, with the results and discussion presented in Section 4 and conclusions in Section 5. The purpose of developing this scheduling model was to follow in the literature's current trend and demonstrate a more rounded view of the decarbonisation problem for aviation. High fidelity and accurate design tools are beneficial advancements for the challenge but incorporating operational impacts and downstream effects is critical to achieving more influential technological developments and implementation. Additionally, the fleet scheduling model will enable design space characterisation of the multi-disciplinary, inter-connected attributes of the aircraft's parameters and the fleet-wide utilisation of said aircraft's design within an airline's operations. Elucidating key relations between operation, aircraft design, additional factors such as fuel selection, energy demands, infrastructural changes, etc. are central points of interest that can be studied through the development of this model. The fleet scheduling model has been created with this holistic design space characterisation goal in mind, and therefore will seek to be informed by and feedback information to the predictive design tool developed by Gallagher et al. [20, 21]. Using data for a full day of operations and knowledge of the evolution of prevailing emissions legislation with respect to time, the current study will utilise the performance predictions for a B737-800 aircraft (henceforth referred to as an NG aircraft) from Gallagher et al. [20] to assess the operational impact on an airline's sustainability for a fleet that includes varying compositions of the improved B737-8200 replacements (henceforth referred to as MAX aircraft). In addition to the operational impacts on sustainability, the study aims to project how closely the real world adoption of improved technologies correlates with what is expected in key policy documents and therefore assess the feasibility of progressing sustainability agendas through fleet renewal and technology advancements alone.

3. Methodology

The setup of the model used within this analysis comprises of two sub-models: an aircraft performance model and a fleet scheduling model. The aircraft performance model is used to determine the fuel burn associated with each aircraft type given the flight's mission range (MR) and takeoff weight (TOW). The fleet scheduling scales up from single aircraft performance to a fleet-wide level and assesses the environmental and economic impact a preset configuration and case of operations has. The fleet scheduling model seeks to maximise the objective function, simultaneous environmental and economic sustainability, through the allocation of the available aircraft fleet to the necessary routes given the network of airports and passenger demand.

3.1 Aircraft Performance

As briefly mentioned in Section 2, the work of Gallagher et al. has established and validated an aircraft performance model that is capable of accurately recreating an aircraft's flight path and determining its fuel burn with an error of less than 5% across a wide range of real world flights [20]. This model implicitly captures all aerodynamic and propulsive behaviours of the given aircraft throughout the flight using a coupled analysis in the Stanford University Aerospace Vehicle Environment (SUAVE) and Numerical Propulsion System Simulation (NPSS) software, respectively. From Gallagher et al.'s model, a surrogate version with a reduced computational overhead was developed to be incorporated into the fleet scheduling model such that aircraft dependent flight times, paths, fuel burns and general performance may be captured and therefore inform the optimisation of an airline's sustainability. The reason for using a surrogate version of the aircraft performance model is to enable the accurate characterisation of key operational parameters for different aircraft with minimum interference from any confounding variables. When incorporated into the scheduling sub-model, the desired goal is to understand what aspects of an aircraft's performance are critical to an airline's fleet composition-related decisions. In other words, how do different aircraft perform when they can be operated in an ideal manner, on a like-for-like basis, without external interferences or biases like air traffic control (ATC) and what decisions should be taken by an airline with regards to fleet renewal, adoption and deployment of the latest, most advanced technology.

To create this aircraft performance sub-model, the industry collaborator, Ryanair supplied real world flight data with approximately 3000 individual flights flown by B737-8200 (MAX) and B737-800 (NG) type aircraft. An idealised flight profile was fitted to each of these real world flights to develop seven key control points from which a flight profile fitting tool for MAX and NG type aircraft was generated. This enabled generalised flight profiles to be developed for each of these aircraft types given their MR and TOW. The seven control points are the climb angle, maximum altitude (cruise ceiling), descent angle and then a bi-linear fit of airspeed versus altitude; two slopes and two intercepts used to piecewise linearly relate true airspeed to altitude. An important note, the reason the generalised fitting tool was trained on a combination of MAX and NG Ryanair data and was fitted to an idealised flight profile was twofold: Firstly, Ryanair use the MAX and NG aircraft interchangeably on routes given that they are from the same family and the MAX is essentially a newer, more fuel efficient version of the NG with a slightly higher seat count. Secondly, Ryanair run a consistent cost index (CI) when it comes to flight profiles [22, 23]. The CI influences the flight profile as it decides the climb and descent angles as well as cruise ceiling hence generalising a flight profile can be done using key control points (elucidated from the data) without straying from an accurate recreation of a MAX or NG flight profile.

From the original near 3000 flights, 1706 flights had flight profiles that could be recreated using the generalised seven control points with a coefficient of determination (R^2-value) of 95% or more. In Figure 1, two example real world versus approximated flight profiles are shown with their respective R^2-values as well. The left plot is an example of a poor fit whereas the right is an example of a faithful recreation. Flights with approximations like that of the left plot (sub-95% R^2-value) are discarded from use in the creation of the generalised flight profile fitting tool. The reason many real world flights suffer a poor fitting approximation is due to unpredictable influences such as ATC delays/changes to the flight plan, which are inherently stochastic in nature. This can be seen by the stepped descent in the poorly fitted flight profile example of Figure 1.

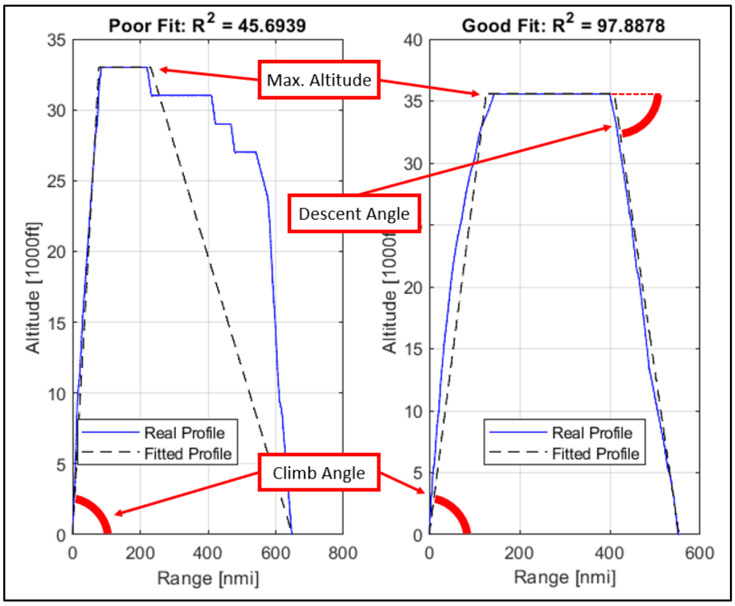


Figure 1: Comparison of a poor versus good approximation of a real world flight

Following the preprocessing of the raw data to only include flights that are well approximated using the idealised flight path, the real world fuel burn data were compared to the simulated fuel burn figures to validate the model's accuracy. The method for determining the simulated fuel burn values is as follows:

1. Establish a flight profile using the generalised fitting tool for the given type of aircraft, MR and TOW. Split this flight profile into small distance steps of 100m as this offers an optimal balance between computational speed and profile resolution.
2. Assuming no acceleration in each step within the profile, resolve the force balance on the aircraft, see Figure 2 for the free-body diagram relating these forces acting on the aircraft.
3. Using Eq. (1), the lift (L) is related to the weight (W) of the aircraft in that step through the flight path angle (θ).

$$L = W cos\theta \tag{1}$$

4. In Eq. (2) and (3), the lift coefficient (C_L) is determined knowing the lift, density (ρ), wetted area (S) and true airspeed (V_∞) within that step.

$$L = 0.5\rho C_L S V_\infty^2 \tag{2}$$

$$C_L = \frac{W cos\theta}{0.5\rho S V_\infty^2} \tag{3}$$

5. Knowing the lift coefficient for the current step, a drag coefficient (C_D) can be determined using a drag polar informed by the detailed, validated airframe model (SUAVE) of Gallagher et al. [20]. See Eq. (4) and Figure 3 for the comparison of drag polars between the NG and MAX airframes.

$$C_D = C_{D,0} + kC_L^2 \tag{4}$$

6. Using Eq. (5), the drag force (D) on the aircraft in the current step can then be found.

$$D = 0.5\rho C_D S V_\infty^2 \tag{5}$$

7. With the drag and weight in the current step known, the required thrust (T) can be found through Eq. (6).

$$T = D + W sin\theta \tag{6}$$

8. With a required thrust and knowing the altitude and true airspeed for the current step, the propulsion surrogates developed by Gallagher et al. [20] are used to interpolate the thrust specific fuel consumptions (TSFC) for the given aircraft type (CFM56-7B26-3 engine for the NG and LEAP-1B27 engine for the MAX).
9. The fuel flows are tracked throughout the flight path for each step and then integrated with respect to time over the flight profile to determine the total simulated fuel burn associated with each flight.

