DATA-DRIVEN MULTI-RANGE MISSION-BASED OVERALL AIRCRAFT CONCEPTUAL DESIGN OPTIMIZATION

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Abstract

Conventional aircraft design is typically optimized based on a nominal mission with a specified range. However, data from our airline partner show that 33% of its operations are in the off-design ranges, resulting in suboptimal fuel economy. This motivates the formulation of a new aircraft design optimization process that also considers off-design range missions early in the design process. In this study, we propose an overall aircraft conceptual design framework for aircraft sizing purposes based on multi-range missions. The development of this new framework involves new optimization formulation to take into account multiple range missions, a data-driven approach to identify the target missions, and the introduction of fuel economy as an objective function of aircraft design optimization to capture the fuel and environmental costs of various flight mission ranges. Key to this process is a detailed flight mission analysis procedure. Here, we develop an accurate and yet efficient mission analysis platform by combining high-fidelity and low-fidelity models, to enable a detailed representation of a flight mission while keeping the computational time within a practical limit. The usefulness of the framework is demonstrated by the fuel economy comparison between three single-range mission-based designs optimized for maximum takeoff weight and a multi-range mission-based design optimized for fuel economy.

Keywords: Overall aircraft design, aircraft conceptual design, data-driven multiple range missions, fuel economy

Nomenclature

sfc	=	specific fuel consumption $(\mathrm{kg/N/s})$
L	=	lift (N)
D	=	drag (N)
T	=	thrust (N)
m_{fuel}	=	mission fuel (kg)
m_P	=	mission payload (kg)
$MTOW$	=	maximum takeoff weight (kg)
MLW	=	maximum landing weight (kg)
OEW	=	operation empty weight (kg)
MEW	=	manufacturer empty weight (kg)

1 Introduction

In an aircraft design optimization process, the top-level aircraft requirements (TLARs) serve as the core driver and constraints for the entire process [1]. As a result, the final design output is highly dependent on the TLARs setting. Civil aircraft manufacturers have been attempting to set appropriate TLARs by predicting future airlines' needs based on their experience and market research [2]. However, the operational conditions of aircraft, factors determining TLARs, often change due to unpredictable fluctuations in demand and market situations, which leads to frequent off-design operations. For example, the pandemic that occurred between 2019 and 2022 [3] changed the origin and destination flow networks around the globe [4]. Short-haul flights using aircraft designed for long-haul flights often occur as tag-on services for long-haul flights[1]. To be flexible in confronting such issues, airlines often purchase oversized aircraft and use them in diverse operating conditions for many years despite the possibility of higher fuel consumption and operating costs [5]. Such a practice also supports fleet commonality, which benefits airlines in terms of various costs, such as crew and maintenance costs. Therefore, TLARs must be adjusted to consider these various operational changes to design an aircraft that is optimized for actual airline operations.

Investigating the relationship between the design target of an aircraft, existing aircraft performance, and its operating conditions can be done by evaluating the fuel economy [6]. Fuel economy is an important aircraft performance factor that indicates the energy efficiency of aircraft. We analyze data provided by our airline partner, Cathay Pacific Airways Limited (CX). The data contain a subset of flights flying to and from Hong Kong International Airport (HKIA) in 2019. A total of 36,939 CX flights which departed from or arrived at Hong Kong International Airport in 2019 is investigated. Among them, the Boeing 777-300ER was one of the dominant aircraft types, accounting for 28.7% of the total number of flights. Flight data of the Boeing 777-300ER are first clustered depending on the flight distance and time, as shown in Fig. 1.The variance of the Euclidean distance difference among normalized flight data is minimized, classifying the data into three clusters: short, medium, and long haul. Figure 2a illustrates the proportion of different flight ranges operated by the Boeing 777-300ER. Figure 2b illustrates the relationship between the flight range and fuel economy of the Boeing 777-300ER, in which the fuel economy values are normalized for confidentiality reasons. The aircraft is designed for long-haul missions, but a total of 33.1% operated in off-design missions, during which the fuel economy performance was not optimal. Although 66.9% of flights were operated in the long-haul missions, the notable differences in fuel economy performance observed in a short-haul mission, Hong Kong to Taipei (HKG-TPE), and medium-haul mission, Hong Kong to Singapore (HKG-SIN), can result in poor fuel economy overall. This observation implies that considering only one design mission might lead to a suboptimal "net" performance of the aircraft, when considering the entire spectrum of flight operations. Therefore, it calls for a more comprehensive aircraft design formulation that can consider the tradeoff between aircraft performances under different missions to minimize performance degradation at off-design missions.

Changes in the mission range requirement significantly impact the overall aircraft size and configuration, which is usually determined during the conceptual design phase. Hence, in this study, we propose an aircraft conceptual design framework that gives optimum airplane size and configuration based on multi-range missions. This framework is built upon several important components, namely a conventional overall aircraft design framework integrated with mission analysis using flight dynamic simulations, an optimization formulation for multi-range mission considerations, and data analysis to derive the mission scenarios for the optimization. To better investigate the impact on the fuel efficiency of an aircraft under various flight ranges, we adopt fuel economy as an objective function in design optimization. We also improve the computation time of mission analysis in the design loop by simplifying the cruise part of flight dynamic simulations with a minor sacrifice of its modeling accuracy.

This study includes the sizing phase at the aircraft conceptual design stage. In particular, all of

[1] `https://simpleflying.com/worlds-shortest-widebody-routes/` (last accessed on 14 June 2024).

