Optimizing for sustainability as an objective function within airline fleet scheduling: An Ireland – EU mobility case study

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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, centered 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 hydrogen technology adoption 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 a liquid hydrogen fueled version of the B737-8200 MAX aircraft, with the balance of the population being the traditional B737-8200 MAX aircraft. The scheduling model is capable of completely scheduling an airline's fleet and crucially, generating solutions that are influenced by the performance capabilities, both in-flight and with respect to ground operations, of the aircraft comprising its fleet. This important functionality within the model ensures that the solution offered by the optimization algorithm is intrinsically linked to and dependent upon both the airline's operational attributes and the specific aircraft parameters. Airline sustainability was analyzed to determine the business case and environmental benefits of adopting varying compositions of hydrogen fueled aircraft by a European airline, to characterize the role of alternative fuels on a fleet-wide basis and to help inform and provide insight into the role of hydrogen technology on the route to net-zero. It was found that 8.77% of CO_2 emissions could be eliminated with only three airports adopting hydrogen technology, with higher CO_2 reductions achievable for increased numbers of hydrogen infrastructure at airports. Hydrogen aircraft offered significant sustainability gains but were prevented from universal adoption across the network of operations due to their higher associated operating costs therefore highlighting the imperative need for policy and legislation to incentivize the insertion of this technology within the sector.

I. Nomenclature

ASK	=	*Available Seat Kilometers [seat.km]*
ATC	=	*Air Traffic Control*
ATI	=	*Aerospace Technology Institute*

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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 Kilometer [cent/km]*
CI	=	*Cost Index*
CO_2	=	*Carbon Dioxide*
CORSIA	=	*Carbon Offsetting and Reduction Scheme for International Aviation*
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 Organization*
ID	=	*Identification*
k	=	*Lift Dependent Constant of Proportionality [-]*
KPI	=	*Key Performance Indicator*
L	=	*Aerodynamic Lift [N]*
LH_2	=	*Liquid Hydrogen*
LHV	=	*Lower Heating Value [MJ/kg]*
LTAG	=	*Long Term Aspirational Goal*
MILP	=	*Mixed-Integer Linear Programming*
MR	=	*Mission Range [nmi]*
NPSS	=	*Numerical Propulsion System Simulation*
PSEC	=	*Productivity Specific Energy Consumption [-]*
r	=	*Route Vector*
R^2*-value*	=	*Coefficient of Determination [-]*
RASK	=	*Revenue Per Available Seat Kilometer [cent/km]*
RPK	=	*Revenue Passenger Kilometers [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]*
TTW	=	*Tank-to-Wake*
V_∞	=	*Freestream Velocity / True Airspeed [m/s]*
W	=	*Weight of Aircraft [N]*
θ	=	*Flight Path Angle [°]*
ρ	=	*Air Density [kg/m^3]*

II. Introduction

A. Literature Review

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 decarbonization [1]. Airbus have committed to developing a hydrogen fueled 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 fueled [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. Characterizing the performance of such new technologies within the context of the real-world operations of an airline is of pivotal importance. In the "Destination 2050" report, it is asserted that the adoption of hydrogen fueled aircraft may reduce CO_2 emissions by up to 20% by 2050 [8]. Hydrogen fueled aircraft have no tail-pipe CO_2 emissions, but they offer significant challenges with regards to refueling, operation and energy consumption compared to traditional kerosene fueled aircraft. Therefore, forecasting and studying the fleet-wide benefits of this technology adoption is of pivotal importance since this very attractive CO_2 reduction comes at the cost of revolutionizing the practices and behaviors within the aviation sector. Hydrogen technology adoption requires large, disruptive changes to the value chain of aviation. The aviation sector and its stakeholders must have confidence in the technology before it can be financially support and feasibly incorporated within the sector to become a key driver for sustainability. To develop this confidence in the technology, operational simulations of hypothetical future fleet configurations must be undertaken to forecast the best way to utilize and deploy the technology for optimal sustainability.

"Necessity is the mother of all invention" is a phrase that aptly describes why there is a contemporary trend among manufacturers and other stakeholders to undertake and invest in sustainable technological developments. Legislation, policy and regulatory measures are coming into effect now and in the coming years that will require airlines to reduce their emissions with financial penalties being put in place to punish those in breach. From a European Union (EU) and Irish context, mandates such as "RefuelEU" and "EU ETS" and then on an international level, "CORSIA" all necessitate the aviation sector to decarbonize to remain a profitable and viable business in the future [9, 10, 11]. The RefuelEU aviation initiative is to lower CO_2 emissions through increasing the supply of and demand for SAF. Fuel suppliers will have to increase their percentage of SAF from 2% in 2025 to 70% by 2050. As well as this, airlines will have limits on "tankering" at EU airports (carrying additional fuel in excess of the mission requirement to avoid additional refueling costs at destination airports) as additional fuel weight leads to increased emissions [9]. The EU Emissions Trading System (ETS) enforces the polluter to pay for their CO_2 emissions through the use of emissions' allowances whereby airlines must surrender enough to account for their emissions or risk heavy fines being imposed [10]. The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) is a market-based measure, created by the International Civil Aviation Organization (ICAO), that outlines emissions mitigation measures, offsetting measures and reporting requirements for airlines to track their international CO_2 emissions accurately. The framework applies to ICAO member states and aims to reduce emissions from international aviation in a harmonized way such that market perturbations are avoided as best as possible [11]. These regulatory measures all seek to reduce the aviation industry's carbon emissions and use financial penalties as a means for compliance. 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. This can be seen in the "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 [12].

System-wide integration analyses, technology utilization assessments, market and policy understanding, and holistic optimization approaches are therefore critical steps in taking technological advancements to application, as seen by Roy et al. [13] 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 optimized 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 optimization 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. [14] 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 decarbonize. 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 utilized to inform and alter the design of an aircraft within iterative and simultaneous optimization 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. [15] wherein a "strategic airline planning model" was constructed that assessed and minimized 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. [16] investigate what influence a kerosene fleet optimized 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 fueled 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-emphasizes 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. [17] 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 decarbonization. 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 decarbonizing the aviation sector. Tetzloff and Crossley [18] 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 utilized. 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 realizable pathway to decarbonization than independent development alone could ever endeavor to achieve.

B. Objectives

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. [19, 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 [19]. In addition, the model has been used to assess the grid scale energy demand resulting from an aircraft fueled 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 [20].

A predictive tool that accurately determines the performance of an aircraft design was established and validated, hence the next steps were 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 was then 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 maximizes its economic and environmental sustainability. The airline's fleet of aircraft, airport network and passenger demand were all set as inputs to the scheduling algorithm and were informed by the industry collaborator, Ryanair. Given these inputs, the scheduling algorithm was tasked with optimization 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 III, with the results and discussion presented in Section IV and conclusions in Section V.