Please note, the propulsion surrogates developed by Gallagher et al. [20] were derived from the validated NPSS models considering the full operating envelope for both engine types and achieve a maximum error of 5.71% compared to the real world fuel burn dataset.

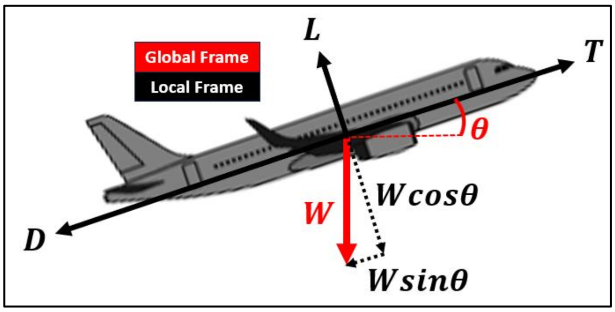


Figure 2: Free-body diagram of the aircraft force balance (vectors not to scale)

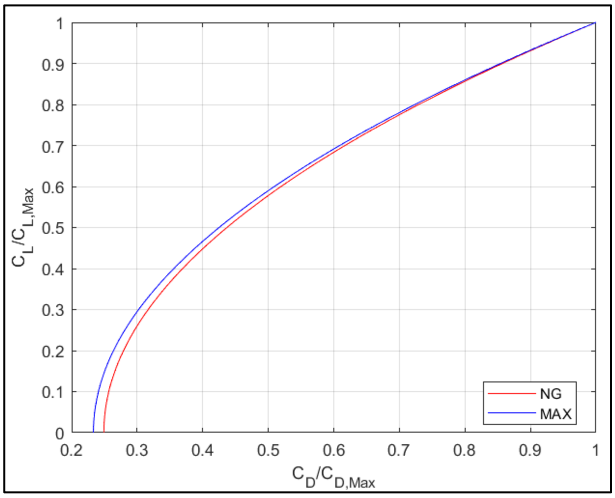


Figure 3: NG versus MAX airframe drag polars (clean configuration)

After comparing the 1706 flights' actual fuel burn values to the simulated ones, an average error of 5.87% was achieved. Example flights with varying aircraft type, MR and TOW combinations are displayed in Table 1 where the real and simulated fuel burns are compared. The simulated fuel burn values were found using a physics-based method that was informed by and based upon the work of Gallagher et al. [20]. Hence the high accuracy achieved when compared to real world flights demonstrates the applicability of using this aircraft performance sub-model within the fleet scheduling platform when investigating the sustainability impacts of different aircraft fleets and configurations.

Table 1: Example actual versus simulated fuel burn values

Aircraft Type	MR [nmi]	TOW [kg]	Act. Fuel Burn [kg]	Sim. Fuel Burn [kg]	Error [%]
NG	281.31	64428.00	2098.20	2077.70	0.97
NG	885.95	65227.00	5228.00	5252.00	0.46
NG	1016.20	66696.00	5988.50	6007.20	0.31
MAX	281.76	57758.00	1595.10	1618.20	1.45
MAX	885.87	67843.00	4468.90	4497.40	0.64
MAX	1019.50	64613.00	4878.00	4919.90	0.86

3.2 Fleet Scheduling

The fleet scheduling analysis is underpinned by the mathematics of networks and solved with the use of linear programming and optimisation methods. A high-level overview of the scheduling algorithm with the fleet scheduling and aircraft performance sub-models included is shown in Figure 4.

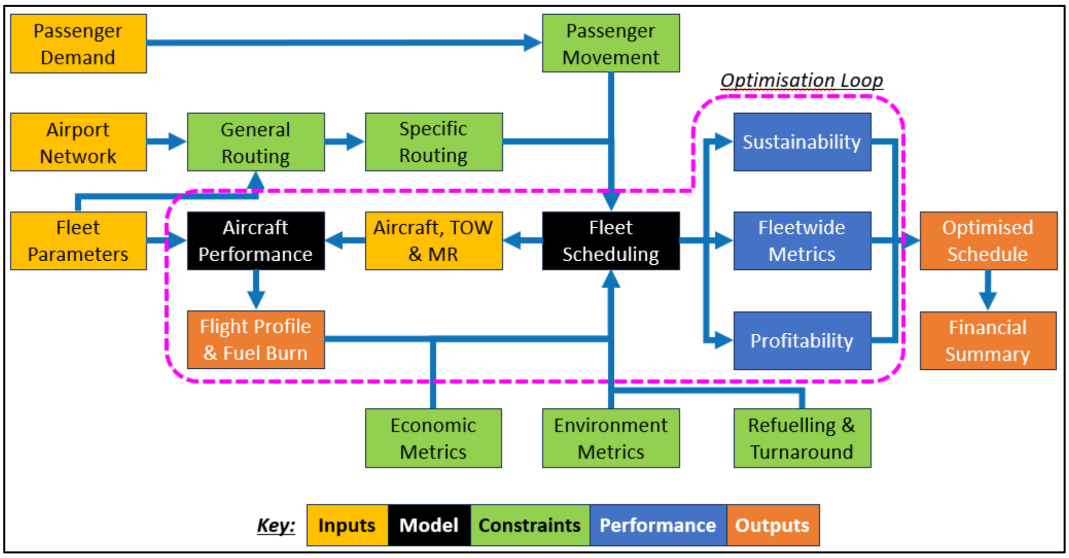
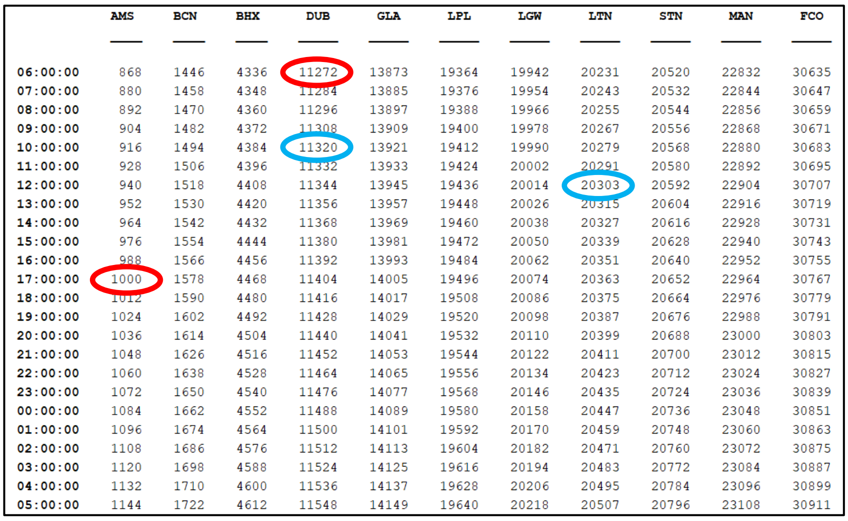


Figure 4: Overall flowchart of the fleet scheduling model

The “Airport Network” component and input is constructed by combining the temporal and spatial elements of the model together into a time-space matrix where columns represent the different airports, and the rows are the individual points in time through the operating period [24]. An operating window of 24 hours, 06:00 – 06:00, is used with a resolution of 5-minute timesteps. The airports chosen to be included in the analysis are Dublin airport (DUB) as the centre of the network and the 10 most popular destinations from DUB, as informed by Ryanair. The reason for developing an Irish-centred model is twofold: 1) Ireland’s mobility and connectivity to the EU, and indeed the rest of the world, depends heavily on aviation with over 94% of travel into Ireland coming through air travel as of May 2023 [25] and Ireland’s tourism industry employing approximately 220,000 people [26]. 2) Ireland is the worldwide hub of the aircraft leasing business, with over 50% market share and €100bn of assets [27]. Hence, Ireland’s involvement in the pathfinding research to decarbonised aviation is critical and can be propelled through leveraging the numerous close ties to influential stakeholders within the sector. The temporal resolution and the network size selected are a balancing point for the computational effort required in solving for an optimised schedule while still being capable of providing insight into the hypothetical behaviour of the network and inform decisions regarding next steps on the pathway to decarbonisation. Each cell within the matrix is assigned a unique number to give it a nodal identification, henceforth referred to as nodal ID. This offers the functionality of giving every time and place a unique reference within the model such that a user may specify a given airport at a certain time by simply calling the nodal ID. For example, see the red highlighted numbers in Figure 5, where it can be seen by referencing nodal IDs 11272 and 1000 is equivalent to referencing airport DUB (Dublin) at 06:00 and the airport AMS (Amsterdam) at 17:00, respectively.