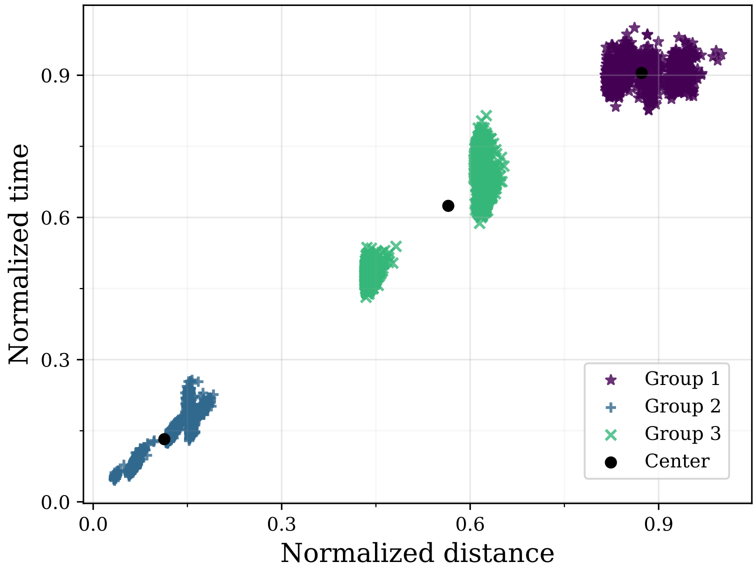
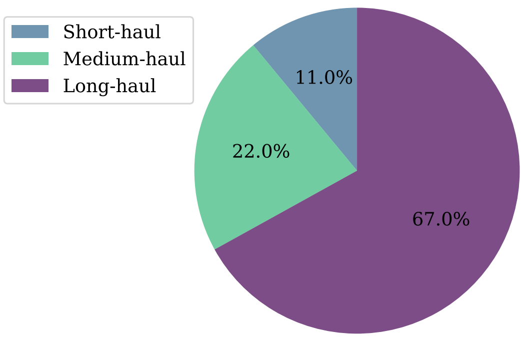
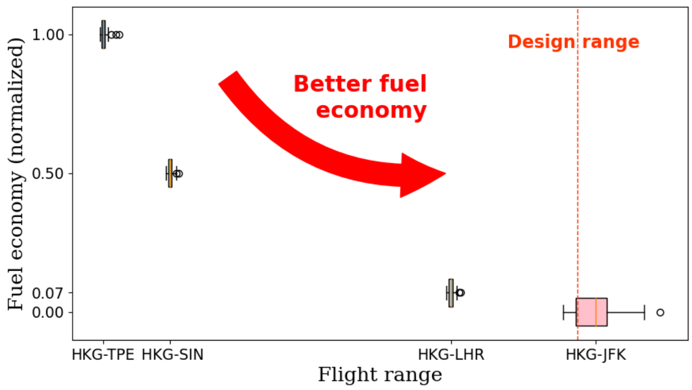


Figure 1 – Flight clusters depending on the normalized flight distance and time.



(a) proportion of different flight ranges



(b) fuel economy (normalized) versus range

Figure 2 – Fuel economy analysis of Boeing 777-300ER.

our analyses of operational conditions are based on flight data provided by CX. In Section 2, we summarize previous works in overall aircraft design frameworks, fuel efficiency metrics, and multi-point and multi-mission aircraft design optimization. Section 3 describes the methodology we propose in this research. The results and discussion are presented in Section 4, which is followed by the conclusion of this work described in Section 5.

2 Literature Review

Aircraft design involves many disciplines and their intricate interdisciplinary relations. To assist in this highly sophisticated process and make the design process more systematic and efficient, various overall aircraft design (OAD) frameworks have been developed. However, most of these frameworks only consider a single mission—the nominal one—in the design process, which may not adequately accommodate the diverse requirements of airlines in real-world operational conditions. To better design aircraft that align with actual operational needs, researchers have derived and demonstrated multi-point and multi-mission optimization formulations with various objectives in optimizations. This section provides a review of the OAD framework, fuel efficiency metrics and existing efforts in multi-point and multi-mission aircraft design optimization, including their limitations.

2.1 Overview of OAD frameworks

The overall aircraft design (OAD) framework, in this study, refers to a computer program that optimizes the size and configurations of aircraft wings, fuselage, and engines for the objective function of interest, considering various disciplines such as aerodynamics, propulsion, and structure. To be effective and realistic, OAD frameworks must efficiently represent the inherently multidisciplinary nature of aircraft systems. Several OAD frameworks have been developed by various academic and research institutions. For example, Stanford University developed the Stanford University Aerospace Vehicle Environment (SUAVE) to analyze unconventional configurations at a conceptual level [7]. A team from the French Aerospace Lab (ONERA) and the *École nationale supérieure de l'aéronautique et de l'espace* (ISAE-SUPAERO) developed Fixed-wing Aircraft Sizing Tool (FAST) for multidisciplinary design analysis (MDA) and sizing, in which an air traffic management (ATM) simulator was added to consider real-world flight routes and ATM constraints [8]. The FAST framework was then extended to include optimization in FAST-OAD [9]. A team of researchers from the *École nationale de l'aviation civile* (ENAC), IRT Saint-Exupéry, and Airbus developed the Multidisciplinary Airplane Research Integrated Library (MARILib)[2], a Python-based open-source MDO framework for OAD [10]. MARILib is designed to be modular, which offers users the flexibility to replace any disciplinary module with a more advanced or higher-fidelity model.

Each OAD framework has its unique characteristics, including the level of open-source, the complexity of usage, and built-in default (empirical) settings related to design, which also lead to different target users. In this study, we use MARILib as the baseline platform due to the ease of its accessibility and usability. MARILib is fully open-source and well-organized by different disciplines, making it easy to understand the overall structure. Users can modify modules as needed since the source code is transparent. The equations used in the framework are mostly based on physical equations with known assumptions or some reproducible statistical regressions of known data or models. The framework was designed for a wide range of aircraft, such as super-jumbos or hybrid propulsion systems. Our research focuses on wide-body commercial aircraft, which is one of the main design targets of MARILib.

2.2 Overview of Fuel Efficiency Metrics

In conventional aircraft design optimization, mission fuel consumption has been used as one of the important objectives to be minimized. However, in the design of aircraft operating in various mission ranges, comparing and minimizing fuel consumption is not a valid method because it increases with mission range. In such case, fuel efficiency, which takes into account the fuel consumption per traveled distance, can be a good alternative measure when comparing the fuel performance of an aircraft with various mission ranges. There are many ways to quantify the fuel efficiency, such as the Corporate Average Fuel Efficiency (CAFE) [11], which is applicable to all types of vehicles. The fuel efficiency metrics for aircraft design should be specifically tailored to meet its purpose.