The purpose of developing this scheduling model was to follow in the literature's current trend and demonstrate a more rounded view of the decarbonization 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 enabled design space characterization of the multi-disciplinary, inter-connected attributes of the aircraft's parameters and the fleet-wide utilization of said aircraft's design within an airline's operations. Elucidating key relations between operation, aircraft design, fuel selection, energy usage, infrastructural demands, etc. were central points of interest that could be studied through the development of this model. The fleet scheduling model was created with this holistic design space characterization goal in mind, and therefore was founded and informed by the predictive design tool developed by Gallagher et al. [19, 20, 21]. Using data for a full day of operations and an understanding of the constraints and logistics associated with liquid hydrogen (LH_2) fueled aircraft, the current study will utilize the aircraft performance predictions for a B737-8200 MAX aircraft and a 50% gravimetric efficiency, LH_2 fueled version (developed by Gallagher et al. [19, 21]) to assess the operational impact on an airline's sustainability under varying fleet compositions. In addition to the operational impacts on sustainability, the study aims to forecast how closely the real-world adoption of improved hydrogen technologies correlates with what is expected in key policy documents and therefore assess the feasibility of progressing sustainability agendas through the adoption of LH_2 aircraft.

III. Methodology

The setup and methodology of the model used within this analytical framework comprises of two sub-models: an aircraft performance model and a fleet scheduling model followed by a problem definition. 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 maximize 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.

A. Aircraft Performance

As briefly mentioned in Section II, the work of Gallagher et al. [19 21] 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. This model implicitly captures all aerodynamic and propulsive behaviors of the given aircraft throughout a 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 optimization of an airline's sustainability. The reason for using a surrogate version of the aircraft performance model is to enable the accurate characterization of key operational parameters for different aircraft with minimum interference from any confounding variables. When incorporated into the scheduling sub-model, the goal was 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 technologies 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 adoption and deployment of said 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 (referred to as the MAX-8) and B737-800 NG type aircraft. An idealized 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-8 and NG type aircraft was generated. This enabled generalized flight profiles to be developed for each of these aircraft types given their MR and TOW. The seven control points were the climb angle, maximum altitude (cruise altitude), 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 generalized fitting tool was trained on a combination of MAX-8 and NG Ryanair data and was fitted to an idealized flight profile was twofold: Firstly, Ryanair use the MAX-8 and NG aircraft interchangeably on routes given that they are from the same family and the MAX-8 is essentially a newer, more fuel efficient version of the NG with a slightly higher, non-standard seat configuration of 197 [24]. 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 altitude hence generalizing a flight profile can be done using key control points (elucidated from the data) without straying from an accurate recreation of a MAX-8 or NG flight profile.

From the original near 3000 flights, 1706 flights had flight profiles that could be recreated using the generalized 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 included. 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 generalized flight profile fitting tool later in the sub-model. The reason many real-world flights suffer a poor fitting approximation was 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.

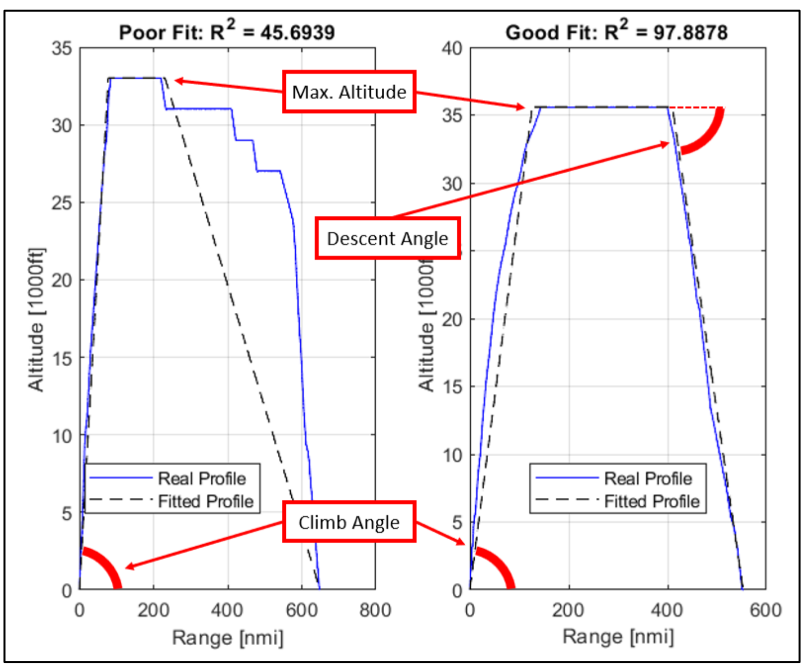

Fig. 1 Comparison of a poor versus good approximation of a real-world flight

Following the preprocessing of the raw data to only include flights that are well approximated using the idealized 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 generalized 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).

$$L = Wcos\theta \tag{1}$$

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. Please note the wetted areas of the traditional MAX and LH_2 MAX aircrafts are slightly different to account for the aircraft redesign based on fuel type.

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

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

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. [19]. See Eq. (4) and Figure 3 for the comparison of drag polars between the traditional MAX and LH_2 MAX airframes. The LH_2 aircraft has a constant wing loading with respect to the traditional MAX aircraft, the same passenger capacity and design range of ~2900nmi [24] resulting in an elongated fuselage of 52.4m [21].

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

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).

$$T = D + Wsin\theta \tag{6}$$

8. With a required thrust and knowing the altitude and true airspeed for the current step, the propulsion surrogate developed by Gallagher et al. [19, 21] is used to find the thrust specific fuel consumption (TSFC) and corresponding fuel flow.
9. The fuel flow for both engines is tracked throughout the flight path for each step and then integrated with respect to time over the flight profile to determine the total simulated mass of fuel burned associated with each flight.
10. For the LH_2 aircraft only, the mass attained in step 9 must be converted from kilograms of kerosene to kilograms of LH_2 consumed. This is seen in Eq. (7) and is formed on an energy basis using the lower heating values (LHV) of both fuels where $LHV_{Jet\text{-}A1}$ = 43.3MJ/kg [25] and LHV_{LH2} = 121MJ/kg [26].

$$m_{LH2} = \frac{LHV_{Jet-A1}}{LHV_{LH2}} m_{Jet-A1} \tag{7}$$

Please note, the propulsion surrogate models developed by Gallagher et al. [19, 21] 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.