	AMS	BCN	BHX	DUB	GLA	LPL	LGW	LTN	STN	MAN	FCO
06:00:00	868	1446	4336	11272	13873	19364	19942	20231	20520	22832	30635
07:00:00	880	1458	4348	11284	13885	19376	19954	20243	20532	22844	30647
08:00:00	892	1470	4360	11296	13897	19388	19966	20255	20544	22856	30659
09:00:00	904	1482	4372	11308	13909	19400	19978	20267	20556	22868	30671
10:00:00	916	1494	4384	11320	13921	19412	19990	20279	20568	22880	30683
11:00:00	928	1506	4396	11332	13933	19424	20002	20291	20580	22892	30695
12:00:00	940	1518	4408	11344	13945	19436	20014	20303	20592	22904	30707
13:00:00	952	1530	4420	11356	13957	19448	20026	20315	20604	22916	30719
14:00:00	964	1542	4432	11368	13969	19460	20038	20327	20616	22928	30731
15:00:00	976	1554	4444	11380	13981	19472	20050	20339	20628	22940	30743
16:00:00	988	1566	4456	11392	13993	19484	20062	20351	20640	22952	30755
17:00:00	1000	1578	4468	11404	14005	19496	20074	20363	20652	22964	30767
18:00:00	1012	1590	4480	11416	14017	19508	20086	20375	20664	22976	30779
19:00:00	1024	1602	4492	11428	14029	19520	20098	20387	20676	22988	30791
20:00:00	1036	1614	4504	11440	14041	19532	20110	20399	20688	23000	30803
21:00:00	1048	1626	4516	11452	14053	19544	20122	20411	20700	23012	30815
22:00:00	1060	1638	4528	11464	14065	19556	20134	20423	20712	23024	30827
23:00:00	1072	1650	4540	11476	14077	19568	20146	20435	20724	23036	30839
00:00:00	1084	1662	4552	11488	14089	19580	20158	20447	20736	23048	30851
01:00:00	1096	1674	4564	11500	14101	19592	20170	20459	20748	23060	30863
02:00:00	1108	1686	4576	11512	14113	19604	20182	20471	20760	23072	30875
03:00:00	1120	1698	4588	11524	14125	19616	20194	20483	20772	23084	30887
04:00:00	1132	1710	4600	11536	14137	19628	20206	20495	20784	23096	30899
05:00:00	1144	1722	4612	11548	14149	19640	20218	20507	20796	23108	30911

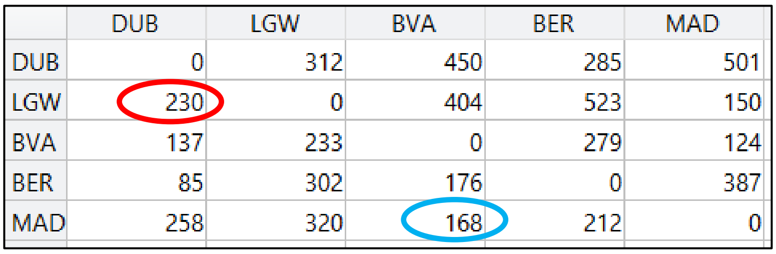
Figure 5: Time-space matrix for the network of airports with nodal IDs

The “General Routing” component in Figure 4 sees the connecting of two nodal IDs to form a flight through the network. By placing two nodal IDs into a vector together, the departure and arrival airports and times are specified for this flight. For example, the route vector $\boldsymbol{r} = \{\mathbf{11320}, \mathbf{20303}\}$, states that a flight departs the first element, nodal ID 11320 and arrives at the second element, nodal ID 20303. Referring to the blue highlighted numbers in Figure 5, this indicates that the flight departs DUB at 10:00 and arrives to LTN (London Luton) at 12:00. This architecture enables the model to generate all possible flights through the network by iterating through all feasible combinations of nodes within the route vector $\boldsymbol{r}$. The question of what a feasible flight through the network is, depends on a variety of factors; what type of aircraft is used, do the airports allow flights between them, is the route physically possible, amongst others. At this stage in the model setup, only one feasibility check is assessed, are the flights physically possible? This check takes the form of two criteria which the flight must meet:

1) Are the departure and arrival nodal IDs’ airports different?
2) Does the arrival nodal ID have a time after the departure nodal ID’s time?

The “Specific Routing” component in Figure 4 makes use of the aircraft available to the fleet, as specified by the “Fleet Parameters” component. The time of flight is aircraft and route dependent, different rates of climb, cruising speeds and design ranges influence how fast an aircraft can complete a given flight. The next set of feasibility checks are to incorporate the type of aircraft used by the airline under analysis such that the times of flight are representative of what a given aircraft can achieve for a particular route. It was stated already that the example route vector $\boldsymbol{r} = \{\mathbf{11320}, \mathbf{20303}\}$ has a departure and arrival time of 10:00 and 12:00, respectively, giving a time of flight of 2 hours. At this stage in the model setup, the specific aircraft are used to determine representative times of flight for each of the routes and ensure only the subset of feasible routes that have these flight times are used within the fleet scheduling later in the model, as seen in Figure 5 whereby the “Specific Routing” component is directed into the “Fleet Scheduling” component. Initially, candidate routes are based solely on physically possible criterion, followed by the incorporation of the specific aircraft dependent time of flight functionality which narrows the general routing to aircraft specific routing for the airline.

Following on from the development of an airport network and the functionality of incorporating aircraft type dependent flights through said network, a demand must be defined to act as the driving force behind generating “flow” through the network. A demand matrix can be defined whereby the rows are departure airports and the columns are arrival airports, hence the number assigned to a cell within this matrix refers to the number of units of “flow” that must travel from that departure airport to the arrival airport. In this model, the demand matrix is defined by the “Passenger Demand” component in Figure 5. The passenger demand specifies exactly how many people need to be flown from one airport to another and must be met such that all customers of the airline are catered to, as conveyed by the green colour assigned to the “Passenger Movement” component in Figure 5. Real passenger demands rarely line up exactly with aircraft seat counts. This results in some aircraft flying with less than unity load factors. Airlines regularly run flights with load factors below 100%, with the IATA measuring the total industry load factor as 81.8% as of May 2023 [28]. Additionally, fleets composed of aircraft types with varying seating capacities will inherently result in different numbers of flights depending on aircraft type, hence the model accounts for but does not constrain the system based on varied flight number requirements only total passenger movement. See Figure 6 for an example passenger demand matrix where the column and row headings are IATA airport codenames. In this example, 230 passengers are to be flown from LGW to DUB (red highlighted cell) and 168 are to be flown from MAD to BVA (blue highlighted cell). Note that the top-left to bottom-right diagonal of the demand matrix is all zeros, this is because non-zero demand here would request infeasible flights to depart and land at the same airport.



	DUB	LGW	BVA	BER	MAD
DUB	0	312	450	285	501
LGW	230	0	404	523	150
BVA	137	233	0	279	124
BER	85	302	176	0	387
MAD	258	320	168	212	0

Figure 6: Example passenger demand matrix for the airport network

An airport network has been mathematically defined, aircraft dependent routes through this network have been generated and the driving force of passenger demand has been created; this fully characterizes the setup of the scheduling model such that an optimisation problem can be solved. MILP is used to solve the optimisation problem of scheduling aircraft from a fleet to meet the demand of an airport network. It is a method that uses optimisation variables, constraints and an objective function. This occurs in the “Fleet Scheduling” component in Figure 4. The optimisation variables refer to the number of flights, number of passengers and which flight routes are selected. As well as this, there are optimisation variables for refuelling and storage of aircraft. The constraints are broad in nature, some are for ensuring operational and logistical feasibility such as a flight cannot depart an airport unless there is an aircraft stored there or a flight has previously arrived and completed its turnaround. Similarly, the fuel status of an aircraft is constrained to being non-negative, this enforces the refuel optimisation variable to top-up low fuelled aircraft when they are close to breaching this non-negative threshold. Other constraints are to ensure the functionality of the model, such as more than one aircraft cannot fly the same route at the same time. Likewise, one aircraft cannot fly more than one route at the same time.

