IMPERIAL

Designing Next-Generation Aircraft and Operations for Sustainable Aviation: from Data and Models to Decisions

Institute for Sustainable Aviation Webinars

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The wonder and importance of the aviation industry

Why do we need air transportation services?

- The demand for air travel (∼ 5 billion passengers)
- The demand for the shipment of goods by air (∼ 61 million tonnes)

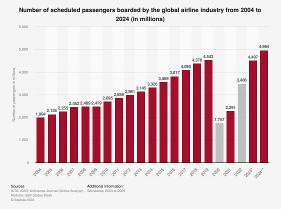
Major economic force: **87.7 million jobs**

- 11.3 million direct jobs
  (e.g., airlines, air navigation service providers, and airports)
- 18.1 million indirect jobs
  (e.g., purchases of goods and services in the air transport industry supply chain)
- 13.5 million induced jobs
  (e.g., retail, customer goods, and services supported by the spending power)
- 44.8 million tourism jobs
  (e.g., aviation-enabled tourism related jobs)

Air traffic size in 2019

1,478 airlines, **3,780** airports, **48,044** routes

Source: Air Transport Action Group (ATAG) https://atag.org/facts-figures



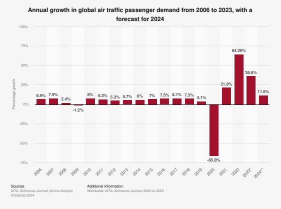


Image source: https://www.statista.com (data from IATA)

Potential negative impact of innovation

"The great accomplishments of the eighteenth through early twentieth centuries nevertheless created their own set of shortfalls or negative impacts on society."

— Dr. Subra Suresh, Dean of the MIT School of Engineering (2007–2010)

Potential negative impact of innovation
With an example in the air transportation industry

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The rapid growth of air transportation has increased environmental concerns

Noise pollution
- Landing and take-off phases (LTO)
- Annoyance, sleep disturbance
- A major constraint on airport planning

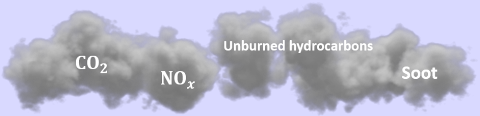
Gaseous exhaust emission from jet engine
- From complete (or non-ideal) fuel combustion
- Accounts for 2.5% of the global CO_2 emissions
- Contributes around 4% to global warming

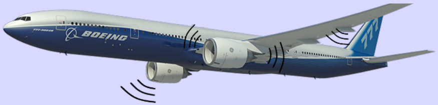
Non-CO_2 aviation emissions
- Contrails
- Aviation-induced clouds
- NO_2 emissions

Designing aircraft and its operations has become a superdisciplinary problem
The design process needs to consider some externalities and impacts

Sustainable: "Capable of being maintained or continued at a certain rate or level" (Oxford Dict.)

Sustainable aviation: reducing and mitigating the environmental impact of aviation





- Operational changes
- Technological changes
- Policy changes
- Shift towards alternative fuel

Requires a concerted effort across **government**, **industry**, **academia**; and also across **different solutions**.

Image sources: https://store.icao.int/en/traffic-flow-global-data-shape-file, boeing.com

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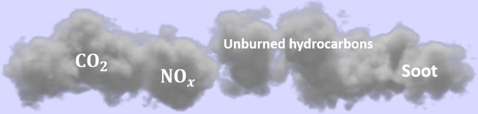

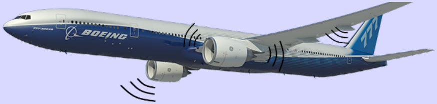

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Operational and technological changes to support sustainable aviation efforts
A system level assessment is needed to truly evaluate the benefits

Examples in technological changes

Improvements in propulsion systems
- **In the 1970s**: high by-pass ratio engine doubled fuel efficiency
- Hydrogen-powered aircraft
- Electric/hybrid-electric aircraft

Improvements in aircraft designs
- Shape optimization for drag reduction
- Wingtip devices: winglets, sharklets, etc.
- New configurations: strut-braced wing, BWB, etc.

Alternative fuel
- Sustainable aviation fuels

Examples in operational changes

Flight operation strategies
- Optimize flight path/flight planning
- Optimize fuel loading decision
- Reduce engine use (e.g., during taxi)

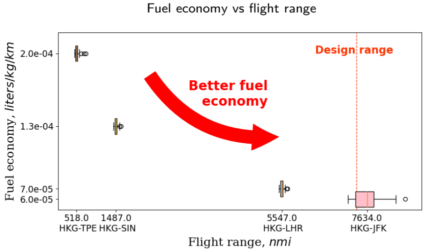
Changes in air traffic management/airspace
- Flexible air traffic management
- Apply continuous descent/climb operations

Ground support improvements
- Airport infrastructure improvements
- Aircraft maintenance improvements

How the analyses and optimization of aircraft and operations are performed
Can siloed analyses achieve truly optimum designs?

Operation-**unaware** aircraft design

- Aircraft is designed at its **design mission**
- However, it is used for various missions in operations
- **Fuel economy**: the amount of fuel burned per payload per range (in liters/kg/m)



Fuel vs noise

- Reducing 1-2 dB in a long-range aircraft traded a 1-2% increment in fuel burn[a]
- Aircraft's drag and noise minimizations do not lead to the same optimal shape[b]

[a] M. Pacull. "Transport Aircraft Noise Technologies". In: *Proceedings of the International Symposium: Which Technologies for Future Aircraft Noise Reduction?* Association Aéronautique et Astronautique de France. 2002.

[b] Beckett Y. Zhou, Tim Albring, Nicolas R. Gauger, Thomas D. Economon, Francisco Palacios, and Juan J. Alonso. "A Discrete Adjoint Framework for Unsteady Aerodynamic and Aeroacoustic Optimization". In: *16th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference.* Dallas, TX, 2015.

Designing the next-generation aircraft and operations

Towards developing a "future-ready" design framework

Design as a decision-making process

- Requires an **abstraction** to describe the product/service/system

The models need to be as realistic as possible

Multidisciplinary design optimization (MDO)

- Accounts for the **coupling** in the system
- Automatically performs the **optimal interdisciplinary tradeoffs**

The MDO problem formulation also needs to be realistic to yield truly relevant results

How to account for uncertainties and operational variability?

Infuse **data** into the model derivation and MDO problem formulations.

Fourth paradigm of science – using *data exploration* to unify data, theory, and simulation[a]

[a] Tony Hey, Stewart Tansley, and Kristin Tolle, eds. *The Fourth Paradigm: Data-Intensive Scientific Discovery*. Microsoft Research, 2009.