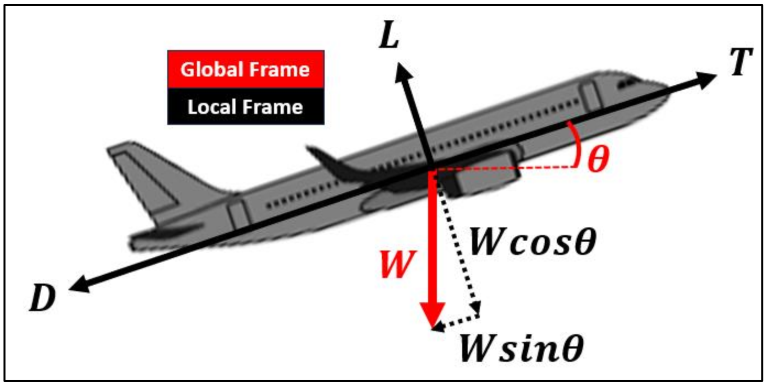

Fig. 2 Free-body diagram of the aircraft force balance (vectors not to scale)

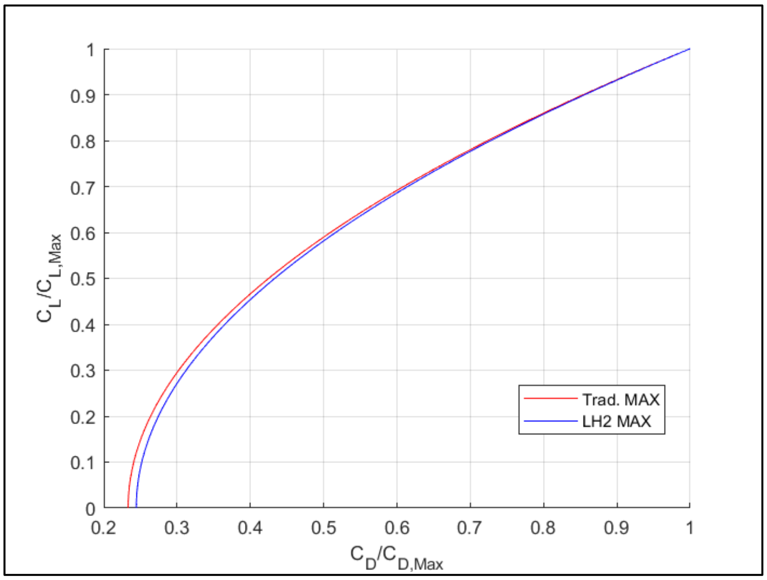

Fig. 3 Traditional versus LH_2 MAX airframe drag polars (clean configuration)

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 MR and TOW combinations for the traditional MAX aircraft 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. [19, 21]. Hence the high accuracy achieved when compared to real world flights demonstrates the applicability of using this aircraft performance sub-model in an exploratory capacity 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 for the traditional MAX aircraft

MR [nmi]	TOW [kg]	Act. Fuel Burn [kg]	Sim. Fuel Burn [kg]	Error [%]
281.76	57758.00	1595.10	1618.20	1.45
885.87	67843.00	4468.90	4497.40	0.64
1019.50	64613.00	4878.00	4919.90	0.86

Following the validation of the aircraft performance sub-model with real world data, LH_2 aircrafts' energy penalties compared to the traditional MAX aircraft can be assessed, as seen in Table 2. The higher operating empty weight (OEW), slightly larger wetted area and different fuel storage of the LH_2 aircraft mean that it consumes more energy for the same mission as a traditional MAX aircraft. In this instance, the same missions refer to the same number of passengers flown, same distance to travel and same starting energy stored on-board between aircraft types.

Table 2 Example energy penalties for LH_2 versus traditional aircraft

Mission Details			Traditional MAX			LH2 MAX			Energy Penalty [%]
MR [nmi]	Pax. [-]	Energy Stored [MJ]	Fuel Level [%]	TOW [kg]	Energy Consumed [MJ]	Fuel Level [%]	TOW [kg]	Energy Consumed [MJ]	
500	197	500000	52.82	71352.34	124863.20	60.94	78176.23	139147.80	11.44
1000	197	600000	63.39	73661.81	230403.10	73.13	79002.68	255523.17	10.90
1500	197	700000	73.95	75971.28	337925.59	85.32	79829.12	369441.19	9.33

B. Fleet Scheduling

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

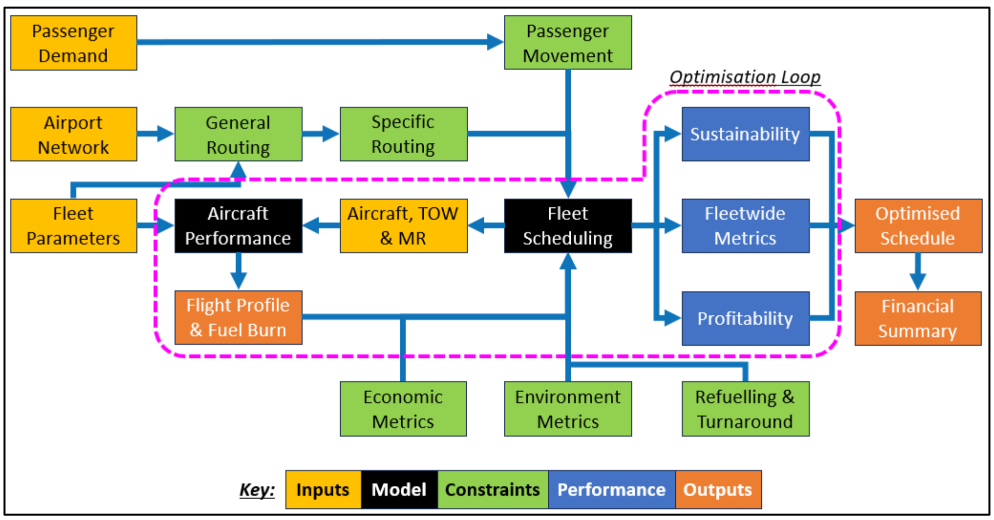

Fig. 4 Overall flowchart of the fleet scheduling model

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 [27]. 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 were Dublin airport (DUB) as the center of the network and the 10 most popular destinations from DUB, as informed by Ryanair. The reason for developing an Irish-centered model was 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 [28]. In addition, Ireland's tourism industry employs approximately 220,000 people [29].
2) Ireland is the worldwide hub of the aircraft leasing business, with responsibility for over 50% market share and €100bn of assets [30]. Hence, Ireland's involvement in the pathfinding research to decarbonize 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 were a balancing point for the computational effort required in solving for an optimized schedule while still being capable of providing insight into the hypothetical behavior of the network and inform decisions regarding next steps on the pathway to decarbonization. Each cell within the matrix was 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 for 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

Fig. 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 was 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 were 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 were 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 were used within the fleet scheduling later in the model, as seen in Figure 4 whereby the “Specific Routing” component is directed into the “Fleet Scheduling” component. Initially, candidate routes were 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 was 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 was defined by the “Passenger Demand” component in Figure 4. 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 color assigned to the “Passenger Movement” component in Figure 4. 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 [31]. 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 was 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

Fig. 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 characterized the setup of the scheduling model such that an optimization problem can be solved. MILP was used to solve the optimization problem of scheduling aircraft from a fleet to meet the demand of an airport network. It is a method that uses optimization variables, constraints and an objective function. This occurs in the "Fleet Scheduling" component in Figure 4. The optimization variables refer to the number of flights, number of passengers and which flight routes were selected. As well as this, there were optimization variables for refueling and storage of aircraft. The constraints were broad in nature, some were for ensuring operational and logistical feasibility such as a flight cannot depart an airport unless there was an aircraft stored there or a flight has previously arrived and completed its turnaround. Similarly, the fuel status of an aircraft was constrained to being non-negative, this enforced the refuel optimization variable to top-up low fueled aircraft when they were close to breaching this non-negative threshold. Other constraints were 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 optimization 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. For example, 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 optimization variables and constraints developed and implemented – the objective function was defined such that the most optimal solution from all feasible solutions may be selected, therefore solving the scheduling problem in the "best" way. This optimization occurs inside the pink outlined 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 were all returned to the scheduling sub-model. This loop was cycled throughout the design space until an optimized solution was arrived upon. For this analysis, a holistic sustainability metric was optimized that included the environmental and economic impact of the solution, therefore the "best" was the most environmentally and economically sustainable solution offered. To do this, environmental and economic sustainability metrics needed to be defined and incorporated into the objective function such that representative values be calculated and compared across the design space of optimization variables and their feasible solutions.