The purpose of optimisation variables is to create a design space that offers solutions to the scheduling problem – different combinations of passenger numbers, routes flown, refuel amounts, etc. will contribute to unique solutions for the schedule that meet the passenger demand. Constraints force these solutions to only exist in feasible regions of the design space, i.e a schedule could use a single aircraft to fly all routes simultaneously and meet the demand, but this is obviously an infeasible solution hence it is disregarded, instead multiple aircraft flying simultaneously are used to solve the scheduling problem. Finally, with optimisation variables and constraints developed and implemented – the objective function is defined such that the most optimal solution from all feasible solutions may be selected, therefore solving the scheduling problem in the “best” way. This optimisation occurs inside the pink highlighted loop in Figure 4 which combines the two sub-models of aircraft performance and fleet scheduling. The scheduling passes parameters for aircraft type, TOW and MR to the aircraft performance sub-model which will determine the flight profile, and therefore flight time as well as a fuel burn that are all returned to the scheduling sub-model. This loop is cycled throughout the design space until an optimised solution is arrived upon. For this analysis, a holistic sustainability metric is optimised that includes the environmental and economic impact of the solution, therefore the “best” is the most environmentally and economically sustainable solution offered. To do this, environmental and economic sustainability metrics need to be defined and incorporated into the objective function such that representative values can be calculated and compared across the design space of optimisation variables and their feasible solutions.

Within Figure 4, the blue performance components “Profitability” and “Sustainability” can be understood to consider the economic and environmental sustainability performance of the schedule, respectively. The “Profitability” component directly considers the economic performance and is broken down into key performance indicators (KPI) within the aviation sector: available seat kilometres (ASK), revenue passenger kilometres (RPK), revenue per available seat kilometres (RASK), cost per available seat kilometres (CASK) as well as yield and the traditional, overall revenue, costs and profit. The revenue is solely generated from passenger fares, which are calculated by the sum of a base rate fare and a distance weighted fare per passenger. The costs are more varied but are still representative of common costs incurred by airlines: landing costs, handling costs, storage costs, wage costs, fuel costs and emissions' penalty costs. It should be noted, the financial metrics use representative values for costs and revenue (partially informed by the IATA's "chart of the week" financial breakdown [13] and the Federal Aviation Administration's (FAA) "Aircraft Operating Costs" document [29]) rather than exact values since some financial information is commercially sensitive. Lastly, the environmental performance of the fleet can be assessed from the accumulated fuel consumptions and selected operation of each aircraft, as considered in the "Sustainability" component. Metrics such as total mass of CO_2 produced and CO_2 intensity (gCO_2/pax.km) which combines CO_2 emissions, passenger numbers (referred to as "pax") and distance travelled. These environmental indicators and performance data, when compared across the scenarios, enable key insights to be drawn about the influence that fleet renewal has on the environmental and economic sustainability of an airline when scaling individually superior aircraft to a fleet-wide level of operations.

3.3 Problem Definition

The scheduling model considers three scenarios to investigate the impact of fleet renewal on airline sustainability. The three scenarios vary the composition of the airline's fleet as follows:

- Case 1: 100% NG and 0% MAX aircraft
- Case 2: 75% NG and 25% MAX aircraft
- Case 3: 50% NG and 50% MAX aircraft

For all three cases, the overall size of the fleet (20 aircraft), passenger demand and network of airports remains the same. The passenger demand is derived from real world data for a full day of Ryanair's operations and has been refined to only include departures and arrivals to/from Dublin (DUB) and the top 10 most popular routes to/from DUB. The decision to curtail the operations was borne out of focusing the study on the Ireland-EU connectivity context with particular attention being paid to how influential fleet renewal may be for an airline's central hub. The network of airports therefore centres around DUB with the 10 other airports ranging in distance from 100 to 1200nmi with a total passenger movement of over 17 thousand people in a 24-hour period. The network of airports is shown in Figure 7.

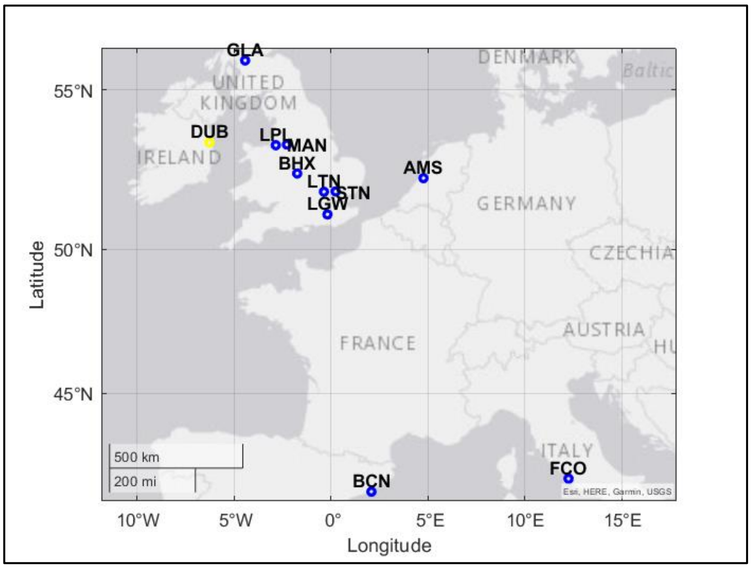
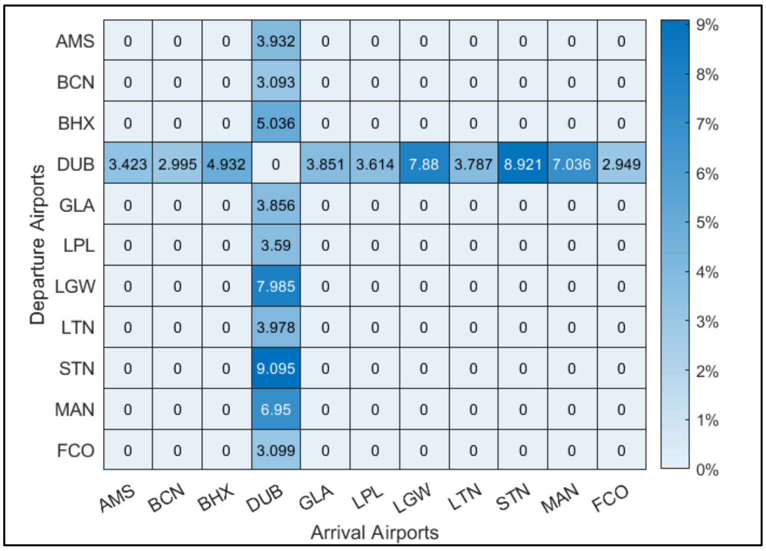


Figure 7: Airport network input to the fleet scheduling model

The passenger demand for this network, broken down by percentage share of the overall passenger count, is displayed in Figure 8. The most popular routes are STN-DUB with 9.095% and DUB-STN with 8.921% share of the passenger demand. This passenger demand matrix is based on real world passenger data supplied by Ryanair which embeds realistic passenger movements through the given network of airports both from a spatial and temporal perspective. The Ryanair passenger data was provided with all pertinent information such as takeoff and landing times (temporal), destination and departure airports (spatial) and number of passengers on board therefore enabling the capture of real world passenger behaviour that may be used and replicated within the scheduling model. This replication of real world passenger behaviour reinforces the confidence in decisions that can be made from the results of this model's simulations as the algorithm considers real scenarios and optimises accordingly to offer feasible and practicable airline schedules. The two aircraft types considered within the analysis are the 189 seat, CFM56-7B26-3 powered B737-800 (NG) and the 197 seat, CFM-LEAP-1B27 powered B737-8200 (MAX), both fuelled with Jet A-1 kerosene. All scenarios follow the same setup with regards to an operating window of 24 hours and are subjected to the same optimisation constraints and objectives regarding economic and environmental sustainability. The simulation of each scenario was completed using MATLAB R2023a with the optimisation toolbox installed to enable the use of MILP solvers.