Presentation Overview

Fuel assessment models to serve different purposes (and different stakeholders)

Deriving fuel assessment models
We need different models for different purposes

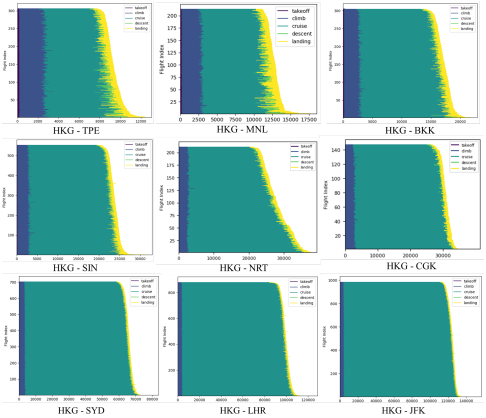
What makes **realistically** modeling fuel burn complex?

- Different aircraft types have different fuel characteristics
- The "performance factor" of each aircraft should be considered (e.g., due to ageing)
- Aircraft fly different routes – even for the same origin-destination pair – with different proportions of climb, cruise, and descent phases

Why do we need different models for different purposes?

Purpose, level of details, available inputs, available computational time

- To support **aircraft design optimization**: the model needs to emulate detailed physics and takes aircraft design parameters as inputs
- To support **air transportation policy assessment**: the total aggregate fuel burn is required and needs to include air traffic frequency and movements
- For **airlines**: supporting fuel budgeting and planning, most of the data/inputs are in-house



Fuel assessment models developed in-house

Most works mentioned below were done at The Hong Kong University of Science and Technology (HKUST)

- To support policy analysis: aggregate fuel burn calculation[1]
- To support airline's fuel budgeting: reserve fuel estimation[2], fuel estimation for new sectors[3]
- To support **detailed aircraft design process**: surrogate-based flight mission analysis[4] and its enhancement with data-driven mission parameterization[5]. (The framework is extended to cater for electric amphibious aircraft[6])
- To support **flight path optimization**: dynamic flight-simulation with data-driven constraints and boundary conditions[7]

[1] Jefry Yanto and Rhea P. Liem. "Aircraft fuel burn performance study: a data-enhanced modeling approach". In: *Transportation Research Part D: Transport and Environment* 65 (2018), pp. 574–595. DOI: 10.1016/j.trd.2018.09.014.

[2] Yuan Lyu, Jefry Yanto, and Rhea P. Liem. "Aircraft Reserve Fuel Study with High-Fidelity Fuel Approximation Model". In: *AIAA Aviation*. AIAA 2019-3509. Dallas, TX, 2019. DOI: 10.2514/6.2019-3509.

[3] Jefry Yanto and Rhea P. Liem. "Cluster-Based Aircraft Fuel Estimation Model for Effective and Efficient Fuel Budgeting on New Routes". In: *Aerospace* 9 (2022), p. 624. DOI: 10.3390/aerospace9100624.

[4] Rhea P. Liem, Charles A. Mader, and Joaquim R. R. A. Martins. "Surrogate Models and Mixtures of Experts in Aerodynamic Performance Prediction for Mission Analysis". In: *Aerospace Science and Technology* 43 (2015), pp. 126–151. DOI: 10.1016/j.ast.2015.02.019.

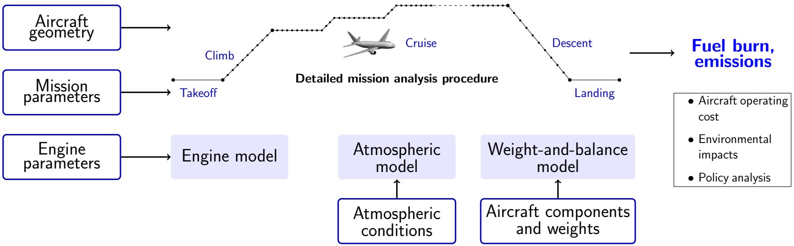
[5] Yuan Lyu and Rhea P. Liem. "Flight performance analysis with data-driven mission parameterization: mapping flight operational data to aircraft performance analysis". In: *Transportation Engineering* 2.100035 (2020). DOI: 10.1016/j.treng.2020.100035.

[6] James M. Shihua, Yuan Lyu, and Rhea P. Liem. "Multidisciplinary Design and Mission Analysis of an Electric Amphibious Flying Vehicle". In: *AIAA AVIATION Forum*. 2023. DOI: 10.2514/6.2023-3907.

[7] Dajung Kim, Arjit Seth, and Rhea P. Liem. "Data-enhanced dynamic flight simulations for flight performance analysis". In: *Aerospace Science and Technology* 121.107357 (2022). DOI: 10.1016/j.ast.2022.107357.

Fuel assessment with detailed surrogate-based flight mission analysis[8]

Considering geometry, aerodynamics, mission, engine, atmospheric conditions

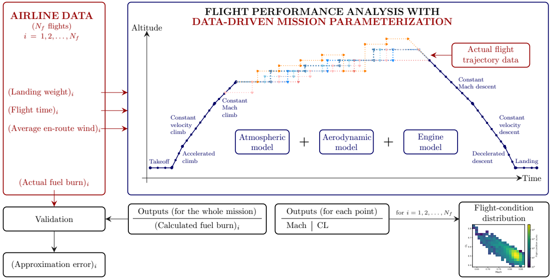


- Analyze all mission phases, from takeoff to landing, by **solving the range equation using numerical integration**
- **Computational challenge**: it requires millions of aerodynamic performance evaluations
- **Solutions**: use **surrogate models** to approximate the aerodynamic force and moment coefficients

[8] Rhea P. Liem, Charles A. Mader, and Joaquim R. R. A. Martins. "Surrogate Models and Mixtures of Experts in Aerodynamic Performance Prediction for Mission Analysis". In: *Aerospace Science and Technology* 43 (2015), pp. 126–151. DOI: 10.1016/j.ast.2015.02.019.

Data-enhanced flight mission analysis procedure[9]

Mapping airline flight data into flight simulation



Complementarity between data- and physics-based models

- **Data-based models**: not interpretable, not transparent enough
- **Physics-based models**: cannot model the operational variations

Hybrid approach: combining the strengths of both models

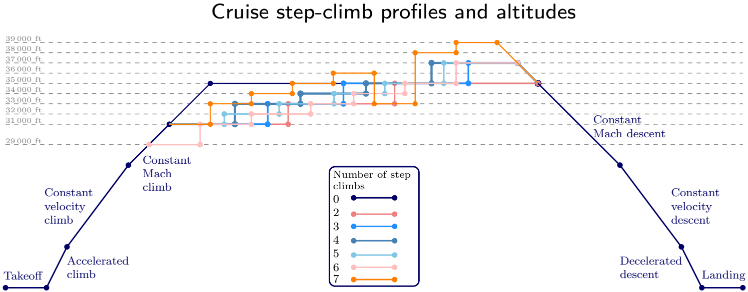
- Use a **physics-based model** that can take flight operational data as inputs, simulate the flights, and provide useful information such as fuel burn
- Use **actual flight trajectory data**[a] to parameterize the mission profiles in the derived flight performance analysis module, to better represent the flight trajectory variation in each origin-destination (OD) pair

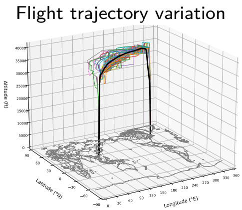
[a]The data are obtained under the Data Partnership Agreement between **Cathay Pacific Airways Ltd** and the Department of Mechanical and Aerospace Engineering, HKUST

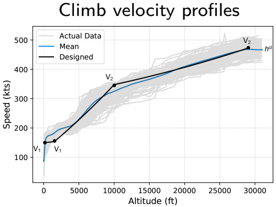
[9]Yuan Lyu and Rhea P. Liem. "Flight performance analysis with data-driven mission parameterization: mapping flight operational data to aircraft performance analysis". In: *Transportation Engineering* 2.100035 (2020). DOI: 10.1016/j.treng.2020.100035.