There are mainly two approaches to quantifying aircraft fuel efficiency performance: 1) full mission metrics 2) instantaneous metrics. Full mission metrics encompass all flight phases and require a large set of assumptions. The instantaneous approach can either measure fuel efficiency performance at one point or multiple points. Yutko [12] derived the specific air range (SAR), an instantaneous metric, that measures the aircraft fuel efficiency performance at a single point in time. SAR is used in a case study for D8.5 (concept commercial transport aircraft developed by MIT) to evaluate the impact of new aircraft technology on fuel efficiency performance. Green [13] formulated the payload fuel efficiency (PFE) as the measurement of fuel efficiency during a full mission with the assumption of the aircraft operated in a cruise-climb mode, at a constant Mach number and lift coefficient. Nangia [14] extended Green's work on PFE (renamed as PRE by the author), introducing two

[2] `https://github.com/marilib/MARILib` (last accessed on 27 December 2023).

additional fuel efficiency metrics, VEOPX (Nangia value efficiency parameter) and VEMPX (Nangia emissions efficiency parameter) to take into account noise emissions and operating costs within fuel efficiency evaluation. Hileman *et al.* [15] formulated payload fuel energy efficiency (PFEE) for fuel efficiency evaluation on a fleet-wide basis. Doganis [16] suggested specific hourly productivity (SHP) for aircraft economics evaluation which is defined as the product of payload and flight speed, divided by the required block fuel. The metric was widely used as criteria/cost function for fuel efficiency evaluation/optimization [17]. In this study, we derive a full mission fuel efficiency metric, the fuel economy, as the cost function for our design optimization, in which the flight distances, mission payloads, and amount of fuel consumption of diverse mission ranges can be taken into account in one objective. The details of derivation are described in Section 3.2.

2.3 Overview of Multi-point and Multi-mission Optimization

In aircraft design optimization, single-point design optimization refers to an optimization formulation where the design is obtained by considering only one single flight condition, which typically corresponds to the dominant cruise condition. Single-point optimization results often exhibit poor performance at operational points other than the design point [18]. To overcome this issue, multi-point optimization that considers multiple operational conditions with their ratios in actual operations [19] was introduced. Some of the works, however, pertain to the detailed design stage of an aircraft, instead of the conceptual design or sizing stage. In which case, the "point" refers to the aircraft's specific flight condition (e.g., a combination of Mach number and lift coefficient). Mark Drela [20] conducted single-point and multi-point optimizations for a transonic and low Reynolds number airfoil. He suggested that single-point optimization should be transformed into a multi-point optimization problem to suppress undesirable local optimization. He also demonstrated the superiority of multi-point optimization in consideration of multiple flight conditions. Liem *et al.* [21, 22] suggested a novel approach for choosing operational points and their weightings in the multi-point optimization, based on actual operational data, in the context of aerostructural and aerodynamic shape optimization. The method integrated multi-mission profiles within the aircraft's payload-range envelope.

The development of multi-point formulation is less prominent in OAD. In OAD, we believe that the multi-point formulation should be formulated as a multi-range formulation to consider several "target" mission ranges that represent the aircraft's diverse future operations. To achieve this, we use MARILib upon integrating a flight dynamic simulation model in the mission analysis module to be able to simulate different flight operations for given target ranges in the optimization. This is a follow-up of previous work by some of the authors; Kim *et al.* [23] integrated flight dynamic simulations into MARIlib and conducted design optimization based on the TLARs derived from the data analysis. During the flight dynamic simulations in the design optimization process, all operational points of a mission are taken into account.

3 Proposed Methodology

This section presents the OAD framework proposed in this work, which is built upon MARILib and incorporates three key enhancements. The first one is the linear scalarization formulation of design optimization to take into account the multi-range missions, which is presented in Section 3.1. The second one is the use of fuel economy as the objective function in design optimization to subtly consider the impact of flight distance traveled, as described in Section 3.2. The third one is the mixture of the flight dynamics model and the Bréguet range equation in the flight simulation module to reduce the computational time, as explained in Section 3.3.

3.1 OAD optimization formulation

The OAD optimization process is illustrated as an eXtended Design Structure Matrix (XDSM) diagram[3] in Fig. 3. Figure 3a shows the structure of the base framework, which originated from MARILib [10], and Fig. 3b shows the OAD framework structure developed and used in this study. In the base framework, wing area $S_{\text{wing}} \in \mathbb{R}$ and reference thrust $T_{\text{ref}} \in \mathbb{R}$ were optimized for one of the objective functions $J \in \mathbb{R}$, which can be maximum takeoff weight (MTOW), mission fuel, CO_2 emission, cash operating cost, or direct operating cost. This base framework can design an aircraft specifically optimized for a single mission. In the proposed framework, however, multiple MDA is performed within one optimization loop. This enables the evaluation of the optimization objective across various missions, providing a comprehensive assessment of aircraft fuel performance on multi-range missions. Further details of the framework will be provided in the subsequent section. Six performance constraints $g_1, \ldots g_6$ were applied: vertical climb speed $V_{z_{\text{climb}}}$, cruise speeds $V_{z_{\text{cruise}}}$, time to climb t_{climb}, takeoff field length d_{TOFL}, approach speed $V_{x_{\text{approach}}}$, and one engine inoperative performance γ_{OEI}. The required values for the performance constraints $\mathbf{g}^{\text{constraint}} \in \mathbb{R}^6$ and TLARs, such as design range $d_{\text{design}} \in \mathbb{N}$, cruise Mach number $M_{\text{cruise}} \in \mathbb{R}$, cruise altitude $h_{\text{cruise}} \in \mathbb{N}$, number of passengers $n_{\text{pax}} \in \mathbb{N}$, and propulsion type $\text{eng}_{\text{type}} \in \{1,2\}$ are set as the input parameters.

In our framework, two design variables are optimized for the weighted sum of fuel economy, which will be explained later in this section. Each fuel economy value is computed by repeating the MDA process multiple times depending on the number of groups in multi-range missions, which will also be detailed later in this section. A generalized optimization formulation for both frameworks is presented in Eq. (1).

$$\begin{aligned}
\underset{\mathbf{X}_{\text{design}} \in \{(S_{\text{Wing}}, T_{\text{ref}})\}}{\text{minimize}} \quad & J\left(\mathbf{X}_{\text{design}}, \mathbf{X}_{\text{TLARs}}\right) \\
\text{subject to} \quad & \mathbf{g}(\mathbf{X}_{\text{design}}, \mathbf{X}_{\text{TLARs}}) - \mathbf{g}^{\text{Constraint}} \leq 0, \quad \mathbf{g} = \{g_j \mid j = 1, \ldots, 6\}, \\
& \mathbf{X}_{\text{design}_{min}} \leq \mathbf{X}_{\text{design}} \leq \mathbf{X}_{\text{design}_{max}},
\end{aligned} \tag{1}$$