Within Figure 4, the blue performance components "Profitability" and "Sustainability" considered the economic and environmental sustainability performance of the schedule, respectively. The "Profitability" component directly considered the economic performance and was broken down into key performance indicators (KPI) within the aviation sector: available seat kilometers (ASK), revenue passenger kilometers (RPK), revenue per available seat kilometers (RASK), cost per available seat kilometers (CASK) as well as yield and the traditional, overall revenue, costs and profit. The revenue was solely generated from passenger fares, which were calculated by the sum of a base rate fare and a distance weighted fare per passenger. The costs were more varied but were 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 used representative values for costs and revenue (partially informed by the IATA's "chart of the week" financial breakdown [12] and the Federal Aviation Administration's (FAA) "Aircraft Operating Costs" document [32]) rather than exact values since some financial information is commercially sensitive. Lastly, the environmental performance of the fleet could 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 hydrogen technology has on the environmental and economic sustainability of an airline when scaling individually superior aircraft to a fleet-wide level of operations.

C. Problem Definition

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

- Case 1: 100% traditional MAX and 0% LH_2 MAX aircraft
- Case 2: 75% traditional MAX and 25% LH_2 MAX aircraft
- Case 3: 50% traditional MAX and 50% LH_2 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 was 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 hydrogen technology adoption may be for an airline's central hub. The network therefore centers around DUB with the 10 other airports ranging in distance from 120 to 1020nmi with a total passenger movement of over 17 thousand people in a 24-hour period. The network of airports is shown in Figure 7.

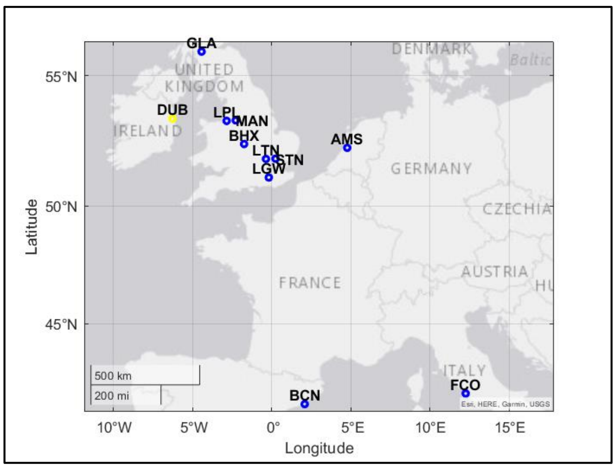

Fig. 7 Airport network input to the fleet scheduling model

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 was 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 behavior that may be used and replicated within the scheduling model. This replication of real-world passenger behavior reinforces the confidence in decisions that can be made from the results of this model's simulations as the algorithm considers real scenarios and optimizes accordingly to offer feasible and practicable airline schedules. All scenarios followed the same setup with regards to an operating window of 24 hours and were subjected to the same optimization constraints and objectives regarding economic and environmental sustainability. The simulation of each scenario was completed using MATLAB R2023a with the optimization toolbox installed to enable the use of MILP solvers.

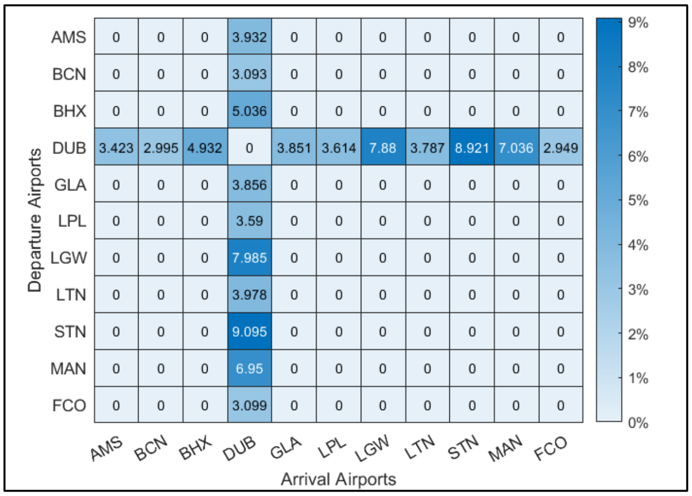

Fig. 8 Demand matrix input to the fleet scheduling model

The turnaround functionality referenced in Figure 4 is defined differently for the traditional and LH_2 aircraft to account for a balanced view of hydrogen's technology readiness level, which was assumed to not allow simultaneous refueling with passengers on board. Consequently, the turnaround time for the LH_2 aircraft in the fleet was dependent upon the amount of refueling required. A block diagram breaking down the specific accumulated times within the overall turnaround time is shown in Figure 9.

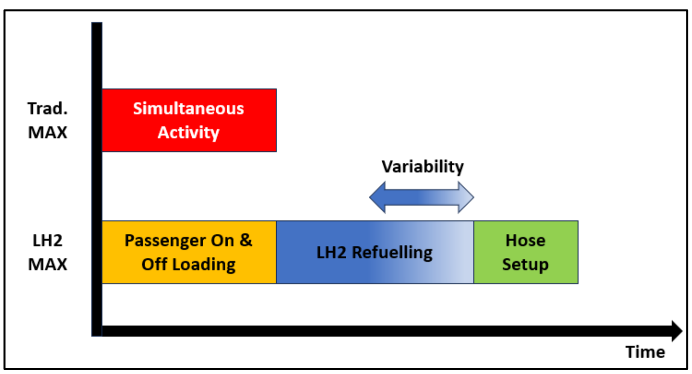

Fig. 9 Turnaround breakdown for each aircraft type

Since the passenger capacity and door layout was identical for both aircraft, a preset passenger on and off-loading time of 25mins was used in both cases [33]. This can be conducted simultaneously as refueling for the traditional MAX aircraft so the minimum turnaround constraint on these aircraft was 25mins. The refuel rate of 2000L/min was used within the study for the LH_2 MAX aircraft, which was informed by the work of Abel et al. [34]. Finally, the disconnecting and reconnecting of hoses which is much more time consuming for LH_2 compared to Jet-A1, due to the behavior of the different fuels and added safety concerns surrounding the cryogenic nature of LH_2. Thus, the disconnecting and reconnecting time for the refuel hoses (referred to as "Hose Setup" in Figure 9) was set at 15mins. This was inferred from the Aerospace Technology Institute's (ATI) document on hydrogen refueling [35], where a narrowbody aircraft has a fill time of 9mins or ~5mins using two hoses (as was assumed in this study), with the corresponding time for a non-simultaneous turnaround of a narrowbody LH_2 aircraft being quoted at ~46mins [35]. It can be understood that if there was no refueling required, the LH_2 aircraft would turnaround in 25mins like the traditional MAX since only on and off-loading of passengers and baggage would be required.