Mission parameterization

An example with Hong Kong to New York (HKG-JFK) flights





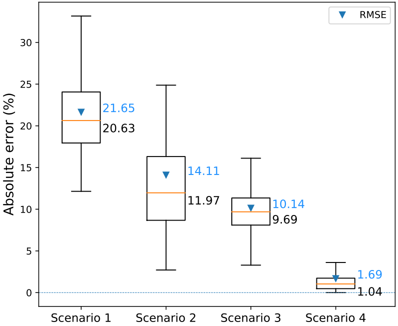


Model enhancement substantially improves fuel approximation accuracy[10]

The model is validated by comparing calculated fuel against airline data

List of scenarios

- **Scenario 1** Nominal case, assuming that no flight information is available
- **Scenario 2** Assume that landing weight, flight time, and ground speed information are available to characterize different flights
- **Scenario 3** Add wind correction to the previous scenario to account for wind effect on actual speed and flying distance
- **Scenario 4** Perform the flight performance analyses with the full data-driven mission parameterization



Observations

- Adding more features → improves the fuel burn estimation accuracy
- Infusing data into a physics-based model yields more realistic results

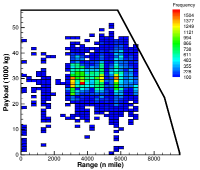
[10] Yuan Lyu and Rhea P. Liem. "Flight performance analysis with data-driven mission parameterization: mapping flight operational data to aircraft performance analysis". In: *Transportation Engineering* 2.100035 (2020). DOI: 10.1016/j.treng.2020.100035.

How can this model help improve aircraft design process?
Enables incorporating flight operational aspect into the problem formulation

1 Generate realistic flight condition distributions from flight data

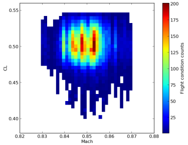
- **Simulate flight operations** based on mission profile and aircraft parameters
- Obtain **flight condition information** at different points along the mission profile
- Analyzing multiple flight missions ➠ realistic flight condition distributions

Mission data

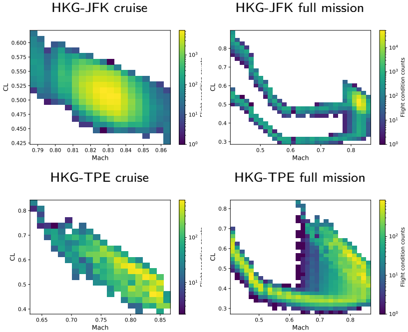


Surrogate-based mission analysis

Flight-condition data



(The distributions below are obtained from the **data-enhanced** mission analysis)



2 Accurately evaluate flight fuel consumption

- To be used in **objective function formulation** and/or **post-optimality analyses**

Data-driven dynamic flight simulation model[11]

With detailed segment-by-segment analysis

Equations of motion

(with a point-mass rigid body assumption)

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

Changes in velocity $\Delta\vec{V}$ and position $\Delta\vec{r}$ are calculated via numerical integration

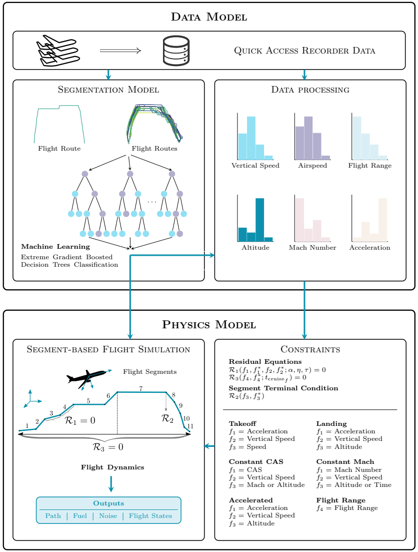
Data-driven constraints

Use **QAR data** to extract segments' boundary conditions and flight simulation constraints (speed and altitude profiles).

Validation

Compare the flight time and fuel consumption to those in QAR data ($<$ 5% error)

This model has been used in **flight path planning**



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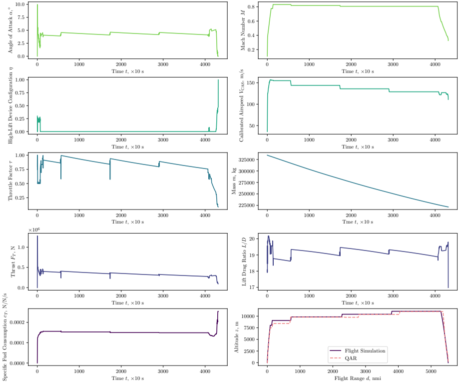
Result example: HKG-LHR flights



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Operation-aware aerodynamic shape optimization for fuel-efficient aircraft design

Aircraft design as a numerical optimization problem

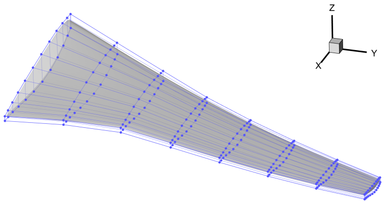
Conceptual design stage

Preliminary sizing, as a function of the top level aircraft requirements (TLARs).

Detailed design stage

Aerodynamic shape optimization (ASO) ✓

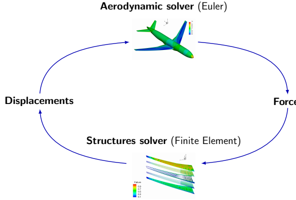
Minimize	Drag (as a proxy of **fuel**)
With respect to	Wing geometry parameters
Subject to	Lift constraint
	Moment constraint
	Geometry constraints



Aerostructural optimization

This optimization includes structural design variables and constraints.

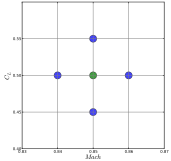
> ASO and aerostructural optimizations are traditionally performed at the **nominal condition**.