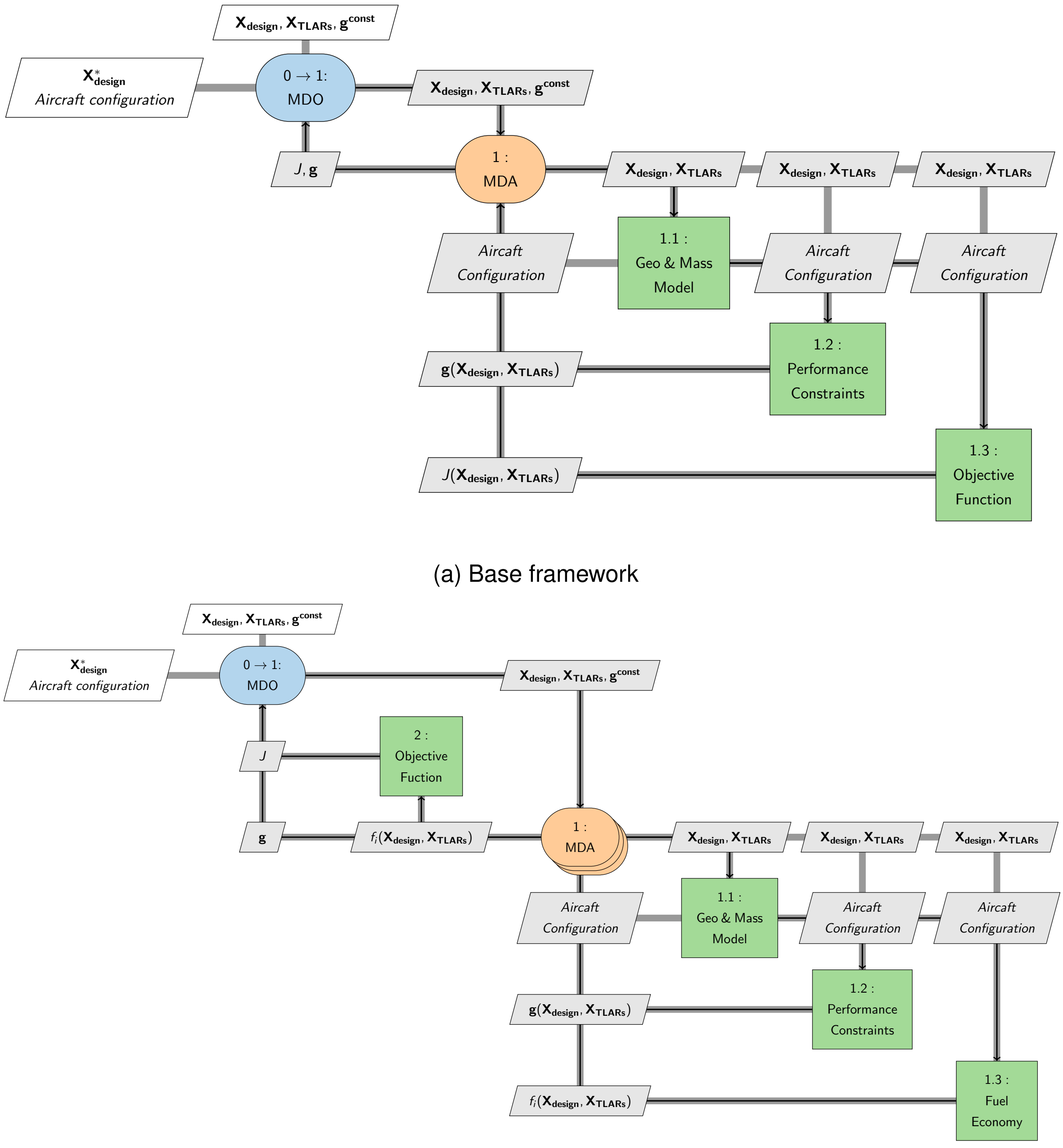
where $\mathbf{X}_{\text{design}}$ represents design variables and $\mathbf{X}_{\text{TLARs}}$ are the fixed inputs other than design variables, including TLARs and default configuration parameters that users can change. Multi-range mission consideration is achieved by formulating J with linear scalarization as shown in Eq. (2).

$$\begin{aligned}
J\left(\mathbf{X}_{\text{design}}, \mathbf{X}_{\text{TLARs}}\right) &= \sum_{i=1}^{n} \omega_i f_i, \\
\text{where} \quad f_i &= f\left(\mathbf{X}_{\text{design}}, \mathbf{X}_{\text{TLARs}\,i}\right).
\end{aligned} \tag{2}$$

The weighting ω_i is determined by the frequency of the same (or similar) range mission occurrence from flight data analysis. In other words, ω_i, as shown in Eq. (3), represents the number of flight data belonging to a specific cluster i among all flight data m. $\mathbf{1}_{P_i}(p_k)$ is an indicator function which gives 1 if $p_k \in P_i$, otherwise the value is set to 0. P_i is the set of points in the i-th group, p_k is a point in flight data, m is the total number of data, and n is the total number of groups. The center of each group is used to set the design ranges and cruise speeds in $\mathbf{X}_{\text{TLARs}\,i}$.

$$\omega_i = \frac{\sum_{k=1}^{m} \mathbf{1}_{P_i}(p_k)}{m}, \quad \text{where } i = 1, \ldots, n. \tag{3}$$

[3] `https://github.com/mdolab/pyXDSM` (last accessed on 27 December 2023).



(a) Base framework

(b) Proposed framework

Figure 3 – XDSM of overall design optimization processes.

3.2 OAD optimization objective function

To better evaluate the impact of considering multi-range missions in the design process, we adopt fuel economy f as an objective of the optimization. The fuel economy is a metric that relates the distance traveled to the amount of fuel consumed, as expressed below,

$$f = \frac{m_{\text{fuel}}}{m_P \times d \times \rho_{\text{fuel}}}, \tag{4}$$

where m_{fuel} is the fuel mass, m_P is the payload mass, d is the distance travelled, and ρ_{fuel} is the density of fuel. This metric represents the efficiency of the vehicle by calculating the fuel volume consumed per distance traveled and per unit mass of payload; the smaller the value, the better is the fuel economy (i.e., more desirable). Although fuel consumption and other weight-related factors are important criteria in aircraft design, manufacturing, and pollution measures, fuel economy can provide a more comprehensive measure of fuel efficiency for an aircraft operating under different operational conditions.

