

Contingency Fuel Prediction with Explainable Machine Learning for Airline Operations

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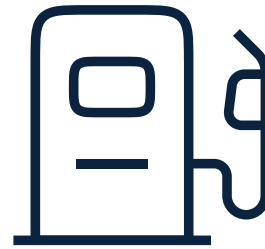
01

Introduction

Aviation's Climate Targets and Pathways to CO₂ Reduction



Route Optimization



Fuel Efficient Technologies

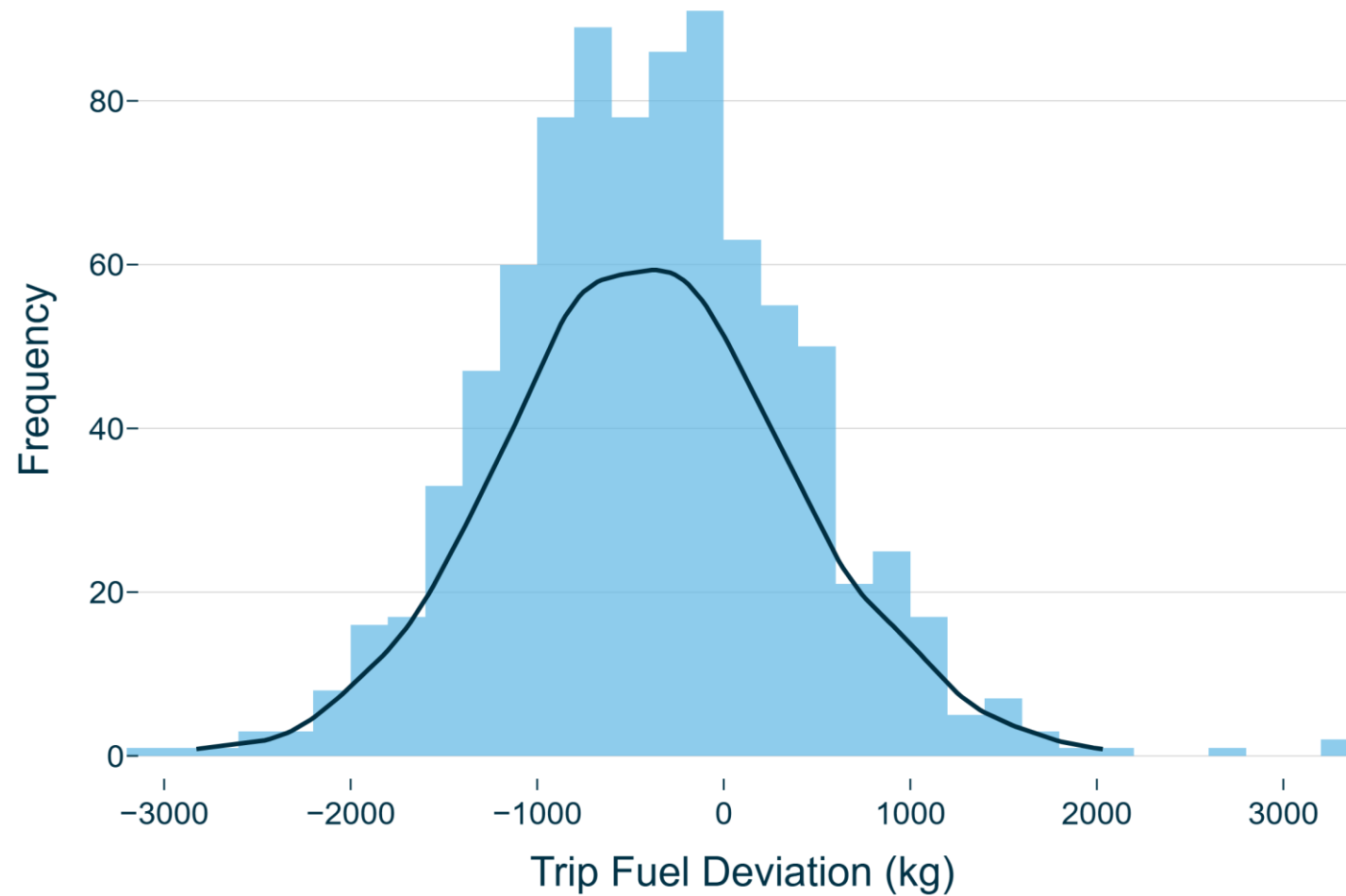


Weight Reduction

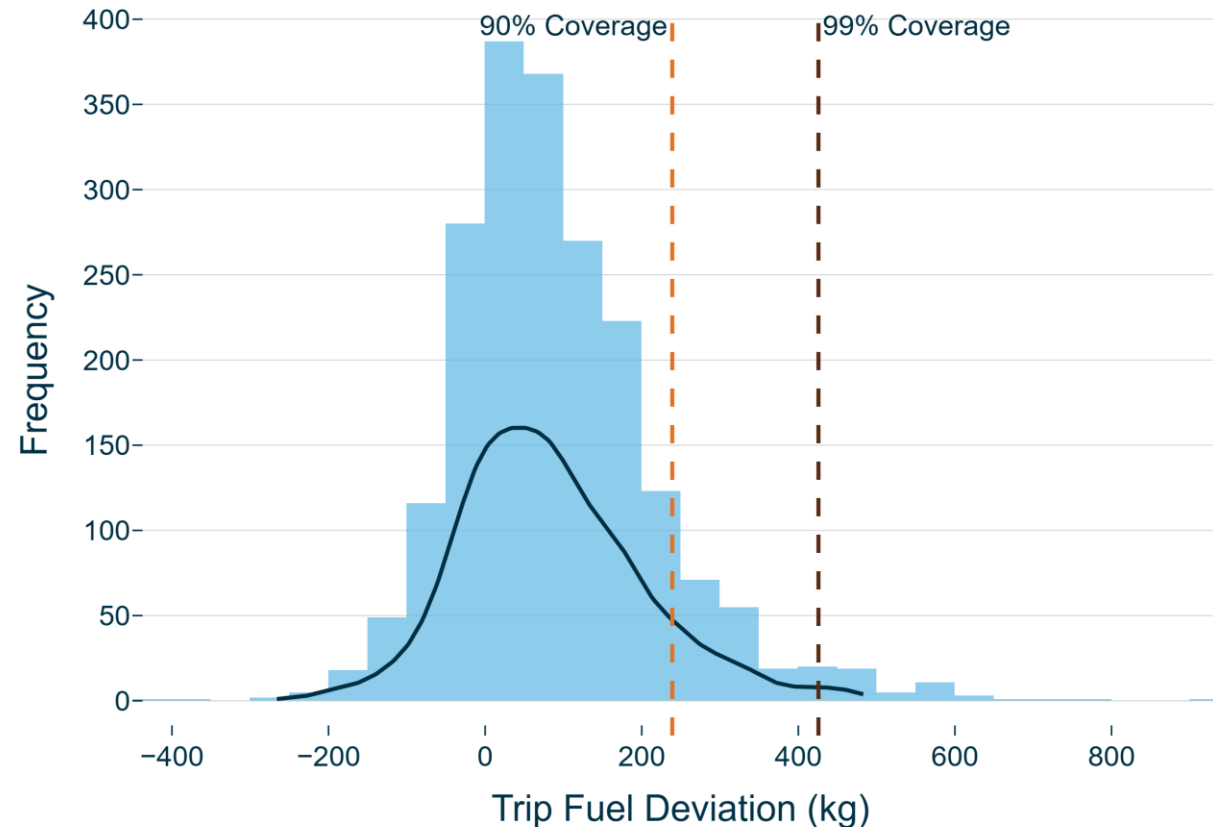
Study Airline Fuel Components

Mission Fuel	Taxi Fuel	Fuel used prior to take-off.
	Trip Fuel	Fuel for take-off, climb, cruise, descent, approach and landing.
Variable Fuel	Additional Fuel	Fuel required due to specific operational constraints.
	Contingency Fuel	Fuel to compensate for unforeseen circumstances.
	Discretionary Fuel	Fuel at the discretion of the commander.
Safety Fuel	Alternate Fuel	Fuel for missed approach at destination until landing at alternate aerodrome.
	Final Reserve Fuel	Required 30 minutes of fuel at holding speed at 1500ft above destination aerodrome.

Statistical Contingency Fuel



Statistical Contingency Fuel



- Coverage level of flight based on operational risk profile:
 - Traffic features
 - Weather features
- Minimum of 5 minutes of contingency fuel required!