Expanding ASO capability to consider actual aircraft operations

From single-point to multipoint to mission-based/operation-aware

Single-point ● ➪ Multipoint ●



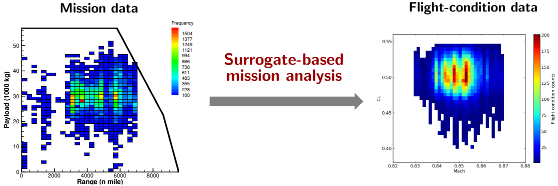
- **Multipoint optimization**: avoids off-design performance degradation[a]

$$f_{\text{obj}} = \sum_{i=1}^{N} w_i f_i \qquad \sum_{i=1}^{N} w_i = 1$$

- **Key challenges**: find the right points and weights

[a] Mark Drela. "Pros and Cons of Airfoil Optimization". In: *Frontiers of CFD 1998*. Ed. by D. A. Caughey and M. M. Hafez. World Scientific, 1998, pp. 363–381.

Towards an **operation-aware** multipoint ASO formulation



- Obtain flight condition distribution from actual flight data
- **Early work**: relied only on payload and range data, and focused on cruise[a,b]
- **Latest work**: more data, better mission analysis, aided with ML

[a] Rhea P. Liem, Gaetan K. W. Kenway, and Joaquim R. R. A. Martins. "Multimission Aircraft Fuel Burn Minimization via Multipoint Aerostructural Optimization". In: *AIAA Journal* 53.1 (2015), pp. 104–122. DOI: 10.2514/1.J052940.

[b] Rhea P. Liem, G. K. W. Kenway, and Joaquim R. R. A. Martins. "Expected Drag Minimization for Aerodynamic Design Optimization Based on Aircraft Operational Data". In: *Aerospace Science and Technology* 63 (2017), pp. 344–362.

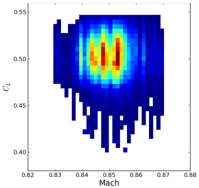
Multipoint ASO – Formulating the expectation integral approximation[12]

Approximating the **expected value** of C_D in the [Mach, C_L] space:

$$\mathbb{E}\left[C_D\right] = \iint_{\Omega} C_D\left(M, C_L\right) p\left(M, C_L\right) \mathrm{d}M \mathrm{d}C_L$$

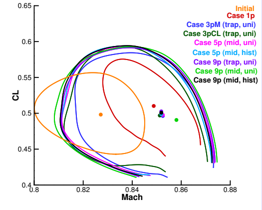
$$\approx \sum_{i=1}^{n} \sum_{k=1}^{m} \tau_{ik} C_D\left(M_i, C_{L_k}\right) p\left(M_i, C_{L_k}\right)$$

Using the generated **flight-condition distribution** to derive $p\left(M_i, C_{L_k}\right)$



Key results

- More accurate expectation integral approximation – is it important?
- **Not much difference** with other multipoint optimization results in terms of range performance ($\sqrt{M}L/D$)
  Is it, then, worth doing?



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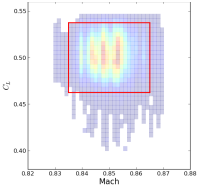

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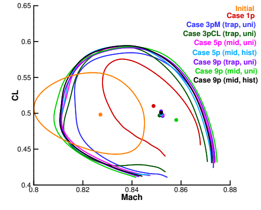

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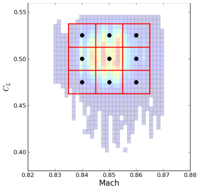

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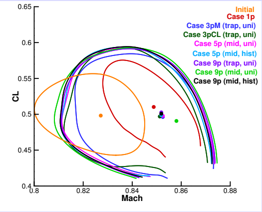


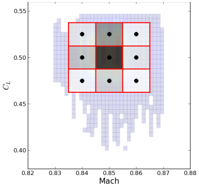
[12] Rhea P. Liem, G. K. W. Kenway, and Joaquim R. R. A. Martins. "Expected Drag Minimization for Aerodynamic Design Optimization Based on Aircraft Operational Data". In: *Aerospace Science and Technology* 63 (2017), pp. 344–362.

Multipoint ASO – Formulating the expectation integral approximation[12]

Approximating the **expected value** of C_D in the [Mach, C_L] space:

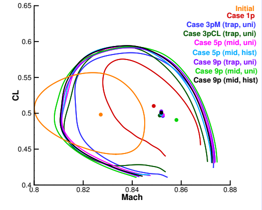
$$\mathbb{E}\left[C_D\right] = \iint_{\Omega} C_D\left(M, C_L\right) p\left(M, C_L\right) \mathrm{d}M \mathrm{d}C_L$$
$$\approx \sum_{i=1}^{n} \sum_{k=1}^{m} \tau_{ik} C_D\left(M_i, C_{L_k}\right) p\left(M_i, C_{L_k}\right)$$

Using the generated **flight-condition distribution** to derive $p\left(M_i, C_{L_k}\right)$



Key results

- More accurate expectation integral approximation – is it important?
- **Not much difference** with other multipoint optimization results in terms of range performance ($\sqrt{M}L/D$)
  Is it, then, worth doing?



[12] Rhea P. Liem, G. K. W. Kenway, and Joaquim R. R. A. Martins. "Expected Drag Minimization for Aerodynamic Design Optimization Based on Aircraft Operational Data". In: *Aerospace Science and Technology* 63 (2017), pp. 344–362.

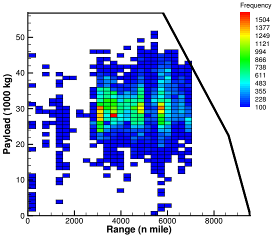
Multipoint aerostructural optimization to minimize weighted average fuel burn

Converting a multimission problem into a multipoint one[13]

Objective function

Multimission fuel burn

$$\overline{W}_{\text{fuel}} = \sum f^k W^k_{\text{fuel}}$$



Conversion into a multipoint problem through linearization

$$\underbrace{\overline{W}_{\text{fuel}}}_{\substack{\text{weighted average fuel-burn} \\ \text{from } \textbf{multiple missions}}} \approx \underbrace{\sum_{p=1}^{N} \frac{\partial \overline{W}_{\text{fuel}}}{\partial D_p} D_p}_{\substack{\text{drag forces at } \textbf{multiple} \\ \textbf{flight operating points}}} + \frac{\partial \overline{W}_{\text{fuel}}}{\partial W_s} W_s$$

$$f_{\text{obj}} = \sum_{p=1}^{N} \mu_p D_p + \lambda W_s$$

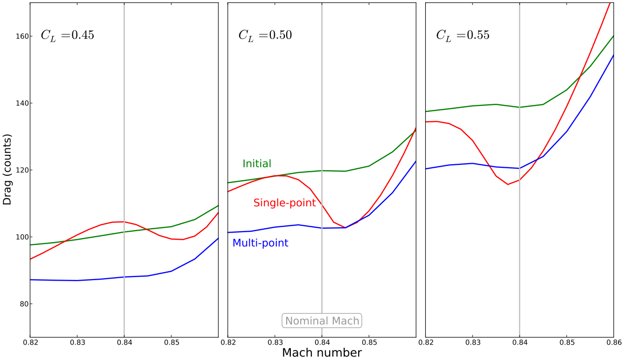
- Perform the mission analysis offline to calculate fuel burn
- Perform first order Taylor series expansion to compute μ_p and λ
- Kriging samples (for the mission analysis) become the flight condition to evaluate D_p

---

[13] Rhea P. Liem, Gaetan K. W. Kenway, and Joaquim R. R. A. Martins. "Multimission Aircraft Fuel Burn Minimization via Multipoint Aerostructural Optimization". In: *AIAA Journal* 53.1 (2015), pp. 104–122. DOI: 10.2514/1.J052940.