	AMS	BCN	BHX	DUB	GLA	LPL	LGW	LTN	STN	MAN	FCO
AMS	0	0	0	3.932	0	0	0	0	0	0	0
BCN	0	0	0	3.093	0	0	0	0	0	0	0
BHX	0	0	0	5.036	0	0	0	0	0	0	0
DUB	3.423	2.995	4.932	0	3.851	3.614	7.88	3.787	8.921	7.036	2.949
GLA	0	0	0	3.856	0	0	0	0	0	0	0
LPL	0	0	0	3.59	0	0	0	0	0	0	0
LGW	0	0	0	7.985	0	0	0	0	0	0	0
LTN	0	0	0	3.978	0	0	0	0	0	0	0
STN	0	0	0	9.095	0	0	0	0	0	0	0
MAN	0	0	0	6.95	0	0	0	0	0	0	0
FCO	0	0	0	3.099	0	0	0	0	0	0	0

Figure 8: Demand matrix input to the fleet scheduling model

The scheduling model uses these airport network and passenger demand inputs to define the network flow problem alongside the aircraft fleet configuration in each case, and is tasked with solving it to find an optimal sustainable solution (simultaneously balancing economic and environmental perspectives). The model's output takes the form of a complete airline schedule with all critical flight information such as departure and arrival airports, takeoff and landing times, flight times, distances flown, number of passengers on board, load factors, takeoff weights, aircraft IDs, fuel burn values and refuel amounts, amongst others. As previously mentioned, the financial and environmental metrics considered in the analysis are also summarised within the scheduling output giving a more holistic and complete assessment of how sustainable the airline operated with the given configuration of network, demand and fleet.

4. Results & Discussion

A snippet of the flight schedule output for Case 2, the scenario of a 75%-25% split between aircraft types, is shown in Tables 9a and 9b. The "Plane ID" column indicates which aircraft type is being used. If the ID begins with "A" then it is an NG aircraft whereas if it begins with "B" it is a MAX variant. Between Tables 2a and 2b, each of the flights' specific performance data can be read with particular interest being paid to load factors, takeoff weights, fuel burns and refuelling amounts alongside the resulting gCO$_2$/pax.km values for the given flight. The flight schedule allows for the complete monitoring and control of every asset belonging to the airline which is crucial for optimal operations. This schedule has been determined using an optimisation algorithm with this ideal-operations goal in mind. Hence, through the study of the schedule produced, one can learn about the technology implementation as well as the infrastructure and policy influencing why the optimisation has opted for the scheduled behaviour shown and therefore make informed decisions regarding next steps on the pathway to decarbonisation.

Table 2a: Snippet of Case 2's flight schedule – Part 1

Flight No. [-]	Plane ID [-]	Dep. City [-]	Arv. City [-]	Dep. Time [hh:mm:ss]	Arv. Time [hh:mm:ss]	Flight Time [hh:mm:ss]	Range [nmi]	No. Pax [-]	Load Factor [%]
40	A006	GLA	DUB	11:30:00	12:30:00	01:00:00	160.15	189	100.00
41	B001	DUB	BCN	11:45:00	14:20:00	02:35:00	802.86	197	100.00
42	A001	BHX	DUB	12:15:00	13:20:00	01:05:00	173.81	189	100.00
43	A008	LTN	DUB	12:30:00	13:45:00	01:15:00	234.35	121	64.02
44	A007	DUB	BHX	12:35:00	13:40:00	01:05:00	173.81	189	100.00
45	A011	DUB	LPL	12:45:00	13:40:00	00:55:00	122.74	189	100.00
46	B004	DUB	LGW	12:55:00	14:20:00	01:25:00	261.87	197	100.00
47	B005	LGW	DUB	13:25:00	14:50:00	01:25:00	261.87	197	100.00
48	A004	DUB	MAN	13:45:00	14:45:00	01:00:00	143.25	158	83.60
49	A007	BHX	DUB	13:45:00	14:50:00	01:05:00	173.81	189	100.00
50	A001	DUB	BHX	14:15:00	15:20:00	01:05:00	173.81	189	100.00
51	B001	BCN	DUB	14:25:00	17:00:00	02:35:00	802.86	197	100.00
52	B003	DUB	FCO	14:30:00	17:35:00	03:05:00	1019.27	197	100.00
53	B005	DUB	LGW	14:55:00	16:20:00	01:25:00	261.87	197	100.00
54	A011	LPL	DUB	15:55:00	16:50:00	00:55:00	122.74	129	68.25
55	B004	LGW	DUB	16:10:00	17:35:00	01:25:00	261.87	197	100.00
56	B002	DUB	AMS	16:15:00	17:50:00	01:35:00	405.52	131	66.50
57	B005	LGW	DUB	16:25:00	17:50:00	01:25:00	261.87	197	100.00
58	A005	MAN	DUB	16:30:00	17:30:00	01:00:00	143.25	189	100.00
59	A003	DUB	LTN	17:10:00	18:25:00	01:15:00	234.35	189	100.00
60	A004	MAN	DUB	17:25:00	18:25:00	01:00:00	143.25	189	100.00

Table 2b: Snippet of Case 2's flight schedule – Part 2

Flight No. [-]	Plane ID [-]	T-Off Weight [kg]	T-Off Fuel [L]	Fuel Burn [L]	Land Fuel [L]	Refuel [L]	CO2 [kg]	Intensity [gCO2/pax.km]
40	A006	60269.51	4195.85	1593.35	2602.50	1486.43	4225.36	75.38
41	B001	66550.58	7459.03	4856.53	2602.50	4856.53	12878.93	43.97
42	A001	60342.12	4282.28	1679.78	2602.50	1679.78	4454.58	73.22
43	A008	55025.06	4428.64	1826.14	2602.50	2189.94	4842.71	92.21
44	A007	60342.12	4282.28	1679.78	2602.50	1679.78	4454.58	73.22
45	A011	60070.67	3959.13	1356.63	2602.50	1147.71	3597.61	83.74
46	B004	64079.54	4517.30	1914.80	2602.50	1914.80	5077.83	53.15
47	B005	64079.54	4517.30	1914.80	2602.50	1914.80	5077.83	53.15
48	A004	57609.03	3980.99	1378.49	2602.50	1486.43	3655.58	87.21
49	A007	60342.12	4282.28	1679.78	2602.50	1620.59	4454.58	73.22
50	A001	60342.12	4282.28	1679.78	2602.50	1679.78	4454.58	73.22
51	B001	66550.58	7459.03	4856.53	2602.50	4856.53	12878.93	43.97
52	B003	67539.05	8635.77	6033.27	2602.50	6033.27	15999.51	43.02
53	B005	64079.54	4517.30	1914.80	2602.50	1914.80	5077.83	53.15
54	A011	55095.18	3750.21	1147.71	2602.50	1356.63	3043.59	103.79
55	B004	64079.54	4517.30	1914.80	2602.50	1914.80	5077.83	53.15
56	B002	59282.93	5092.78	2490.28	2602.50	2695.92	6603.91	67.12
57	B005	64079.54	4517.30	1914.80	2602.50	1914.80	5077.83	53.15
58	A005	60179.70	4088.93	1486.43	2602.50	1486.43	3941.83	78.61
59	A003	60663.95	4665.42	2062.92	2602.50	2062.92	5470.61	66.69
60	A004	60179.70	4088.93	1486.43	2602.50	1486.43	3941.83	78.61

The environmental performance of each cases' fleet is compiled on a case-by-case basis with an additional breakdown according to the sub-fleets (NG and MAX aircraft). The data of interest includes statistics about the fleet as a whole (in the rows named "Fleet" per case) as well as sub-fleet specific statistics (in the rows named "NG" and "MAX" per case). There are also performance values given for the environmental metrics of total mass of CO_2 produced and gCO_2/pax.km. These are compared in Table 3, where Case 1 is the baseline case for comparison on a sub-fleet and fleet-wide basis. Looking to Table 3, the number of aircraft in each case can be seen to be 20 but the total flights used to cater to the demand within the network varies. Case 1 used the most flights at 110 flights whereas Cases 2 and 3 both used 104 flights with different numbers of missions being completed by the two aircraft types. The column "Avg. Usage" is the total number of flights divided by the fleet or sub-fleet size in each case to convey the utilisation of the airline's assets. Following this, a reduction in refuelling requirements is seen across the cases with over 250 thousand litres used in the baseline scenario and just under 225 thousand litres used in the third case. This stark reduction of 12.38% in fuel required is equivalent to approximately 84,300kg of CO_2 reduction a day for this subset of European operations. This reduction in CO_2 can be converted to financial savings through the Emissions Trading System that currently charges €80/1000kg of CO_2 [30] thus saving the airline over €6700 day under these operations. It is directly attributable to the higher fuel efficiency of the MAX aircraft compared to the NG aircraft. The average CO_2 produced per flight therefore reduces as expected with more MAX aircraft in the fleet. From Case 1's baseline average CO_2 per flight, Cases 2 and 3 see a 3.36% and 7.29% reduction in average CO_2 produced per flight. Similarly, the CO_2 intensity sees a reduction in the average of this metric per flight across cases. Importantly, within Cases 2 and 3, the average CO_2 intensity for the MAX is lower than the NG aircraft flights. The MAX's average CO_2 intensity in Case 2 is slightly smaller than that of the MAX in Case 3. This is a perhaps unexpected result but can be explained by the fact that twice as many MAX flights are taking place in Case 3 as in Case 2 (60 versus 30). In Case 2, the fewer MAX aircraft are prioritised on optimal payload-range flights whereas in Case 3 with extra MAX aircraft available, they inevitably get allocated on less optimal missions but crucially are still more beneficial than NG aircraft on the same mission.