The scheduling model used the airport network and passenger demand as inputs to define the network flow problem alongside the aircraft fleet configuration in each case and was 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, mission ranges, 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 summarized 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.

IV. Results & Discussion

A snippet of the schedule produced from Case 3, the 50/50 split between traditional and LH_2 MAX aircraft is shown in Figures 10a and 10b. Within this schedule, under the "Plane ID" column, the ID's starting with "A" refer to traditional MAX aircraft whereas the ID's beginning with "B" were LH_2 aircraft. The complete control and monitoring of each asset belonging to the airline was made available through the schedule. All flight-based metrics from passengers on board to fuel burned were tracked with all pertinent information being saved and stored for review by the hypothetical airline to understand and monitor the utilization of their fleet.

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	A008	MAN	DUB	12:20:00	13:20:00	01:00:00	143.25	197	100.00
41	B004	DUB	STN	12:20:00	13:40:00	01:20:00	254.42	197	100.00
42	A005	DUB	BHX	12:45:00	13:50:00	01:05:00	173.81	119	60.41
43	B010	MAN	DUB	12:55:00	13:55:00	01:00:00	143.25	119	60.41
44	A003	STN	DUB	13:30:00	14:50:00	01:20:00	254.42	197	100.00
45	A008	DUB	MAN	13:45:00	14:45:00	01:00:00	143.25	197	100.00
46	A005	BHX	DUB	14:15:00	15:20:00	01:05:00	173.81	119	60.41
47	B001	MAN	DUB	14:35:00	15:35:00	01:00:00	143.25	197	100.00
48	B010	DUB	MAN	14:40:00	15:40:00	01:00:00	143.25	119	60.41
49	A006	DUB	AMS	15:10:00	16:45:00	01:35:00	405.52	157	79.70
50	A007	FCO	DUB	15:10:00	18:15:00	03:05:00	1019.27	197	100.00
51	A009	LGW	DUB	15:50:00	17:15:00	01:25:00	261.87	197	100.00
52	B009	MAN	DUB	16:10:00	17:10:00	01:00:00	143.25	119	60.41
53	B006	GLA	DUB	16:35:00	17:35:00	01:00:00	160.15	197	100.00
54	B004	STN	DUB	16:40:00	18:00:00	01:20:00	254.42	197	100.00
55	A001	LGW	DUB	16:45:00	18:10:00	01:25:00	261.87	119	60.41
56	A006	AMS	DUB	17:10:00	18:45:00	01:35:00	405.52	197	100.00
57	B003	LGW	DUB	17:10:00	18:35:00	01:25:00	261.87	119	60.41
58	A010	LGW	DUB	17:15:00	18:40:00	01:25:00	261.87	197	100.00
59	B008	DUB	LPL	17:15:00	18:10:00	00:55:00	122.74	190	96.45
60	A002	DUB	BHX	17:25:00	18:30:00	01:05:00	173.81	119	60.41

Fig. 10a Snippet of Case 3's schedule – Part 1

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	A008	63537.7	3872.3	1269.8	2602.5	1269.8	3367.3	64.43
41	B004	75795.0	17926.5	8362.8	9563.8	8362.8	0.0	0.00
42	A005	57233.1	3795.4	1192.9	2602.5	1192.9	3163.4	82.58
43	B010	69317.5	14577.0	5013.3	9563.8	5013.3	0.0	0.00
44	A003	64045.5	4476.8	1874.3	2602.5	4856.5	4970.4	53.55
45	A008	63537.7	3872.3	1269.8	2602.5	1269.8	3367.3	64.43
46	A005	57233.1	3795.4	1192.9	2602.5	2452.9	3163.4	82.58
47	B001	75625.9	15541.9	5978.2	9563.8	5013.3	0.0	0.00
48	B010	69317.5	14577.0	5013.3	9563.8	5013.3	0.0	0.00
49	A006	61431.0	5173.8	2571.3	2602.5	2695.9	6818.7	57.83
50	A007	67539.0	8635.8	6033.3	2602.5	6023.9	15999.5	43.02
51	A009	64079.5	4517.3	1914.8	2602.5	1874.3	5077.8	53.15
52	B009	69317.5	14577.0	5013.3	9563.8	5668.6	0.0	0.00
53	B006	75651.6	15904.3	6340.6	9563.8	5538.2	0.0	0.00
54	B004	75795.0	17926.5	8362.8	9563.8	7954.5	0.0	0.00
55	A001	57635.4	4274.3	1671.8	2602.5	1852.5	4433.3	76.82
56	A006	64735.7	5298.4	2695.9	2602.5	1914.8	7149.3	48.32
57	B003	69497.9	17121.4	7557.7	9563.8	7557.7	0.0	0.00
58	A010	64079.5	4517.3	1914.8	2602.5	1914.8	5077.8	53.15
59	B008	75028.6	15015.4	5451.6	9563.8	4573.3	0.0	0.00
60	A002	57233.1	3795.4	1192.9	2602.5	1192.9	3163.4	82.58

Fig. 10b Snippet of Case 3's schedule – Part 2

The fleet-wide environmental metrics are summarized in Table 3 with metrics pertaining to traditional MAX (see the "MAX" rows), LH_2 MAX (see the "LH_2" rows) and the fleet as a whole (see the "Fleet" rows) for each of the three cases. Within this table the total number of aircraft, the number of each aircraft type, the number of flights and the average utilization of the aircraft within the fleet and total energy consumed by the fleet are all shown giving an indication of how the different fleet configurations amongst the same network of airports and same passenger demand were operated. As well as this, statistics on the environmental performance of each sub-fleet and fleet as a whole can be seen under the "CO_2 Production [kg]", "CO_2 Intensity [gCO_2/pax.km]" and "PSEC [-]" headings. The CO_2 produced is simply a mass-measure of how much CO_2 was produced on a tank-to-wake (TTW) basis, whereas the CO_2 intensity is a per-flight measure of the CO_2 produced divided by the product of the passengers flown and distance travelled. This metric can be thought of as the ratio of environmental harm to societal benefit whereby a lower CO_2 intensity indicates a better use of the aircraft such that more people travel a further distance for a given amount of CO_2 produced. However, this metric only provides insight into CO_2 producing fuels but LH_2 aircraft have no tail-pipe carbon emissions, therefore a different version of this metric was also used, the productivity specific energy consumption (PSEC). It is defined as the ratio of the energy consumed and the energy of the payload (mass of passengers multiplied by the distance travelled multiplied by the acceleration due to gravity) and is therefore a dimensionless number that essentially describes how efficiently the given payload of passengers were flown for each flight. Like the CO_2 intensity metric, it describes how beneficial the flight was from a passenger mobility perspective by considering the number of passengers and how far they travelled but the environmental impact is in terms of energy demand rather than CO_2 production.