Benefits of performing operation-aware multipoint aerostructural optimization
(Only payload and range information, and only cruise in mission analysis)

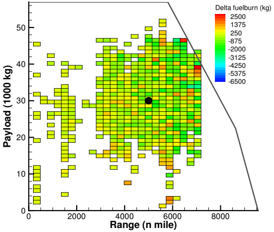
1. More **consistent performance improvement** across different flight conditions
2. Improved **overall fuel efficiency** across different flight missions



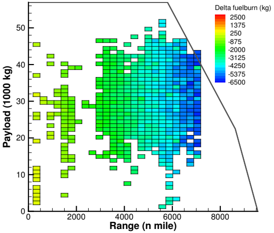
Benefits of performing operation-aware multipoint aerostructural optimization
(Only payload and range information, and only cruise in mission analysis)

1. More **consistent performance improvement** across different flight conditions
2. Improved **overall fuel efficiency** across different flight missions

Single-point optimization



Multipoint optimization



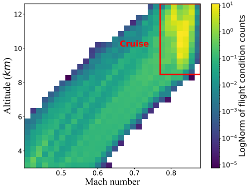
The multipoint optimization reduces fuel burn by 6.6%, whereas the single-point one only reduces it by 1.7%.

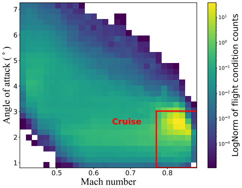
"The airline industry spends $200 billion on fuel per year, so a 2% savings is $4 billion." – Bill Ruh, VP for software at GE Research

Data-driven, operation-aware ASO with machine learning and more data[15]
Using flight conditions generated by data-enhanced mission analysis

Much richer flight condition distribution, thanks to higher-fidelity model and more detailed data

Flight condition distribution obtained from the **QAR data** of 500 flights[14].





Flight condition information: $[M, h, \alpha, C_L]$ (from a total of N timestamps).

Wing geometry
NASA CRM configuration (L3 mesh).

Aerodynamic solver
ADFlow (from the MDO Lab's – at the University of Michigan – MACH-Aero framework) (RANS + Spalart-Allmaras turbulence model).

Key performance evaluation metric
Fuel consumption of 100 representative flight missions.

[14] The flight data are obtained under the Data Partnership Agreement between Cathay Pacific Airways Ltd. and the Dept. of Mechanical and Aerospace Engineering, HKUST (2020–2026).

[15] Aobo Yang, Yuan Lyu, Jichao Li, and Rhea P. Liem. "Operation-Aware Aircraft Wing Design Using Cluster-Based Multipoint Aerodynamic Shape Optimization". In: *Journal of Aircraft* (2025). (Article in advance). DOI: 10.2514/1.C038291.

Multipoint ASO formulation – with a data-driven composite objective function

	Function/variable	Description	Bounds	Quantity
Minimize	$f_{\text{obj}} = \sum_{k=1}^{K} w_k C_{D_k}$	Weighted-average drag coefficient	-	-
With respect to	α_k	Angle of attack	$[1.0, 3.5]$	K
	$\boldsymbol{\lambda}$	Coefficients of wing shape modes	$[\boldsymbol{\lambda}_{\text{lower}}, \boldsymbol{\lambda}_{\text{upper}}]$	50
	$\boldsymbol{\alpha}_{\text{twist}}$	Wing twists	$[-1.0, 1.0]$	7
		Total design variables		$57 + K$
Subject to	$C_{L_k} - C^*_{L_k} \geq 0$	Lift constraints	-	K
	$C_M \geq -0.17$	Moment constraint at nominal condition	-	1
	$\mathcal{V} \geq \mathcal{V}_{\text{initial}}$	Volume constraint	-	1
	$t \geq 0.98 \times t_{\text{initial}}$	Thickness constraints	-	750
		Total constraints		$752 + K$

Important building blocks

- Data-enhanced flight mission analysis procedure: **to obtain C_L at each flight condition and evaluate fuel consumption** [Lyu and Liem, 2020]
- Compact modal parameterization for the wing geometry: **to ensure that the optimization is computationally efficient**[16]
- **[NEW]** Cluster-based multipoint formulation: **to derive the data-driven objective function**

[16] Jichao Li and Mengqi Zhang. "On deep-learning-based geometric filtering in aerodynamic shape optimization". In: *Aerospace Science and Technology* 112 (May 2021), p. 106603. DOI: 10.1016/j.ast.2021.106603.

Data-driven, cluster-based multipoint objective function $f_{\text{obj}} = \sum_{k=1}^{K} w_k C_{D_k}$

Use QAR-based flight condition distribution to determine the points and weights

Data preprocessing ($\mathbf{x} = [M, h, \alpha, C_L] \mapsto \mathbf{p}$)

- **Normalization** $\rightarrow [-1, 1]$
- **Orthogonalization** with Principal Component Analysis (PCA)

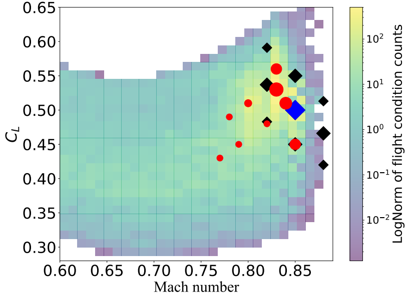
Deriving objective function's points and weights

- Probability function of **Gaussian mixture model (GMM)**

$$p_{\text{GMM}}(\boldsymbol{p}) = \sum_{k=1}^{K} \pi_k \mathcal{N}\left(\boldsymbol{p} \mid \boldsymbol{\mu}_k, \text{cov}_k\right)$$

- π_k is the mixing coefficient, $\boldsymbol{\mu}_k$ is the cluster centroid (in terms of $\mathbf{p}$)
- Multipoint objective function:

$$f_{\text{obj}} = \sum_{k=1}^{K} w_k C_{D_k} = \sum_{k=1}^{K} \pi_k C_D\left(\boldsymbol{\mu}_k \mapsto \boldsymbol{x}\right),$$



(The symbols are sized based on their weights.)