3.3 Mission analysis model

Detailed mission analysis in the design optimization process enhances the accuracy of fuel consumption, flight range, and time computation, resulting in better optimum design. We used a flight simulation model developed by Kim *et al.* [24] for mission analysis of detailed flight segments. The flight simulation is derived based on a flight dynamic model,

$$\vec{F}_T + \vec{F}_A + m\vec{g} = m\left(\vec{a} + \vec{\omega} \times \vec{V}\right), \tag{5}$$

where the acceleration $\vec{a}$ is determined by the mass m, propulsive and aerodynamic force components $\vec{F}_T$ and $\vec{F}_A$, gravitational acceleration $\vec{g}$, velocity $\vec{V}$ and angular velocity $\vec{\omega}$. Equation 5 is discretized in time using first-order finite differences, and numerical integration is performed using the forward Euler method, in which the number of elements in the integration differs depending on the type of segment. $\vec{V}$ at each time step is computed by $\vec{a}$ and $\vec{V}$ at the previous time step as shown in Eq. (6). Flight distance $\vec{r}$ is computed by $\vec{V}$ and r at the previous time step, as shown in Eq. (7).

$$\vec{V}_i = \vec{V}_{i-1} + \vec{a}_{i-1}\Delta t, \tag{6}$$

$$\vec{r}_i = \vec{r}_{i-1} + \vec{V}_{i-1}\Delta t, \tag{7}$$

where Δt is the specified time interval. $-_i$ and $-_{i-1}$ subscripts represent values at ith time step and one time step before the ith time step, respectively.

Mixture of the flight dynamics model and Bréguet range equation

In this work, we simplify the cruise segment calculation, which typically takes most of the computational time especially for medium- and long-haul flights, by replacing it with the Bréguet range equation.

Figure 4 shows the schematic of the proposed mission analysis. Fuel consumption in the cruise segment is estimated by the Bréguet range equation (denoted as BRE in the figure), and fuel consumption from other segments is estimated by the flight dynamic simulation model (HFS). The combination of high-fidelity and low-fidelity models, as shown here, helps to maintain a high accuracy of the flight performance estimations while reducing the computation time. Our model identifies the number of cruise phases and assigns the usage of HFS and BRE based on the identification of different sections. The entire fuel estimation process is shown in Eq. (8).

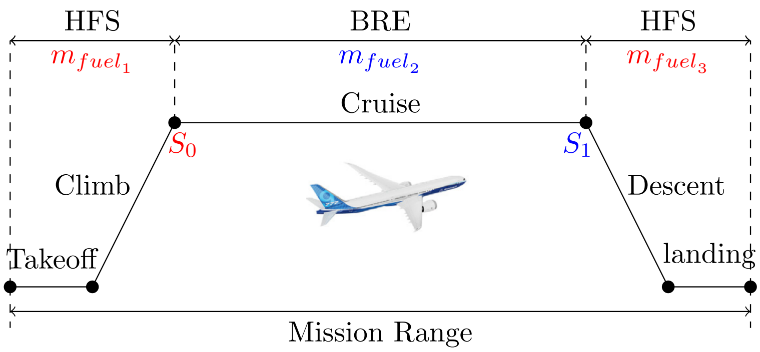


Figure 4 – Schematic of the proposed mission analysis.

$$
\begin{aligned}
m_{\text{fuel}} &= \sum_{l=1}^{q} m_{\text{BRE}_l} + \sum_{l=1}^{s} m_{\text{HFS}_l}, \\
\text{where} \quad m_{BRE_l} &= m_{l_i} - m_{l_f} = m_{l_i}\left(1 - e^{-\frac{d\times sfc\times g}{L/D\times V}}\right) \\
\text{and} \quad m_{HFS_l} &= m_{l_i} - m_{l_f} = \int_{t_{l_i}}^{t_{l_f}} \left(\vec{F_T} \times n_{\text{eng}} \times sfc\right) dt.
\end{aligned} \tag{8}
$$

In Eq. (8), m_{BRE_l} is fuel consumed during cruise and m_{HFS_l} is fuel consumed during the flight other than cruise. q is total number of cruise segments during a flight and s is total number of flight segments other than cruise segments. Hence, the total fuel consumed during the flight equals to the sum of fuel consumed during cruise and other flight phases. Both m_{BRE_l} and m_{HFS_l} are computed from the mass difference at initial l_i and final l_f of flight segment l. Particularly, m_{BRE_l} is derived from the Bréguet range equation, where sfc represents specific fuel consumption, g is gravitational acceleration, L/D is lift and drag ratio, and V is airspeed. m_{HFS_l} is computed from the time integration from t_{l_i} to t_{l_f}, where T is thrust and n_{eng} is the number of engines.

Model validation

To evaluate the impact of a mixture of m_{BRE} and m_{HFS} on both computational efficiency and model accuracy, the mean absolute percentage error (MAPE) and mean computation time (MCT) in Eq. (9) are computed and compared. In Eq. (9), n is the total number of flights considered, $\hat{y}$ is the fuel estimated by models, y is actual fuel consumption, and t is the computational time. The subscript $_i$ indicates the ith flight mission.

$$
MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|, \quad MCT = \frac{1}{n} \sum_{i=1}^{n} t_i \tag{9}
$$

Fig. 5 shows MAPE and MCT of fuel estimations computed on the BRE, a data-driven flight dynamics model (DFD) [23], and the proposed mission analysis model (MDFD). 60 flight missions are evaluated and presented by groups, which are short-, medium-, and long-haul missions. The results in Fig. 5 indicate that the MDFD model outperforms the BRE in terms of MAPE. Although the MAPE values of BRE decrease when the mission range increases, they are always higher than those of the MDFD and DFD models. Furthermore, the MAPE deviation is contained within 3% across different flight ranges, compared to the BRE model that exhibits a notably higher error for short-haul flights due to the assumptions of the Bréguet range equation. Compared to the DFD model, the MDFD model exhibits a substantial improvement in computational efficiency for medium and long-haul missions,