When reviewing the figures for each sub-fleet and fleet as a whole, for each of the cases, the increased population of LH_2 aircraft decreases the CO_2 production and intensity. This was expected as the LH_2 aircraft produce no CO_2 emissions and would therefore lower the CO_2 intensity across the fleet with increased numbers of LH_2 aircraft flights. The PSEC metrics however are fuel agnostic and consider the energy consumption versus passenger mobility of the sub-fleets and fleets. This metric can be seen to have a fleet-wide average of 1.10, 1.19 and 1.23 in Cases 1, 2 and 3, respectively. The increase correlates with an increase in LH_2 aircraft population amongst the fleet and can be attributed to the additional energy penalty associated with operating LH_2 aircraft on equivalent missions compared to traditional, kerosene fueled aircraft. This was further seen when comparing the sub-fleet averages between the traditional and LH_2 MAX aircraft within Cases 2 and 3 where the LH_2 aircrafts have a PSEC of 1.61 and 1.43 versus the traditional aircraft's 1.11 and 1.07 in Cases 2 and 3, respectively. This higher energy demand of the LH_2 aircraft was also seen in Table 2 from Section III.

Table 3 Environmental summary of each case on a sub-fleet and total fleet basis

		Aircraft [-]	Flights [-]	Avg. Usage [-]	Tot. Energy Used [MJ]	CO2 Production [kg]				CO2 Intensity [gCO2/pax.km]			PSEC [-]		
						Minimum	Average	Maximum	Total	Minimum	Average	Maximum	Minimum	Average	Maximum
Case 1	MAX	20	100	5.00	7509275.32	2427.02	5475.01	15999.51	547500.74	43.02	62.68	89.72	0.75	1.10	1.57
	LH2	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fleet	20	100	5.00	7509275.32	2427.02	5475.01	15999.51	547500.74	43.02	62.68	89.72	0.75	1.10	1.57
Case 2	MAX	15	90	6.00	6948892.09	2427.02	5629.37	15999.51	506643.24	43.02	63.48	89.72	0.75	1.11	1.57
	LH2	5	18	3.60	941224.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.43	1.61	1.85
	Fleet	20	108	5.40	7890116.66	2427.02	5629.37	15999.51	506643.24	0.00	52.90	89.72	0.75	1.19	1.85
Case 3	MAX	10	60	6.00	5451276.99	3163.39	6624.20	15999.51	397452.23	43.02	61.23	82.58	0.75	1.07	1.44
	LH2	10	48	4.80	2556162.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	1.43	1.85
	Fleet	20	108	5.40	8007439.96	3163.39	6624.20	15999.51	397452.23	0.00	34.02	82.58	0.75	1.23	1.85

The financial summary of each case, normalized and compared to Case 1 as a baseline is shown in Table 4. The cost of landing and handling increased by 8% for Cases 2 and 3 relative to Case 1, this was directly attributable to the increase in total flight number from 100 to 108 flights. Additionally, the wages and fuel costs rose with an increase in the population of LH_2 aircraft within the fleet. Wage costs were calculated as a function of flight time and turnaround time (operating time for the crew), hence with an increase in total flight number and longer turnaround times for LH_2 aircraft, the wage costs continued to rise as more LH_2 aircraft were included in the fleet. The fuel cost of LH_2 was set at €3.45/kg [36] and the cost of Jet-A1 fuel was set at €0.50/L [37]. By operating more flights and flying aircraft that use the more costly LH_2 fuel, the cost of fueling the fleet increased dramatically by 43.2% in Case 3 compared to the all Jet-A1 fueled Case 1 fleet. As expected, the CO_2 emissions' costs decreased with more LH_2 aircraft as the total CO_2 production of the fleet decreased between Cases 1, 2 and 3. The total CO_2 produced in Cases 1, 2 and 3 was approximately 547,500kg, 506,643kg and 397,452kg, respectively, giving a reduction of 40,857kg and 150,048kg which is equivalent to nearly €3,269 and €12,004 in daily savings for this airline and the current network. The EU

ETS places a financial penalty on the amount of CO_2 produced – an ETS CO_2 penalty of €80/1000kg [10] was used in this study. Airlines will have to proactively seek to avoid being costed out of business through legislation and policies like the ETS CO_2 penalties given that they will increase and further penalize the CO_2 producing components of their business as well as consider non-CO_2 effects. Passenger revenue didn't vary between cases since the same passenger demand was used across each of the cases hence with increases in costs but equal total revenue, the profit decreased further with an increase in, the more costly to operate, LH_2 aircraft within the fleet.

Table 4 Financial summary of each case on a total fleet basis (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	87.80	100.00	100.00	100.00	100.00	100.00
Case2	8.00	8.00	0.00	10.09	18.53	-7.46	0.00	-3.81	-3.81	81.29	5.46	0.00	0.00	-5.26	4.83
Case3	8.00	8.00	0.00	14.79	43.20	-27.41	0.00	-7.65	-7.63	81.29	4.97	0.00	0.00	-4.72	15.86

Following the output of the airline's schedule and environmental and economic summaries, restructuring the results around different metrics and attributes within the fleet can provide more insightful analyses from which tangible and practicable sustainability gains may be achieved. Breaking the results down by case and sub-fleet on a range-basis indicated the type of flights each aircraft was allocated, see Figure 11. It can be seen that LH_2 aircraft are only allocated to short range flights whereas the traditional MAX cater to all ranges. The main reason for this was due to the higher cost of operating LH_2 aircraft which only worsens at longer range, therefore the optimal operation of such technology was to use it on shorter flights.