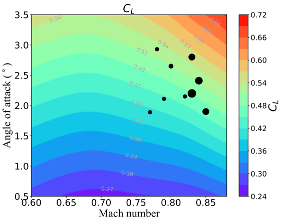
- **Diamonds**: ADODG 9-point case
- **Blue diamond**: nominal case (single-point ADODG)
- **Red circles**: 9-point cluster-based (cruise only)

List of optimization cases – single-point and multipoint cases

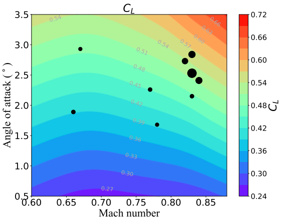
Compared against the AIAA ADODG cases[17] ('CB' denotes 'Cluster-based')

Case	Number of points	Mach	C_L	Flight segment	Data-driven multipoint
1pt-ADODGCruise	1	0.85	0.50	Cruise	-
9pt-ADODGCruise	9	0.82 – 0.88	0.42 – 0.59	Cruise	-
9pt-CBCruise	9	0.80 – 0.84	0.45 – 0.56	Cruise	✓
9pt-CBMission	9	0.65 – 0.84	0.40 – 0.56	All segments	✓
17pt-CBMission	17	0.65 – 0.84	0.38 – 0.57	All segments	✓
22pt-CBMission	22	0.63 – 0.85	0.38 – 0.58	All segments	✓

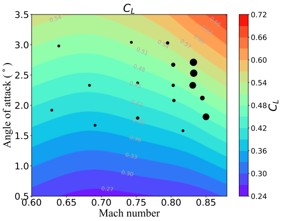
9 points, cruise only



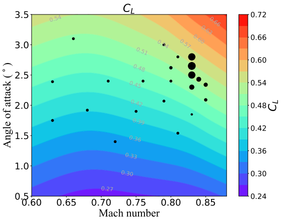
9 points



17 points



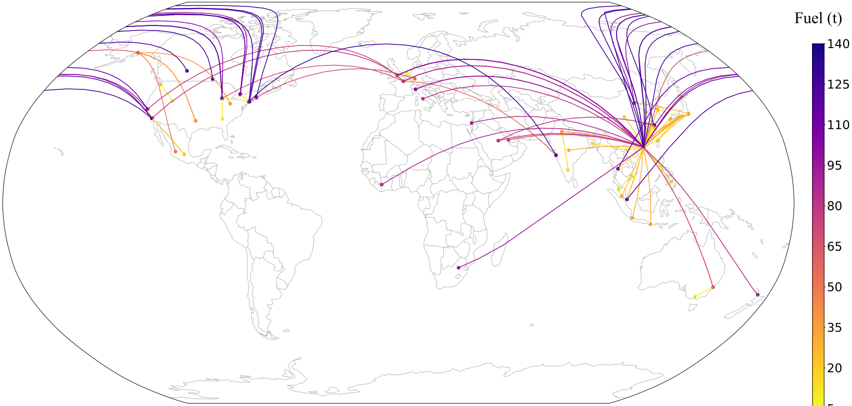
22 points



[17] ADODG: Aerodynamic Design Optimization Discussion Group, https://sites.google.com/view/mcgill-computational-aerogroup/adodg

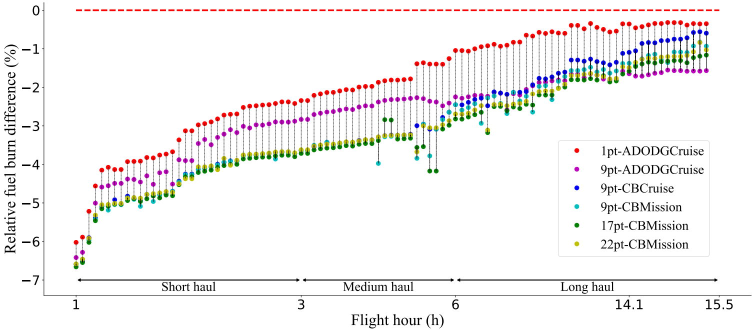
Optimized design comparison – fuel performance evaluations

Using 100 of the most frequent flights (short-, medium-, and long-haul)

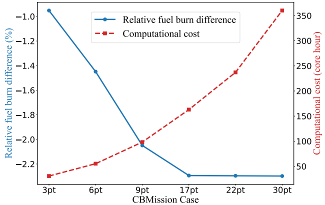


Higher fuel reduction achieved with data-driven, ML-driven multipoint ASO

Comparing relative fuel differences with different optimized configurations



Computational cost



The **relative fuel burn difference** is calculated based on the **total fuel burn** (comprising all representative flights)

- For **short- and medium-haul flights**: cluster-based cases reduce more fuel (good!)
- **As the flight range gets longer**: the 9-point ADODG case catches up with higher fuel reduction
- The overall best performance is the 17-point cluster-based optimization case

What about infusing aircraft system physics in flight profile/trajectory optimization?

Flight departure trajectory optimization for low noise and low fuel

Using data-driven flight simulation for more accurate fuel assessment

The key aim is to support the decision-making processes of Standard Instrument Departure (SID) planning, flight planners, and pilots.

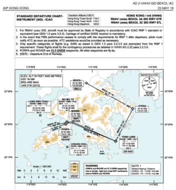
Multi-objective optimization

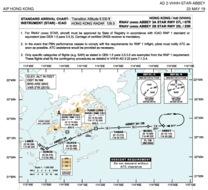
- Noise consideration: using Aircraft Noise and Performance (ANP) database[a] by Eurocontrol
- Fuel consumption consideration: using our **in-house, data-enhanced dynamic flight simulation model**

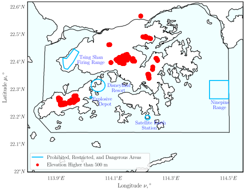
[a] https://www.aircraftnoisemodel.org/

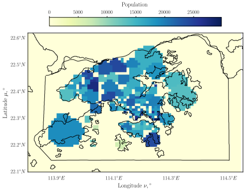
Geography/topography considerations

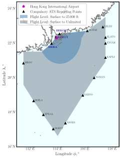
- Guidance points according to flight destinations
- Various regulations provided by Aeronautical Information Publication (AIP)
- Population distribution
- Topographic information



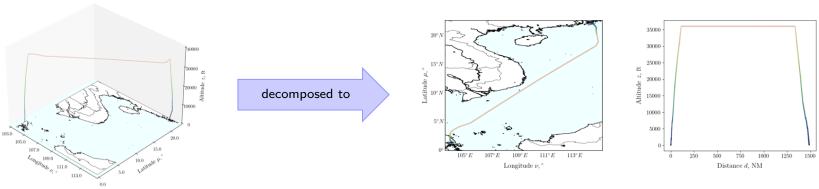








Decomposition-based flight path planning for low perceived noise and fuel[18]



Part 1: Surface path planning

- Shortest path planning constrained by air transportation conditions
- We developed a **population-aware A* with steering constraints (PA*S)** algorithm
- The cost function and searching space of the well-established A* algorithm is reformulated to consider non-preferred regions and the maneuverability of the aircraft

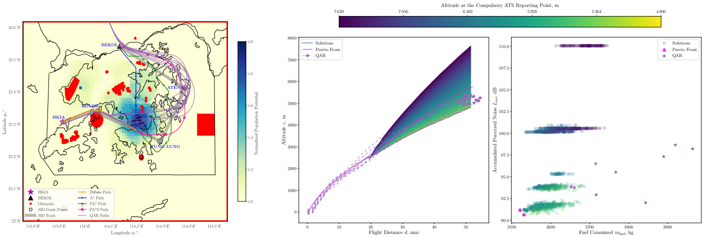
Part 2: Altitude path planning

- Multi-objective path planning for low perceived noise (ANP database model) and low fuel consumption (flight simulation model)

[18] Dajung Kim and Rhea P. Liem. "Population-Aware Sequential Flight Path Optimization for Low-Noise and Low-Fuel Consumption Departure Trajectory". In: *AIAA Journal* 60.11 (2022), pp. 6116–6132. DOI: 10.2514/1.J061603.