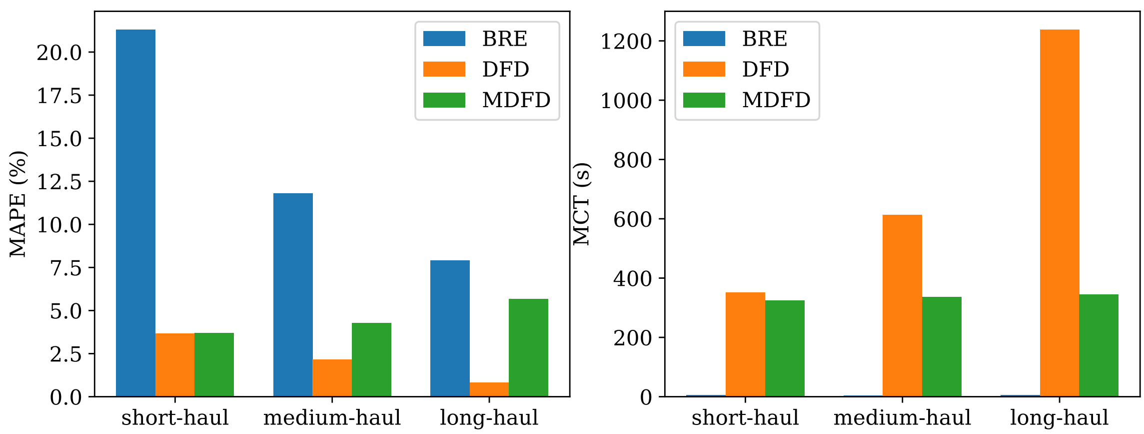


Figure 5 – Fuel estimation comparison of three different methods.

with a reduction in mission computation time (MCT) of 45.2% and 72.1%, respectively, albeit at the expense of a marginal sacrifice in fuel estimation accuracy.

4 Results and Discussion

To demonstrate the benefits of the proposed method in Section 3, we conduct single-range and multi-range mission-based design optimizations for three different-range missions. The mission scenarios are derived from flight data analysis using the eXtreme Gradient Boosting (XGboost) flight classification model in [24]. The reference routes are from Hong Kong International Airport (HKG) to Taiwan Taoyuan International Airport (TPE) for the short-haul mission, Singapore Changi Airport (SIN) for the medium-haul mission, and to Heathrow Airport, London (LHR) for the long-haul mission, as shown in Fig. 6.

In this section, we present single-range mission-based design optimization results and the fuel economy performance of each optimal aircraft configuration under three range missions in Section 4.1. Subsequently, we demonstrate multi-range mission-based design optimization results in Section 4.2. The optimization was performed based on a single-range optimization result and employed fuel economy as the objective function. We also discuss the comparison of the single- and multi-range mission-based optimization in terms of configuration and fuel efficiency in Section 4.2.

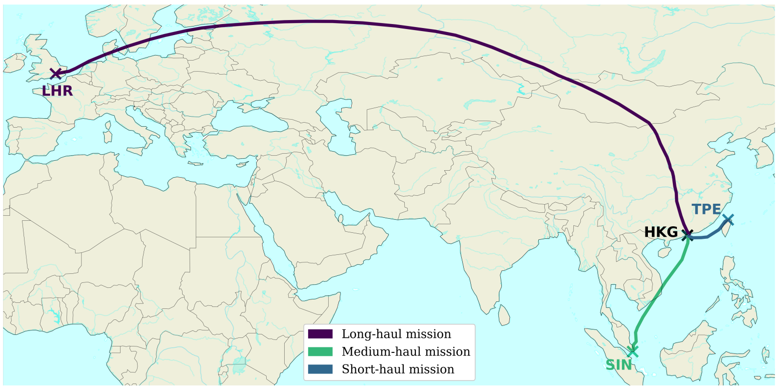


Figure 6 – Reference nominal missions for design

4.1 Single-range mission-based design optimization

This subsection presents three design results of single-range mission-based optimization, where n in Eq. (2) is set to one. Each design is optimized for a specific mission, which can be one of three missions in Fig. 6. MTOW is used as an objective function of the design optimizations, and the fuel economy of each designed aircraft is evaluated under three missions, respectively.

Design ranges and missions are derived from the flight data provided by Cathay Pacific Airways Limited. The optimization algorithm used for three of the optimization cases is the Sequential Least Squares Programming (SLSQP), which can be called from Python's SciPy library[4]. The initial inputs of optimization are shown in Table 1, which are referred from the Boeing 777-300ER specifications.

The design optimization results for the three missions are presented in Table 2 and Fig. 7. As the fuselage size depends only on the number of passengers, all three aircraft have the same fuselage size. There is no significant difference in wing area as the fuselage size is the same. However, longer mission range results in larger wing area. Longer mission range implies more fuel to carry, which leads to heavier weight, higher thrust, and higher lift from larger wing area and larger aspect ratio.

[4]`https://docs.scipy.org/doc/scipy/reference/optimize.minimize-slsqp.html` (last accessed on 20 March 2024).

Table 1 – Specification for single mission-based design optimization

Category	HKG-TPE	HKG-SIN	HKG-LHR
Engine type	Turbofan		
Number of engine	2		
Number of passengers	396		
Cruise Mach number	0.85	0.85	0.83
Design range	Short-haul $R_1 = 493$ NM	Medium-haul $R_2 = 1{,}431$ NM	Long-haul $R_3 = 5{,}345$ NM
Initial values of design variables	$S_{\text{Wing}} = 436.80$ m^2 $T_{\text{ref}} = 514{,}000$ N		

Figure 8 shows the fuel economy when each optimal aircraft flies three different missions. The best fuel economy always occurs at the corresponding optimal range of each airplane. An aircraft optimized for a short-haul mission, which is denoted as a blue-colored line, has the best fuel economy at 493 NM, which is the shortest mission range considered. An aircraft optimized for a medium-haul mission, which is denoted as an green-colored line, has the best fuel economy at 1,431 NM, which is the medium-haul mission. An aircraft optimized for a long-haul mission, which is denoted as a purple-colored line, has the best fuel economy at 5,345 NM, which is the long-haul mission. In addition, we can also observe that the aircraft optimized for the medium-haul mission exhibits the smallest discrepancy between the maximum and minimum fuel economy, suggesting a tradeoff between the different missions considered.

Table 2 – Design optimization result (single-range).