Table 3: Summary of environmental performances across each case

		Aircraft [-]	Flights [-]	Avg. Usage [-]	Tot. Refuel [L]	CO2 Production [kg]				CO2 Intensity [gCO2/pax.km]		
						Minimum	Average	Maximum	Total	Minimum	Average	Maximum
Case 1	NG	20	110	5.50	256775.82	2905.08	6190.35	18642.86	680938.66	52.25	80.52	112.10
	MAX	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fleet	20	110	5.50	256775.82	2905.08	6190.35	18642.86	680938.66	52.25	80.52	112.10
Case 2	NG	15	74	4.93	133889.54	2905.08	4798.09	7650.64	355058.99	65.21	81.28	112.10
	MAX	5	30	6.00	100726.86	4433.33	8903.85	15999.51	267115.54	43.02	55.47	76.82
	Fleet	20	104	5.20	234616.40	2905.08	5982.45	15999.51	622174.53	43.02	73.83	112.10
Case 3	NG	10	44	4.40	72720.97	2905.08	4382.89	7650.64	192847.29	73.22	87.53	112.10
	MAX	10	60	6.00	152263.09	3807.89	6729.72	15999.51	403783.44	43.02	58.29	78.15
	Fleet	20	104	5.20	224984.06	2905.08	5736.83	15999.51	596630.73	43.02	70.66	112.10

An economic summary is produced which compiles the aviation KPI's previously mentioned as well as the costs, revenue and profit breakdowns into a concise, fleet-wide measure of the fleet's performance for each of the cases. These are compared in Table 4, where Case 1 (100% NG aircraft fleet) is the baseline scenario and the succeeding cases' values are the percentage changes in each metric from the baseline. As seen in Table 4, the changes in costs of landing, handling and wages hold constant (-5.45%) between cases as the number of flights in Cases 2 and 3 are the same. The passenger revenue does not change between cases as the same passenger demand is used across each use case within this study. The previously mentioned reduction of 12.38% in refuelling from Table 3 appears again in Table 4 under the "Fuel Cost" column for Case 3. The airline's fuel bill benefits from an increase in the population of MAX aircraft within the fleet with a -8.63% and -12.38% change in fuel cost from the baseline. With a decrease in fuel cost and emissions costs, an expected increase in the airline's overall profit can be seen where Case 2 improves by 3.92% and Case 3 by 5.58%. The KPI's of ASK, RPK, Yield, RASK and CASK are also shown in Table 4. The RPK and Yield metrics see no change as these are a measure of revenue passenger kilometres and revenue per RPK, respectively. Since the total number of paying customers and where they travel to does not change, these metrics will see no variation between cases. Interestingly the ASK decreases slightly in Case 2 and then improves in Case 3, this can be attributed to the fact that the number of flights decreases between Case 1 and 2 therefore reducing the total available seat kilometres to travel for Case 2's decrease. But this decrease is outweighed by the increase in seat count between NG and MAX aircraft (189 and 197, respectively) offered in Case 3. The reciprocal of this relationship is found in the RASK metric between cases as RASK is the measure of revenue per ASK, thus the decrease in ASK sees a growth in RASK and vice versa for a fixed revenue figure across all cases. Since the revenue available to the airline is fixed in each case, as constrained by the same passenger demand being used, the CASK metric is the most interesting from a financial comparative point of view as it summarises the airline's economic performance under the conditions across each case. The CASK is the cost per available seat kilometre and can be thought of as the cost to operate the fleet within the given network. Hence, when comparing the three cases and seeing a beneficial decrease in this metric, one can infer the advantage offered by fleet renewal – it becomes cheaper to operate the aircraft with a higher MAX aircraft composition. Separately but crucially, it should be noted that between Cases 2 and 3, when compared to Case 1, the changes do not scale proportionally with the increase in MAX aircraft within the fleet, in other words the benefits do not double between cases even though the composition of MAX aircraft doubles.

Table 4: Summary of economic performances relative to Case 1 baseline

	Landing Cost	Handling Cost	Storage Cost	Wages Cost	Fuel Cost	CO2 Emissions Cost	Passenger Revenue	Profit	Profit Per Passenger	Avg. Load Factor [%]	ASK	RPK	Yield	RASK	CASK
Case1	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	83.19	100.00	100.00	100.00	100.00	100.00
Case2	-5.45	-5.45	0.00	-4.03	-8.63	-8.63	0.00	3.92	3.92	86.92	-0.29	0.00	0.00	0.19	-8.19
Case3	-5.45	-5.45	0.00	-4.03	-12.38	-12.38	0.00	5.58	5.59	85.83	0.65	0.00	0.00	-0.74	-12.28

Following the production of outputs from each case and their tabular comparisons, more insightful analyses can be conducted by restructuring the outputs from each case and breaking them down by data fields such as routes and distances travelled, rather than summarising each case by accumulative metrics alone. Figures 9a and 9b are a collection of range-based histograms broken down into three case-by-case comparisons to visualise the behaviour of NG versus MAX aircraft in Figure 9a and the fleet-wide behaviour across cases in Figure 9b.

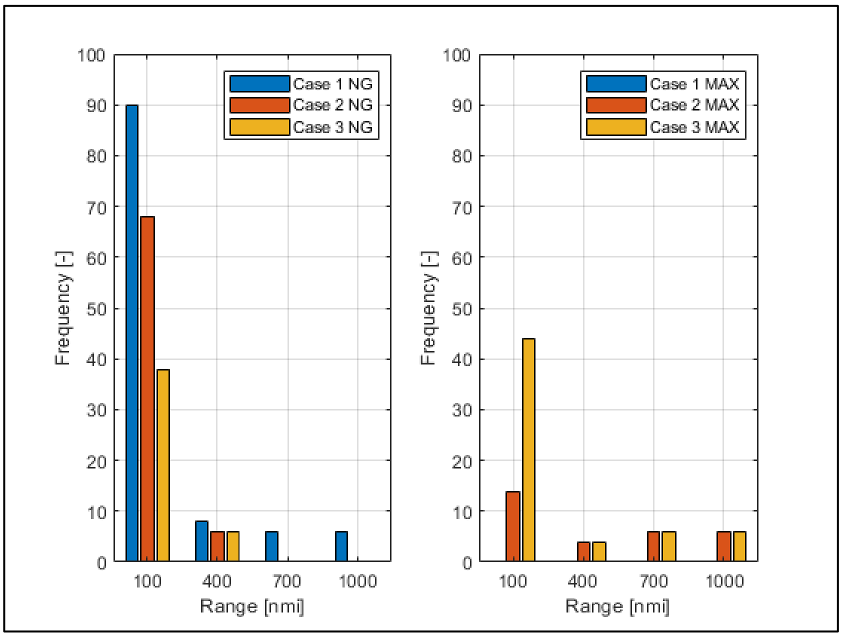


Figure 9a: Range based behaviour for each case per sub-fleet

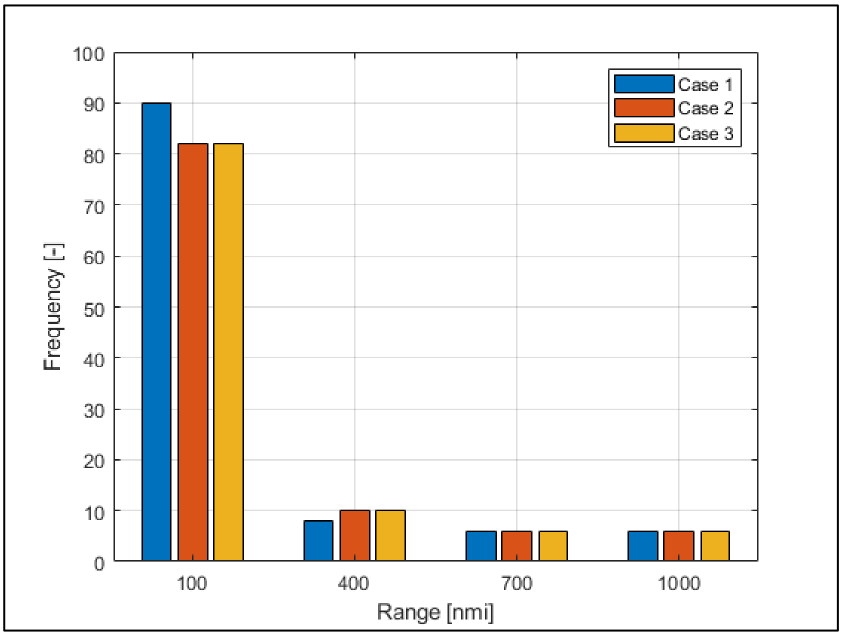


Figure 9b: Range based behaviour for each case as a whole fleet

Similar to Figures 10a and 10b, a load factor based version of the histograms are plotted in Figures 9a and 9b following the same case-by-case fleet behaviour comparative analysis for NG and MAX type aircraft in Figure 10a and a complete fleet in Figure 10b.