Pros

Proven Reliability

Easy to Understand

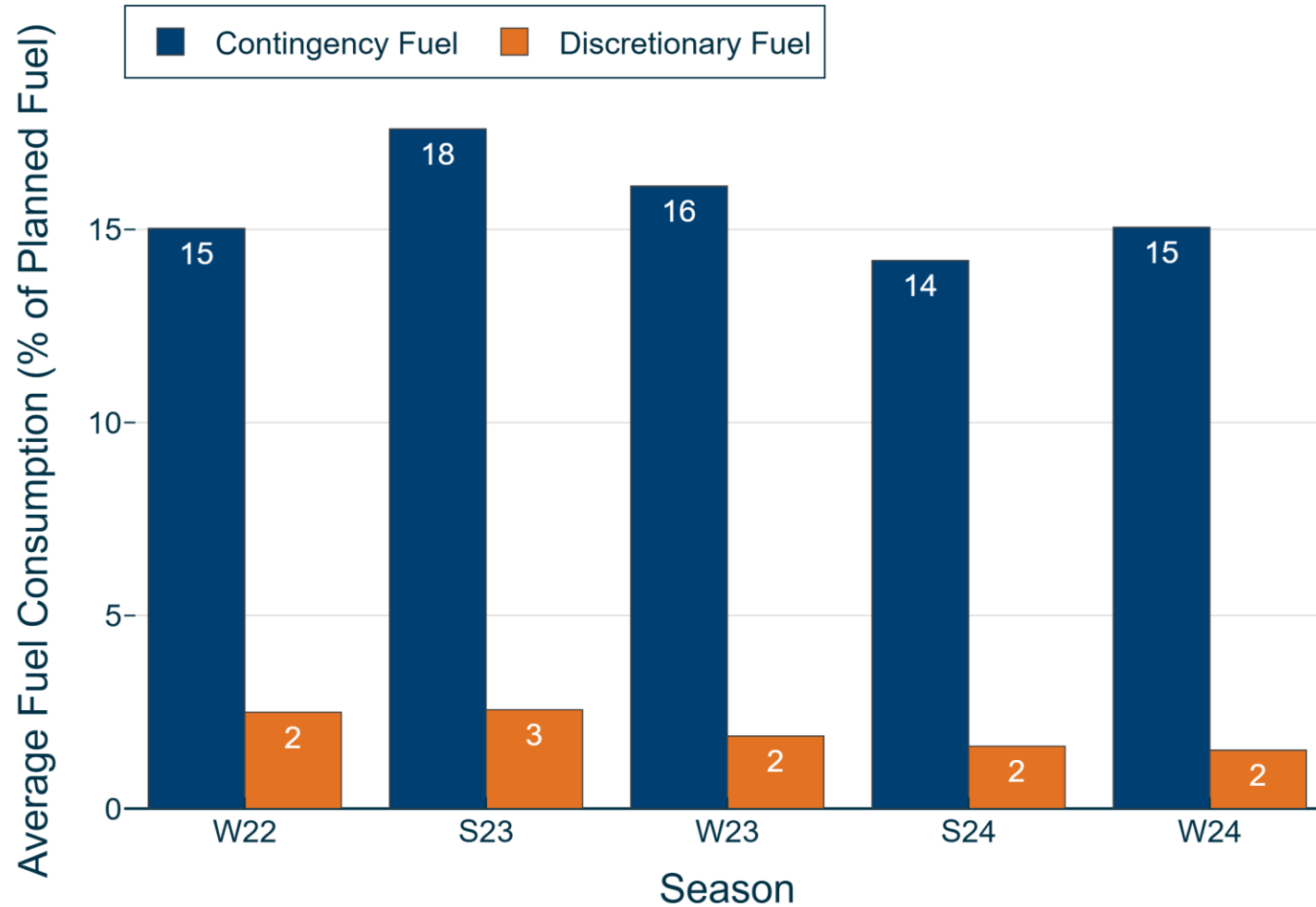
Cons

Limited Input Feature Set:

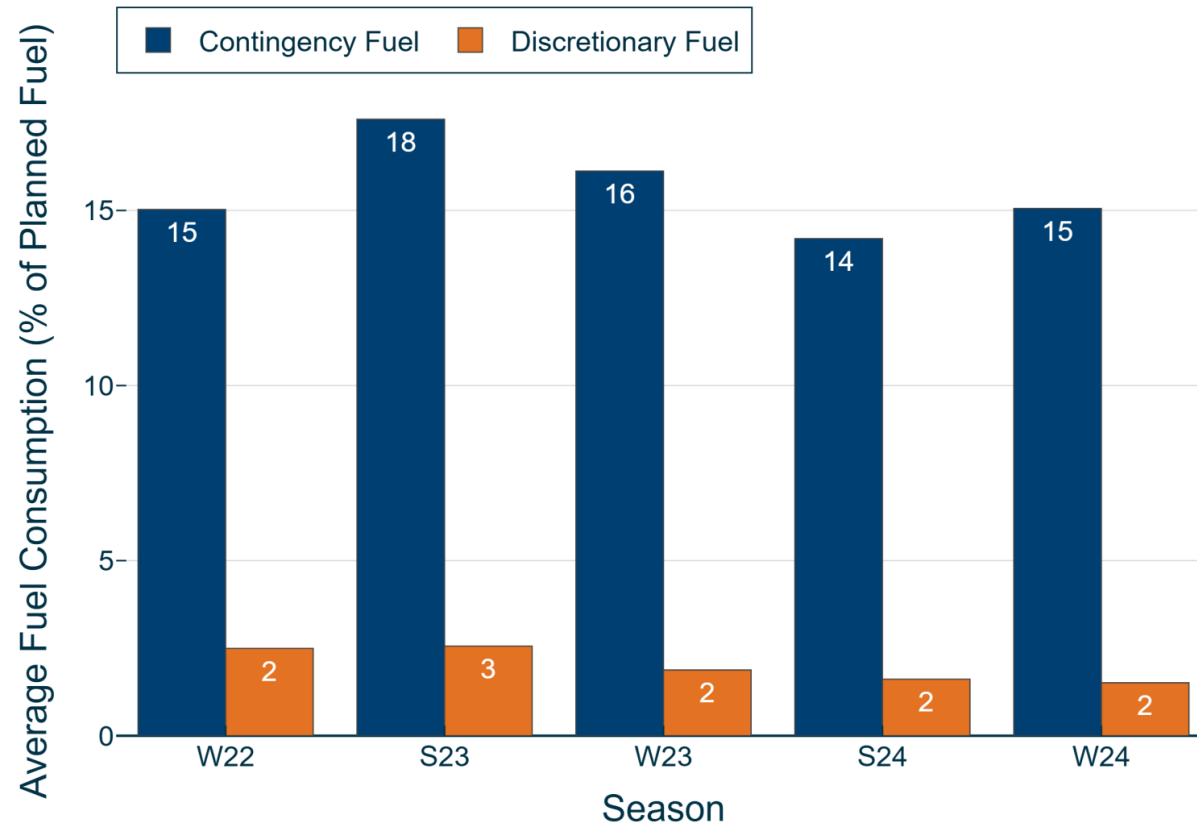
- City Pair
- Aircraft Type

Modelling Assumptions

Variable Fuel Allocation & Usage



Variable Fuel Allocation & Usage



- Up to **1.04% of fuel consumed** is due to carrying unnecessary contingency fuel^[1].
- Promising advancements in using machine learning algorithms for fuel burn predictions^[2-4].
 - Limited access to operational data
 - Data restricted to specific regions or routes

Research Objectives



Develop a **generalizable, network-wide quantile-based ML framework** for contingency fuel prediction.



Reduce **excess fuel carriage** while maintaining or improving **safety** performance.