Category	Item	HKG-TPE	HKG-SIN	HKG-LHR
Engine	Reference thrust (N)	298,793	420,753	481,866
	Bypass ratio	9	9	9
Wing	Wing area (m^2)	414.34	436.81	457.90
	Wing span (m)	61.07	62.70	64.20
Fuselage	Fuselage length (m)	69.98	69.98	69.98
	Fuselage width (m)	6.45	6.45	6.45
Weight	MTOW (kg)	175,218	208,904	283,180
	MLW (kg)	175,210	205,498	237,743
	OEW (kg)	124,328	144,526	167,980
	MEW (kg)	120,481	137,100	145,627

4.2 Multi-range mission-based design optimization

This subsection presents design results of multi-range mission-based optimization, where n in Eq. (2) is set to three. The flight frequency corresponding to ω_i in Eq. (3) is presented in Fig. 9a. The initial values of the two design variables $(S_{\text{wing}}, T_{\text{ref}})$ are set according to the single-range mission-based optimization result, which is the HKG-LHR (long-haul) case presented in Section 4.1 (aligned with the type of mission range Boeing 777-300ER is designed for). The critical inputs for single- (for comparison) and multi-range mission-based optimization are shown in Table 3.

Table 4 presents numerical expressions, while Fig. 10 provides a three-view drawing comparison, both displaying the outcomes of single- and multi-range mission-based optimizations. To facilitate comparison, we have chosen the long-haul mission from the single-range mission-based optimiza-

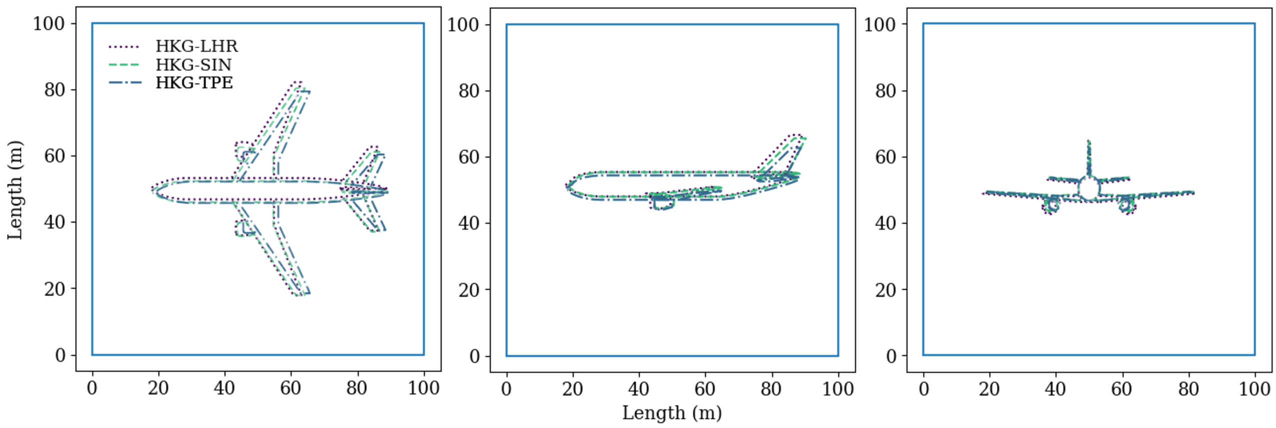


Figure 7 – Three-view drawing of design optimization results.

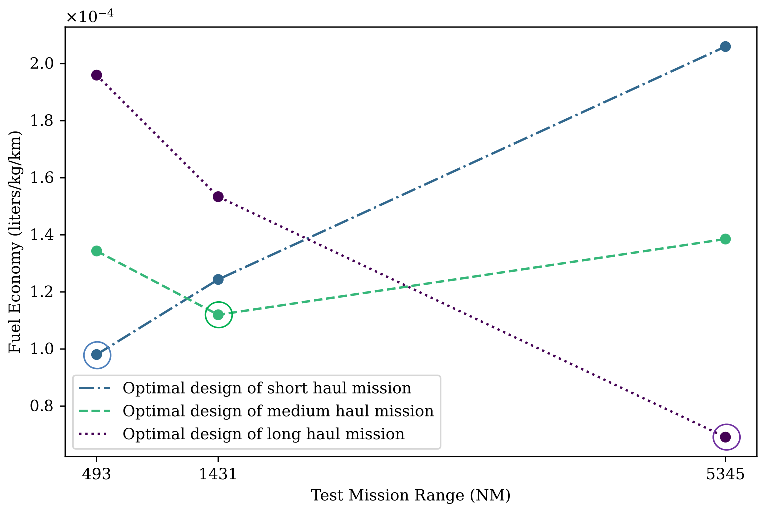
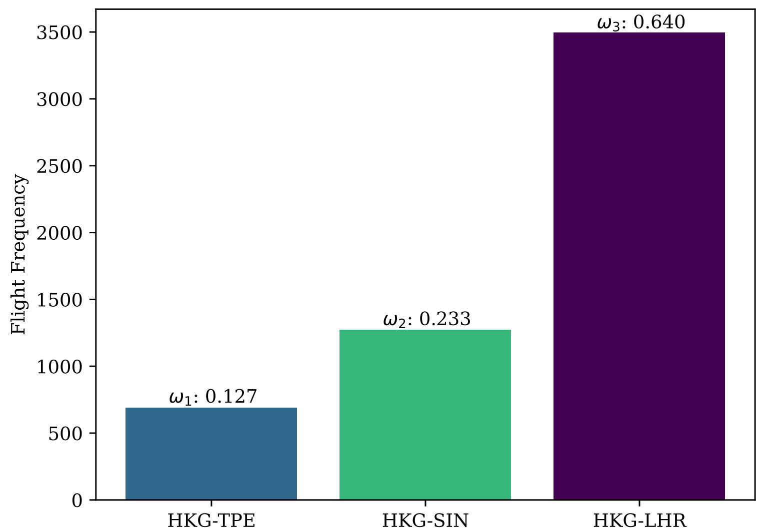


Figure 8 – Fuel economy analysis of optimal solutions with different mission ranges.