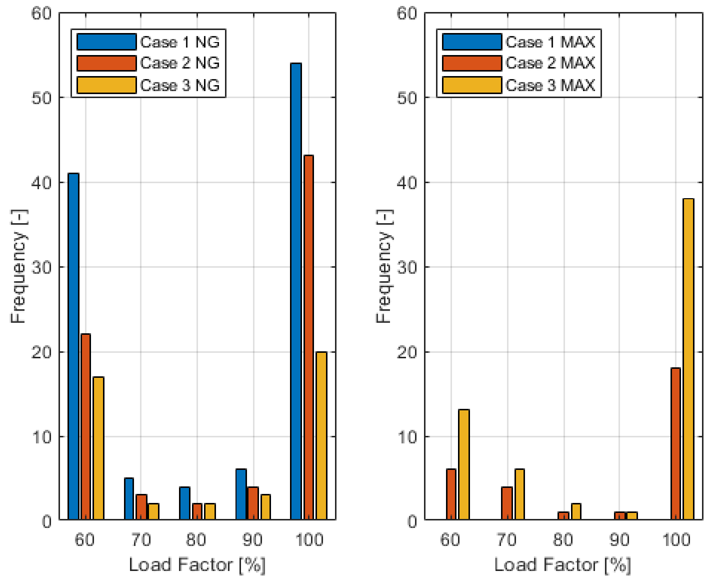


Figure 10a: Load factor based behaviour for each case per sub-fleet

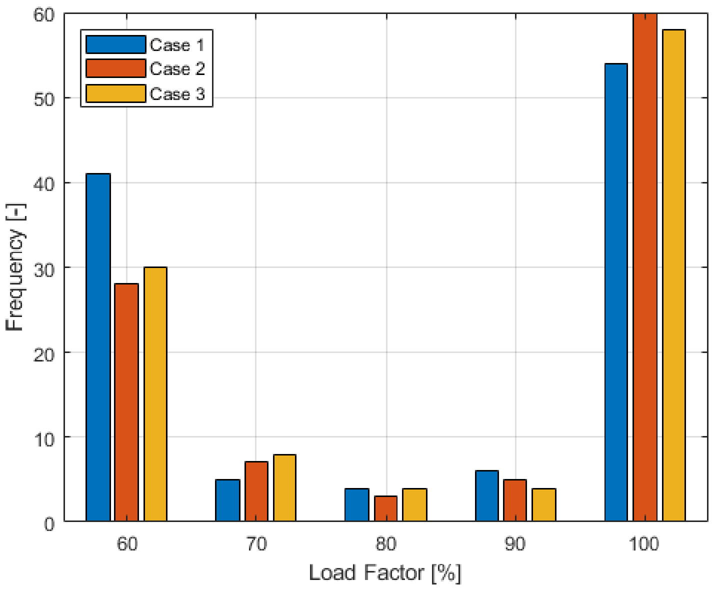


Figure 10b: Load factor based behaviour for each case as a whole fleet

The expected trend of MAX aircraft replacing NG flights occurs across all ranges between cases as the number of MAX aircraft available increases in Figure 9a. Interestingly, the MAX replaces all NG flights in the ranges of 700 to 1000nmi as these flights are usually the most costly with higher associated fuel burn. The optimisation algorithm is operating as expected as it decides to allocate MAX aircraft, which are more fuel efficient and therefore more sustainable to operate on these longer-range flights than the NG aircraft. Figures 10a and 10b convey the load factor behaviour of the fleet and sub-fleets, respectively. Additionally, the average fleet load factor can be seen in Table 4 with the highest average utilisation seen in Case 2 at 86.92%. In all plots across all cases, the majority of flights are fully filled. Not all flights can achieve 100% load factor as passenger numbers are imperfectly divisible by seat counts hence inevitable “overflow” passengers will have to be catered to with underfilled flights. Since the number of passengers going to each point within the network varies, as seen in the passenger demand matrix in Figure 8 from Section 3.3, the number of flights and passengers on board these flights will vary considerably leading to less efficiently operated aircraft – see Table 3 for minimum and maximum statistics on CO_2 production and intensity.

Figures 11 and 12 are route-based breakdowns of the total CO_2 produced and the mean CO_2 intensity of the overall fleet, respectively. The environmental impact of adopting MAX aircraft can be seen as each case varies the proportion of MAX aircraft in their fleet. In Figure 11, Case 3 has the lowest or joint lowest with Case 2 of total CO_2 produced per route. The most popular routes DUB-STN and STN-DUB, as seen from the passenger demand matrix in Figure 8 from Section 3.3, have the largest decrease in CO_2 produced compared to Case 1 indicating that MAX aircraft are utilised more often when made available to the airline. Through this utilisation of more advanced aircraft, the benefit of lower CO_2 emissions is directly achievable and appears to increase alongside an increase in the number of MAX aircraft.