Departure trajectory optimization results (with NSGA-II)

A case study with the HKG-LHR route



Surface path

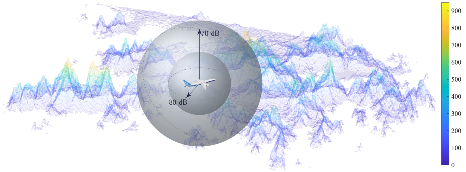
- Most QAR paths traverses the highly-populated area
- The traditional A* path traverses the highly-populated area
- The population-aware A* (PA*) path avoids highly-populated area, but the path is not smooth
- The addition of steering constraints in PA*S path ensures that the path is physically flyable

Altitude path

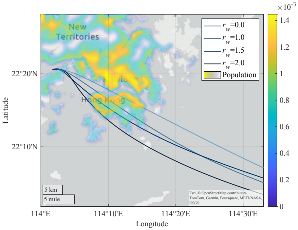
- Noise-minimum path has a lower final altitude than most QAR paths
- Fuel-minimum path has a higher final altitude than most QAR paths

Reinforcement learning with physics-based environment[20]
Considering population density and topography maps for realistic constraints

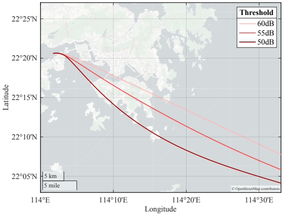
- Objectives: minimum fuel and noise impact on **population on ground**
- Policy gradient algorithm: **Soft-Actor-Critic**
- Simulated environment: AirTrafficSim[19], our in-house open-source, web-based air traffic simulation platform
- Actions: changes in heading $\mathrm{d}\Theta/\mathrm{d}t$, altitude $\mathrm{d}h/\mathrm{d}t$, and calibrated airspeed $\mathrm{d}V/\mathrm{d}t$



Varying the fuel-noise ratio



Varying the allowable noise level

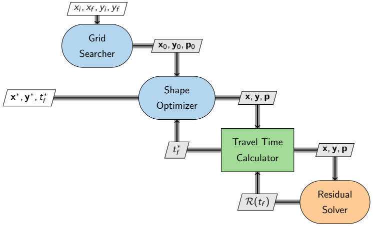


[19] Ka Yiu Hui, Chris H. C. Nguyen, Go Nam Lui, and Rhea P. Liem. "AirTrafficSim:An open-source web-based air traffic simulation platform". In: *The Journal of Open Source Software* 8.86 (2023), p. 4916. DOI: 10.21105/joss.04916.

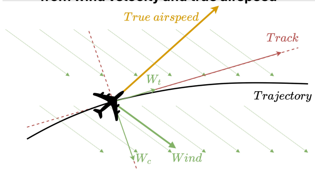
[20] Chris HC. Nguyen, James M. Shihua, and Rhea P. Liem. "Fuel- and noise-minimal departure trajectory using deep reinforcement learning with aircraft dynamics and topography constraints". In: *Communications in Transportation Research* 5 (2025), p. 100165. DOI: https://doi.org/10.1016/j.commtr.2025.100165.

Applying FFD-based shape optimization for cruise trajectory optimization[21]

Another “cross-polination” of aircraft design and air transportation research



Obtaining actual ground speed from wind velocity and true airspeed



Bi-level trajectory minimization in unsteady wind conditions

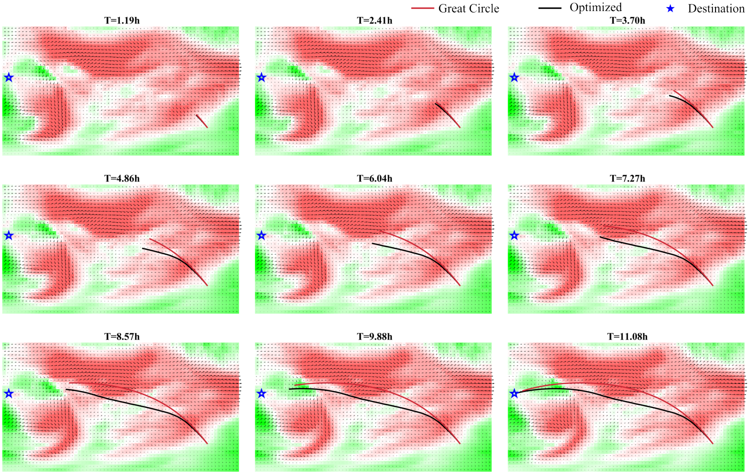
- **Objective**: minimizing travel time
- **Design variables**: trajectory coordinates (latitude and longitude)
- **Constraints**: areas to be avoided (e.g., no-fly zone)
  (implemented via a **penalty function**)
- **Bi-level optimization procedure**:
  1. Time-dependent Dijkstra algorithm with unsteady wind
     (Exploration, low-fidelity, globally optimal)
  2. Wind-optimal trajectory as a shape optimization problem
     (Exploitation, high-fidelity, locally optimal)
- **Average travel time reductions**: 13.1% (HKG ⇔ LHR), 1.7% (HKG ⇔ SYD), 1.2% (HKG ⇔ SIN)
- **Computational cost**: < 4s (with GPU acceleration and CPU multiprocessing)

Not all constraints have been included, but it’s promising!

[21] James M. Shihua, Chris HC. Nguyen, and Rhea P. Liem. “Real-Time Bi-Level Aircraft Trajectory Optimisation under the Presence of Unsteady Wind”. In: *Optimization and Engineering* (2025). In press.