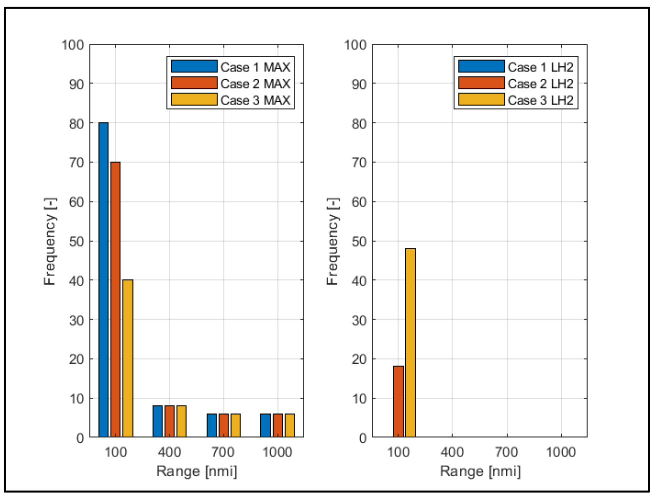

Fig. 11 Range-based histograms for each case on a sub-fleet basis

A route-based breakdown of the number of flights of each aircraft type can be seen in Figure 12. The x-axis labels of routes are ordered from left to right, shortest to longest range with DUB-LPL/LPL-DUB at 120nmi and DUB-FCO/FCO-DUB at 1020nmi. The top plot within Figure 12 depicts the sub-fleet flight count breakdown for Case 2 and the bottom plot depicts Case 3's flight tally. It can be seen that LH_2 aircraft were only placed on certain short-range flights and either nearly or entirely replace the shortest range flights in Case 3. It should be noted, and can be seen in Figure 7 from Section III, that all routes except those including AMS, BCN and FCO are in the UK and therefore are relatively closer to Dublin. These farther destinations were never targeted for hydrogen technology insertion in either Case 2 or 3. With the addition of extra LH_2 aircraft between Case 2 and 3, all shorter-range routes saw some allocation of LH_2 aircraft with the majority of these hydrogen flights being allocated to the shortest (LPL, MAN and GLA bound or originating) flights.

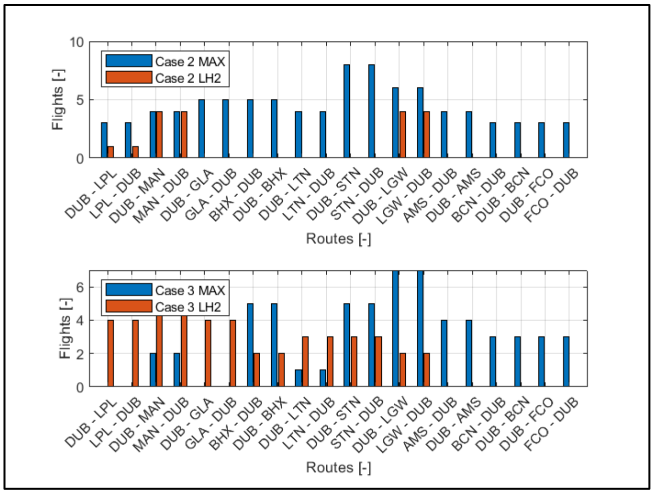

Fig. 12 Number of flights for each sub-fleet per route for each case

Figures 13, 14 and 15 show the total CO_2 produced, mean CO_2 intensity and mean PSEC per route for each case, respectively. These environmental metrics were measured on a fleet-wide basis per case and broken down by their associated routes. This facilitates understanding of which routes were being targeted by the optimization algorithm for the hydrogen technology insertion, as well as how impactful this adoption was. While the total CO_2 and the mean intensity may be understood as how concentrated the given flights were from a carbon emissions perspective, they did not fully capture the impact the hydrogen technology adoption had on the airline in which it operates. The mean PSEC per route indicated how costly, from a fuel agnostic TTW energy demand perspective, it was to operate LH_2 aircraft within the fleet. Total CO_2 decreased with increasing portions of LH_2 aircraft within the fleet except for the DUB-LGW and LGW-DUB routes. The reason for this somewhat unexpected result for the DUB-LGW and LGW-DUB routes was attributed to the decrease in the number of hydrogen flights between Case 2 and Case 3 for these routes as seen in Figure 12. Instead, these flights were allocated to LPL, MAN and GLA bound or originating flights in Case 3 that completely removed the CO_2 produced on the DUB-LPL, LPL-DUB, DUB-GLA and GLA-DUB routes with a majority of CO_2 produced also removed for the DUB-MAN and MAN-DUB routes for Case 3. It can be seen between Figures 12 and 13, that no LH_2 aircraft were allocated to the longer-range flights and therefore their CO_2 emissions remain unchanged across the cases. Looking to Figure 14, these route-based trends repeat however with differing magnitudes for the change in metric from total CO_2 to mean CO_2 intensity. The inclusion of the passenger and range components within this latter metric shifted the magnitudes of the decrements between cases but the general trends of shorter ranged routes benefiting most from hydrogen technology adoption remains consistent.

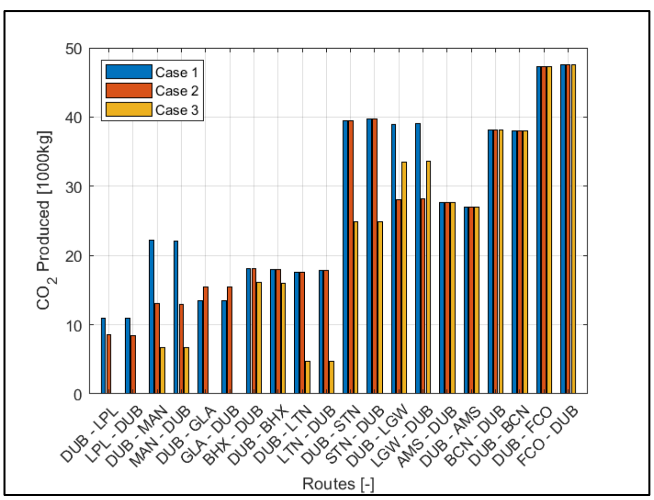

Fig. 13 Total CO_2 production per route for each case

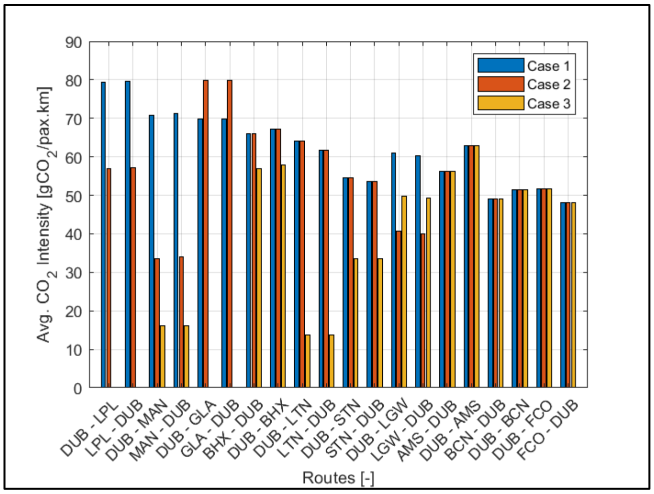

Fig. 14 Mean CO_2 intensity per route for each case

A more holistic, and perhaps fairer comparison across the fleet configurations in each case, was the mean PSEC per route displayed in Figure 15. It was seen that the LH_2 aircraft suffer an energy penalty relative to the traditional MAX aircraft in Table 2 from Section III. These energy penalties varied inversely with respect to range, such that shorter range flights were penalized more significantly than longer range flights. This was expected as the design mission range of these aircraft was approximately 2900nmi [24] meaning these sub-optimal payload-range combinations operated within less desirable regions of the design space for those aircraft with LH_2 aircraft further compounding the performance drop-offs with additional energy penalties. In Figure 15, the mean PSEC for each route increases between cases due to the higher LH_2 aircraft population and share of the flights. The shorter routes suffer from higher average PSEC values than their longer counterparts as more LH_2 aircraft were allocated to these routes and therefore accumulated a higher energy penalty on average.