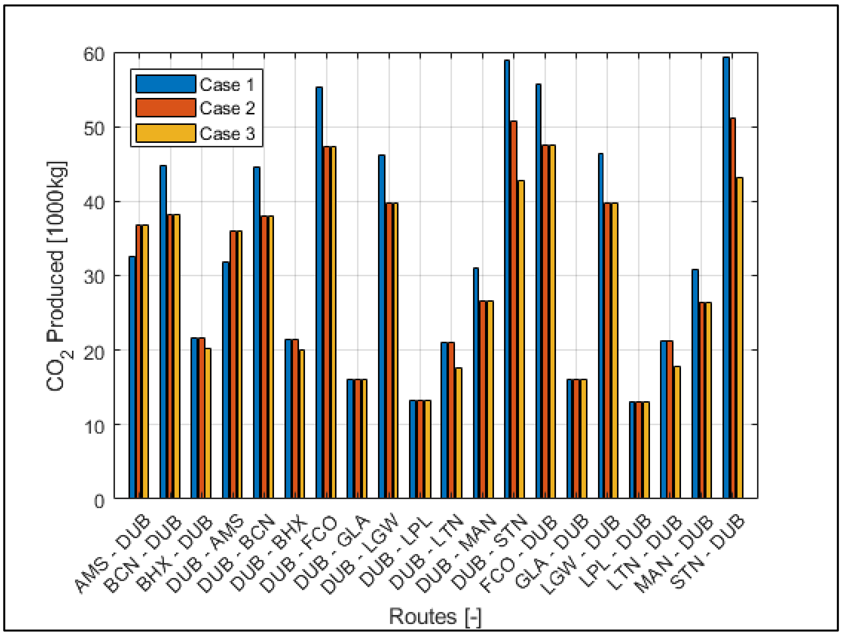


Figure 11: Route-based CO_2 production across each case

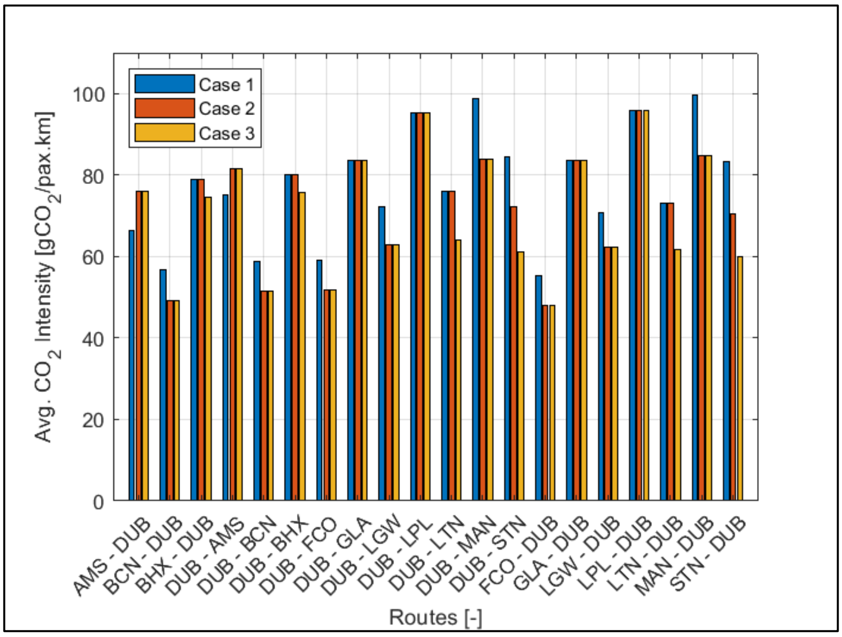


Figure 12: Route-based CO_2 intensity across each case

There is evidence to suggest that the CO_2 reduction benefit does not scale proportionally with the increase in MAX aircraft however. This can be seen on the longest-range routes, DUB-FCO and FCO-DUB. Case 1 has the highest amount of CO_2 produced (~57,000kg) with a decrease for Case 2 (~48,000kg) on these routes but a further decease is not seen for Case 3 despite an increase in MAX aircraft. This can be attributed to the fact that DUB-FCO and FCO-DUB routes only cater to approximately 6% of the overall passenger demand therefore fulfilling the total flight quota and maximising the achievable benefit of MAX replacements in Case 2 and thus negating any further benefit in Case 3 regardless of the extra MAX aircraft available. This limitation is seen for numerous other routes through the network and therefore can be understood to be a point of consideration for airlines when renewing their fleet. MAX aircraft are more sustainable than their NG counterpart but the benefit they offer is limited by the behaviour and constraints of the network the airline operates within.

Aside from total CO_2 produced, the CO_2 intensity breakdown per route and case is also of interest to airlines as it combines the CO_2 produced per flight into a metric that also considers the passengers onboard and distance flown by that flight. The mean of this metric per route is shown in Figure 12 and can be seen to have similar trends to the total CO_2 produced but weighted differently against routes given the passenger and range-based components now under consideration. Again, there are improvements between cases for the CO_2 intensity on the same, popular routes (DUB-STN and STN-DUB) as in Figure 11. However, the routes DUB-LPL and LPL-DUB, which have the lowest total CO_2 production (~12,000kg each) in Figure 11, now have among the highest average CO_2 intensity (~95gCO_2/pax.km each) in Figure 12 which can be attributed to the fact that these routes combined only cater to approximately 7.2% of the passenger demand with a relatively short range to fly (~122nmi). Since the passenger and range values within the CO_2 intensity metric are in the denominator, they contribute to a higher value of gCO_2/pax.km relative to a more popular and longer-range flight. This behaviour also alludes to the importance of synchronising the operations with the technology selection when it comes to fleet renewal, the short range flights lie within a poorer performance region of the payload-range diagram for these aircraft (design mission range of ~2900nmi [10]). Figures 11 and 12 provide insight to airlines as to where the most impactful and beneficial routes may lie when it comes to targeting sustainability gains. By knowing what the metrics of merit are (total mass of CO_2 produced, CO_2 intensity, CO_2 per passenger, etc.) and which are the largest contributors on a route or airport basis, airlines can enact change within their networks that produce tangible benefits from an environmental perspective. As well as this, knowing which routes are impacted the most by the technological improvements between MAX and NG aircraft relays the decisions the optimisation algorithm is making – the aircraft are being allocated to flights and routes such that the environmental and economic sustainability of the airline is being prioritised hence, as an airline, targeting and operating the given aircraft on these allocated flights and routes embeds this sustainability in practice.

5. Conclusions

This study considered the economic and environmental sustainability of three cases. Case 1 was a 100% NG aircraft fleet, Case 2 was a 75% NG and 25% MAX fleet and finally Case 3 was a 50/50 split in NG and MAX aircraft. The same network of airports and passenger demand was used for each case to ensure the study was investigating the impact of technology and fleet renewal alone between the cases. The most important result that was found from conducting this analysis was the ability to deploy physics-based methods, alongside linear programming and optimisation, to accurately characterise the benefits of fleet renewal for a real world case. The crucial insight that was produced was that the level of sustainability gains achievable are specific to the airline and the network it operates within. It was explained throughout Section 3 that the benefits offered through fleet renewal do not scale proportionally with the amount of advanced aircraft replacements within a fleet. The doubling of the MAX aircraft population between Cases 2 and 3 did not offer a doubling in fuel savings or operating costs between the cases. While the magnitude of the benefits offered through fleet renewal consistently improved with the proportion of MAX aircraft in the fleet, the airline only gained an additional 3.75% reduction in fuel costs in Case 3 versus the original 8.63% reduction in fuel costs for Case 2, see Table 4 in Section 4. Trade-off decisions have to be made by airlines when considering fleet renewal and this study gives airlines the ability to forecast, hypothesise and gain insights into these trade-offs. The additional 3.75% savings on fuel when switching from a 75/25 to 50/50 split in the fleet may outweigh the cost to renew the fleet for this hypothetical airline but could possibly bankrupt another. The sustainability gains are clearly visible, but the impact fleet renewal has both economically and environmentally must be considered holistically to achieve sustainability targets but also maintain incentivisation for airlines to undertake these decarbonising options through ensuring continued operability as a profitable business.

The goal of this study was to investigate the impact fleet renewal may have for a European based airline with regards to sustainability. The airline that was studied operated B737-800 (NG) aircraft and replaced different proportions of its fleet with the more advanced B737-8200 (MAX) aircraft. It was stated that a 17% reduction in CO_2 emissions by 2050 was possible through kerosene-based technology improvements (which the MAX vs NG is akin to) in Destination 2050's report [11]. ICAO' LTAG claims 2050 technology levels being responsible for up to 20% reduction in CO_2 emissions [8]. This study found that the total CO_2 produced in each case was 680,938kg, 622,174kg and 596,630kg (as seen in Table 3 from Section 4). This is equivalent to an 8.63% and 12.38% improvement in CO_2 emissions achieved through fleet renewal using the 16% more fuel efficient and 4% higher seating capacity MAX variant with a 25% and 50% fleet population, respectively for this network of airports and set of operations. As briefly touched on before, the CO_2 emissions are expected to reduce further with increased fleet renewal, while not scaling linearly, they will tend upwards given the right network of airports, operating conditions and continued technological improvements offering superior sustainability gains. Furthermore, the cases' schedules were analysed by aircraft type, range, load factor, and route-based metrics to infer and target where the technology adoption was most beneficial. It was found that MAX aircraft replaced NG aircraft for the longer range, higher fuel burn flights in Cases 2 and 3, as the MAX aircraft was more fuel efficient with a higher seating capacity. Consequently, utilising the MAX aircraft offered both reduced total CO_2 emissions and CO_2 intensity metrics, as well as the financial advantage of lower fuel costs compared to the NG aircraft.

Based on the analytical framework which has been developed, airlines can make informed choices regarding fleet renewal and advanced technology adoption and more importantly, decisions regarding their deployment within the networks and operations. Adopting a MAX aircraft and operating it on shorter range flights with low load factors will obviously not garner the same benefit as operating it on longer range, more highly filled flights. As such, the topic of fleet renewal must be addressed as a multi-faceted problem – what is the advanced technology (design range, payload, fuel efficiency, etc.), where will it be operated and how many units are necessary? Adopting "greener" technology will improve the sustainability performance of an airline, but to maximise this improvement the airline must consider where to utilise this technology. Simultaneously, the airline must also decide how many of these advanced aircraft are necessary to improve the sustainability without sacrificing its financial viability. Fleet scheduling in tandem with aircraft performance analysis is a critical step in the decarbonisation of aviation. This study demonstrated that there are sustainability gains to be achieved through fleet renewal alone, but superior gains may perhaps be unlocked through further coupled-analyses and investigations to pin-point better technological enhancements, adoption and ultimately insertion to the sector.

Acknowledgements

The authors would like to thank Ryanair for their technical support of this study through the use their data. This publication has emanated from research conducted with the financial support of the EU Commission Recovery and Resilience Facility under the Science Foundation Ireland 2050 Challenge Grant Number 22/NCF/TF/10933. *#NextGenerationEU*

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