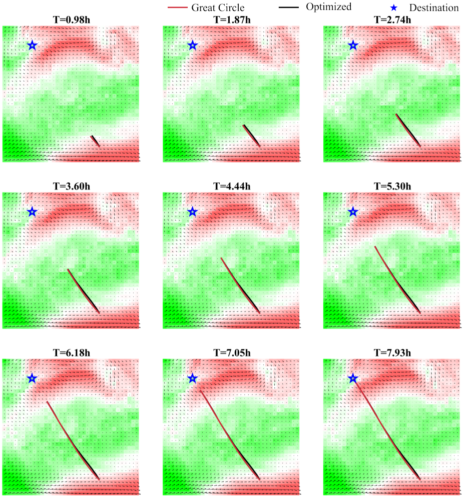
Time-minimal, wind-optimal cruise trajectory results

Notable benefits on HKG-LHR (east-west route) due to the presence of jet streams



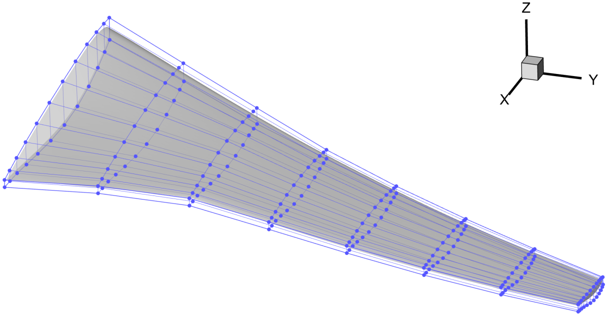
Time-minimal, wind-optimal cruise trajectory results

Marginal benefits on SYD-HKG (south-north) due to small wind variations



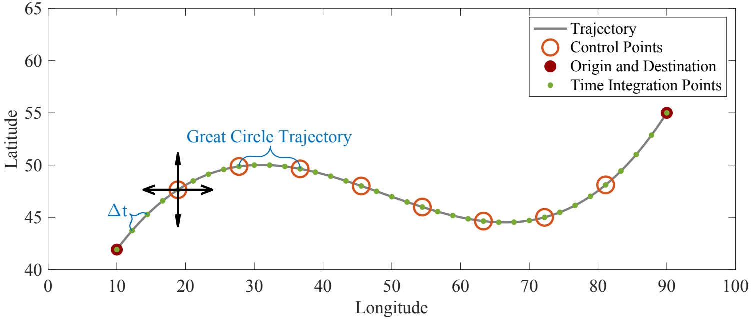
The versatility of shape parameterization and optimization
Using free-form deformation (FFD) method

From parameterizing wing geometry ...



The versatility of shape parameterization and optimization
Using free-form deformation (FFD) method

... to cruise trajectory shape



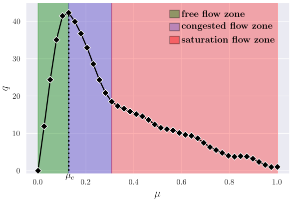
To the best of our knowledge, this is the first effort to do so. There might be many more applications!

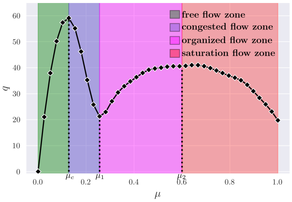
What about data-free, non-physical models? Can they be useful?

Statistical physics modeling – Cellular automata (CA) for arrival dynamics[22]

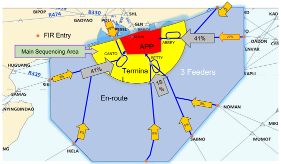
Understanding macroscopic behaviors from microscopic interactions

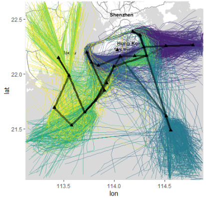
- **Data-free model** to study a system's behaviors based on the interactions of molecular agents in a grid system following some transition rules
- The key aim is to **provide a faithful abstraction of the underlying system properties**
- CA applications: **ground traffic**, population dynamics, crowd evacuation, epidemic spread
- **We derived a CA model suitable for studying the navigation dynamics within arrival TMA**, with considerations of wake turbulence separation minima, air traffic mix, waypoint locations, and navigation flexibility
- Resulting **fundamental diagrams** (q and μ represent traffic flow and TMA occupancy):





Terminal Maneuvering Area (TMA)



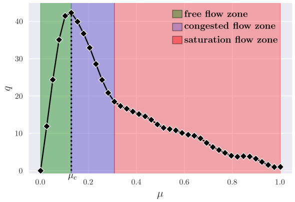


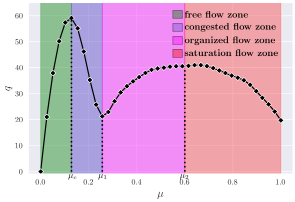
22 Ikeoluwa I. Ogedengbe, Tak Shing Tai, K. Y. Michael Wong, and Rhea P. Liem. "Cellular automata for the investigation of navigation dynamics and aircraft mix in terminal arrival traffic". In: *Physica A* 671 (), p. 130628. DOI: 10.1016/j.physa.2025.130628.

Statistical physics modeling – Cellular automata (CA) for arrival dynamics[22]

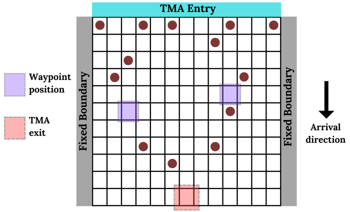
Understanding macroscopic behaviors from microscopic interactions

- **Data-free model** to study a system's behaviors based on the interactions of molecular agents in a grid system following some transition rules
- The key aim is to **provide a faithful abstraction of the underlying system properties**
- CA applications: **ground traffic**, population dynamics, crowd evacuation, epidemic spread
- **We derived a CA model suitable for studying the navigation dynamics within arrival TMA**, with considerations of wake turbulence separation minima, air traffic mix, waypoint locations, and navigation flexibility
- Resulting **fundamental diagrams** (q and μ represent traffic flow and TMA occupancy):





CA representation of the arrival TMA



Apply the fixed strategy when the aircraft are mostly small/medium, and flexible strategy when the traffic mix is more heterogeneous.

[22] Ikeoluwa I. Ogedengbe, Tak Shing Tai, K. Y. Michael Wong, and Rhea P. Liem. "Cellular automata for the investigation of navigation dynamics and aircraft mix in terminal arrival traffic". In: *Physica A* 671 (), p. 130628. DOI: 10.1016/j.physa.2025.130628.

Summary

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from Data and Models to Decisions

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Infusing actual operational data into aircraft performance analysis and design process

- Statistical information of aircraft operations are used to parameterize mission profiles and formulate constraints
- Yields more realistic design space and more relevant optimization results

Embedding physics-based aircraft models into aircraft operation optimization

- Helps ensure that the resulting trajectory is physically flyable
- More accurate fuel consumption estimation

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Hybrid modeling— learning from data through the lens of physics-based models

- Combines the objectivity of data and interpretability and generalizability of physics-based models

What's next: Towards developing a "superdisciplinary" framework for sustainable aviation

Designing Next-Generation Aircraft and Operations for Sustainable Aviation:
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Developing a future-aware framework (because data only reflect the past, not the future)

- "What exactly to learn from data"
- Incorporate **sensitivity analysis**, **forecasting**, and **uncertainty management**

Developing a socio-techno-economic-driven framework

Because we do **NOT** want people in the future to say: *"The great accomplishments of the 21th century nevertheless created their own sets of shortfalls or negative impacts on society".*

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Develop technological solutions with **considerations of social, economic, and environmental impact** early in the design process, and **not as an afterthought**.

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Thank you.
Questions?

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