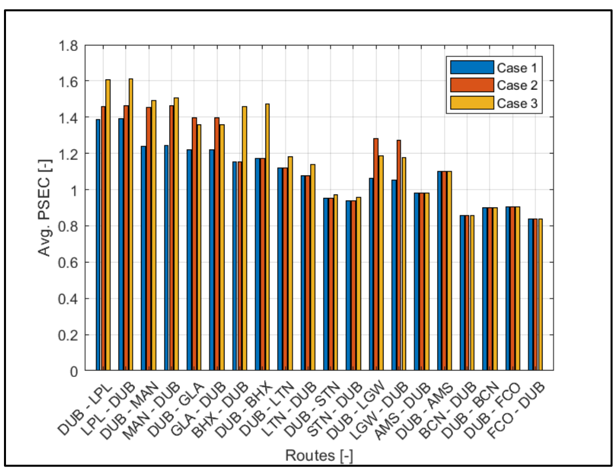

Fig. 15 Mean PSEC per route for each case

Figures 13, 14 and 15 conveyed the importance for airlines to fully understand and scrutinize the performance of their fleet. The hydrogen technology's targeted adoption, as controlled by the sustainability objective function driven optimization algorithm, was elucidated from the route-based breakdown of the airline's performance in each case. This gives the insight of where to develop hydrogen infrastructure and invest in ways to maintain and permit LH_2 aircraft to cater to flights within the network while still allowing airlines to operate as viable businesses. By equipping the airports DUB, LPL and GLA with the necessary hydrogen infrastructure, approximately 48,000kg of Case 1's CO_2 (equivalent to 8.77% of Case 1's total CO_2 emissions) can be eliminated as seen Figure 13 for routes DUB-LPL, LPL-DUB, DUB-GLA and GLA-DUB. Of course, outfitting more airports with hydrogen infrastructure will increase these benefits but this study enables the prioritization of developments to maximize sustainability gains. Furthermore, a more complete understanding of the hydrogen technology's impact was offered as the impressive CO_2 reductions were made clear juxtaposed to their increased energy demands. While this increased energy demand may be offset by the savings in CO_2 emissions' costs for this hypothetical airline, the give and take offered by LH_2 technology in its current form could be too drastic a transition for other airlines to undertake therefore limiting achievable sustainability gains for the sector. For the present study, the cost of operating LH_2 aircraft (higher fuel costs, more energy intensive, longer operating times, etc.) versus the financial benefit of not incurring ETS CO_2 penalties did not yield a sufficiently wide-spread adoption of the hydrogen technology across the full set of operations for this network. Operating costs would need to decrease to a point where the savings from lack of emissions penalties outweighs or negates these costs to see a more universal and ubiquitous adoption of hydrogen technology.

V. Conclusions

Through the study of optimal sustainability fleet scheduling for an airline operating within this network and passenger demand, it was seen that key insights regarding the insertion of hydrogen technology can be garnered and inform future studies and developments for sustainable aviation. The study conducted a baseline analysis in Case 1 with 100% traditional MAX aircraft and then varied the population of LH_2 aircraft to 25% and 50% of the fleet's composition in Cases 2 and 3, respectively. The sustainability of the airline was monitored in each case and the scheduling algorithm was subjected to the same constraints and passenger demand with the only change being in fleet composition to investigate how the hypothetical airline would operate within the same network. It was seen that LH_2 aircraft saw the majority of their adoption in the shortest ranged flights within the network and no LH_2 flights being allocated to the longest-range routes. The determination of fuel burn, and therefore energy demand, of each flight was completed using a physics-based, real world data informed method developed from the work of Gallagher et al. [19, 20, 21]. The traditional MAX aircraft's and LH_2 MAX aircraft's modelled airframes and propulsion units were validated using real world data from Ryanair to give accurate and realistic fuel and energy demands for each flight operated within the scheduling algorithm. This functionality enabled the measuring of the environmental metrics such as total CO_2 produced, CO_2 intensity and PSEC that highlighted and explained why the scheduling algorithm allocated the LH_2 aircraft to the given routes and provided insight as to how these aircraft would perform from a sustainability perspective.

The financial component of the airline's sustainability also played a role within the analysis. It is understood that hydrogen technology is a revolutionary development for aviation to undertake therefore the operating costs associated with such a transition are expectedly greater than through alternative options. This was confirmed in the financial analysis of each case in Table 4 from Section IV where it was seen that the airline's profit decreased by 3.81% and 7.63% for Cases 2 and 3, respectively. CO_2 emissions decreased appreciably which proportionally lowered their emissions' costs between cases. However, these savings were not enough to offset the dramatic increase in fuel costs associated with operating fleets composed of higher amounts of LH_2 aircraft. This is where policy and legislation play a crucial role in the development, adoption and proliferation of hydrogen technology within the aviation sector. The ETS CO_2 penalty discourages the use of carbon-based technology, but the cost of operating alternative options does not synergize effectively enough to incentivize airlines to make the complete transition from traditional MAX to LH_2 MAX aircraft in this study. The aviation landscape looks set to increase ETS CO_2 penalties [10] alongside mandates for increased blending requirements of the more costly SAF [9] which will further strain this already disjointed relationship. Airlines must be sufficiently rewarded for their sustainable practices and incentivized to pursue further sustainability gains in the form of targeting lower CO_2 emissions without succumbing to the financial burdens of ushering in decarbonized aviation. Rigorously studying not only the impact of individual technologies, but their utilization, facilitates more synergistic and harmonized policy-making and legislation decisions that will enable airlines to adapt to the technology progressions without encountering operational choices that effectively pit environmental performance benefits against economic viability. This study has demonstrated that a design tool that involves the specific aircraft technology, operational and logistical operation of said aircraft technology alongside an optimization algorithm primed with sustainability as an objective function can provide physics-based, data driven decisions regarding the adoption of that aircraft technology in a real-world context. LH_2 aircraft were more costly to operate in this study and therefore had their adoption limited to routes and operations that maximized their sustainability benefits while simultaneously limiting their increased economic burden for the airline. Forecasting the impact of varying the values for ETS CO_2 emissions, costs of fuels, aircraft performance capabilities and the plethora of other factors that impact sustainability and technology insertion is made possible by this design space characterizing, optimization model. Informed decisions regarding infrastructure, policy requirements and the feasibility of a given decarbonized technology within the future aviation can be made and hypothesized based on the results of these types of studies.

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