(a) Flight frequency and weight ratios

Figure 9 – Specifications of mission input and weight ratios for optimization.

tion, as it closely aligns with the nominal range of our target aircraft. Due to the prevailing dominance (weighting larger than 0.6) of long-haul missions (HKG-LHR), the final result of the multi-range

Table 3 – Specification for multi-range mission optimization

Category	HKG-LHR	Multi-range
Mission range(s)	R =5,345 NM	$R_1 = 493$ NM, $\omega_1 = 0.127$ R_2 =1,431 NM, $\omega_2 = 0.233$ R_3 =5,345 NM, $\omega_3 = 0.640$
Initial values of design variables	$S_{\text{Wing}} = 436.80$ m^2 $T_{\text{ref}} = 514{,}000$ N	$S_{\text{Wing}} = 457.90$ m^2 $T_{\text{ref}} = 481{,}866$ N

mission-based optimization remains largely unchanged in comparison to those of the single-range mission optimization. In contrast to the optimization results in the HKG-LHR case, the aircraft designed for multi-range mission optimization has a slightly larger reference thrust (increased by 1.84%) and smaller wing area (decreased by 0.49%). This outcome may be attributed to the fact that higher thrust might be more advantageous during the climb phase, thereby enhancing the aircraft's performance during short- and medium-haul missions, given the higher proportion of climb phases in these missions. Additionally, lower OEW requires less lift at the same cruise speed with the same payload, which leads to lower wing area. Nevertheless, the formulation of the proposed optimization that considers multiple mission ranges demonstrates its effectiveness, as evidenced by the fuel economy evaluation across all ranges. Figure 11 depicts the fuel economy of single and multi-range optimized aircraft on three mission ranges. The figure shows an overall improvement in the fuel economy performance of the multi-range optimization in comparison to the single-range optimization. We observe some improvements in fuel economy values for short and medium-haul missions (reduced by 6.63% and 4.56%, respectively), with only a slight sacrifice for long-haul missions (increased by less than 2%). This indicates a tradeoff in the fuel economy, i.e., when the optimization is not concentrated on a specific flight mission.

Table 4 – Design optimization result (multi-range).

Category	Item	HKG-LHR	Multi-range
Engine	Reference thrust (N)	481,866	490,734
	Bypass ratio	9	9
Wing	Wing area (m^2)	457.90	455.67
	Wing span (m)	64.20	63.92
Fuselage	Fuselage length (m)	69.98	69.98
	Fuselage width (m)	6.45	6.45
Weight	MTOW (kg)	283,180	285,429
	MLW (kg)	237,743	235,682
	OEW (kg)	167,980	167,658
	MEW (kg)	145,627	145,324
Criteria evaluation	Fuel economy (L/kg/km)	1.0475×10^{-4}	1.0223×10^{-4}

5 Conclusion

In this study, we proposed an OAD framework that could provide optimum aircraft size and configuration based on multi-range missions to take into account diverse operation conditions when designing aircraft. We adopted fuel economy as an objective function in the design optimization to consider the energy efficiency in multi-range missions. We also simplified the cruise part of flight dynamic simulations with a minor sacrifice of its modeling accuracy and reduced the computation time of mission

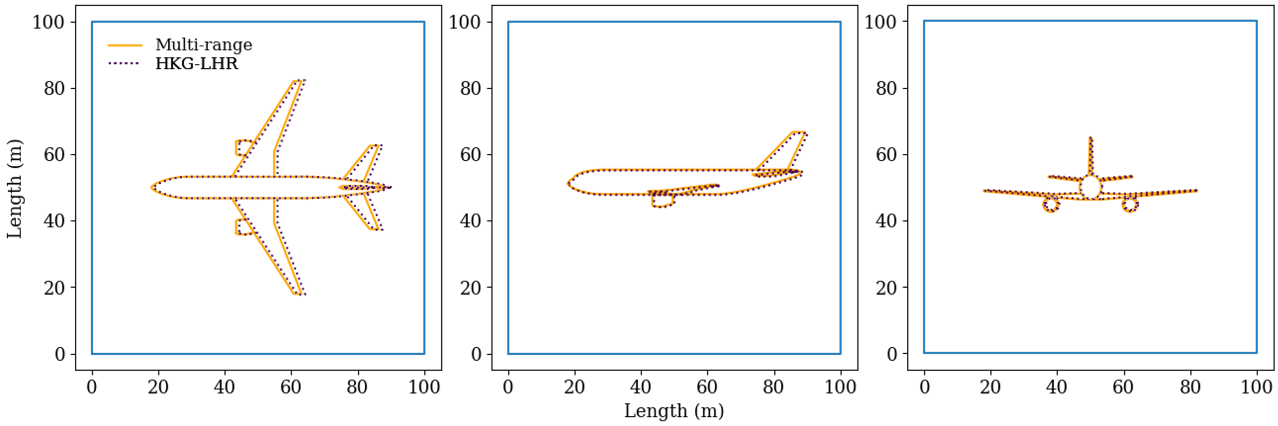


Figure 10 – Three-view drawing of design optimization results (multi-range).

Figure 11 – Fuel economy analysis of single- and multi-range mission-based optimization results.

analysis in the design loop.

Three different-range missions were considered in this study, which were derived from the flight data of the aircraft departing from and landing in Hong Kong in 2019. The data were grouped based on different original and destination (OD) pairs [23] and used for optimization inputs and mission weight ratios (ω_i) calculation. The final result of the proposed design optimization framework included the sizing and configurations of the aircraft. Compared to single-range optimization, the proposed multi-range mission-based optimization provided a better overall fuel economy performance in diverse operational conditions.

The results presented in this study only focused on three of the flight sectors, which were aimed for demonstrating the effectiveness of taking into account diverse operation conditions within aircraft design optimization. However, the diversity of operational conditions in the real-world scenarios could be substantially more complex than the three representative cases selected in this study (e.g., the various flight ranges of Boeing 777-300ER shown in Fig. 1). In the future, we will include flight sectors and corresponding mission specifications from the more comprehensive data analysis with a wider range of data. Specifically, we will use a clustering algorithm to investigate the characteristics of different flight missions and determine the number of groups (n) and weight ratios (ω_i) as mission inputs for design optimization. Once we obtain the optimization results, we will perform a more thorough investigation of the tradeoff and the implications on airline operations—both in environmental and economic metrics.

6 Acknowledgements

This work was supported by the Hong Kong Research Grant Council General Research Fund (Project No. 16206022). The authors would like to thank Cathay Pacific Airways Limited for providing the data used in this study under the Data Partnership Agreement between the airline and the Department of Mechanical and Aerospace Engineering, HKUST.

7 Copyright Statement

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