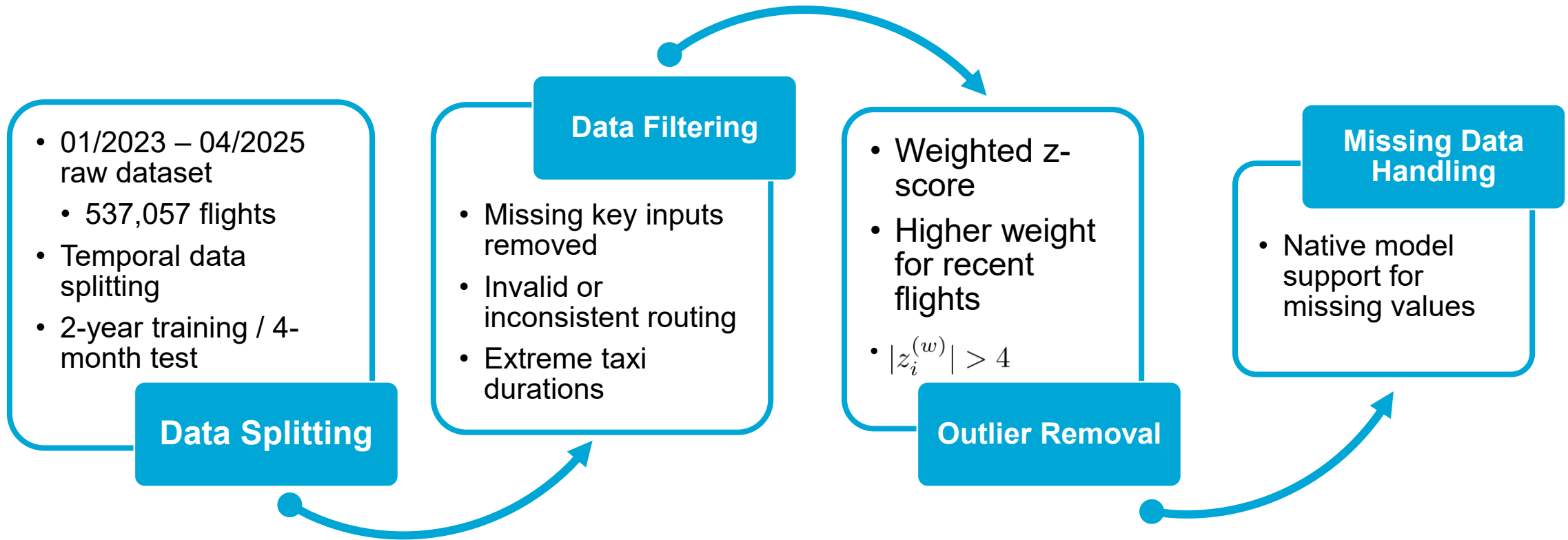


Use **explainable ML techniques** to provide **transparent, interpretable** model outputs for operational decision support.

02

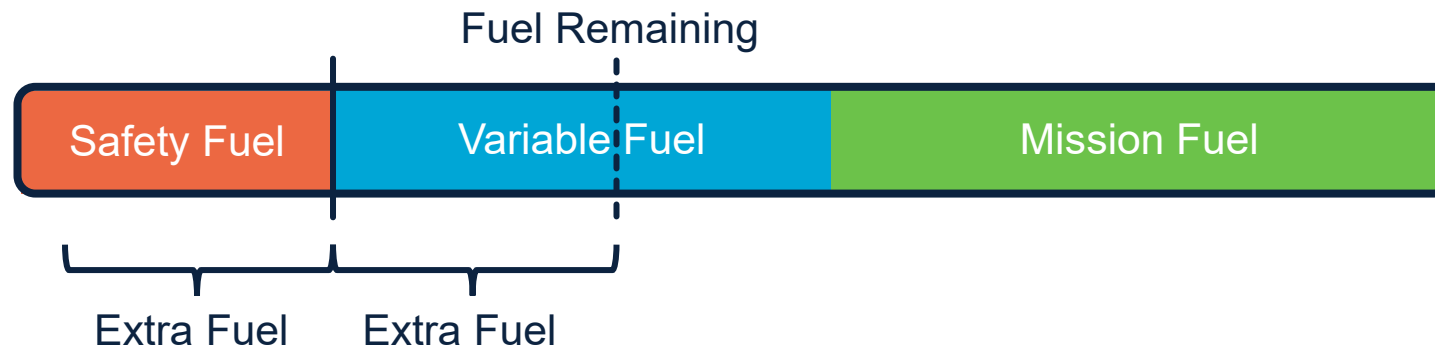
Methodology

Dataset & Preprocessing



Target Variable Development

- Extra fuel used to define the under/over provisioning of fuel onboard:



- Adjust variable fuel components for extra fuel and cost-to-carry of extra fuel:

$$F_{\text{rcf}} = \underbrace{(F_{\text{contingency}} + F_{\text{discretionary}})}_{\text{variable fuel components}} - F_{\text{extra}} + CTC_{\text{extra}}$$

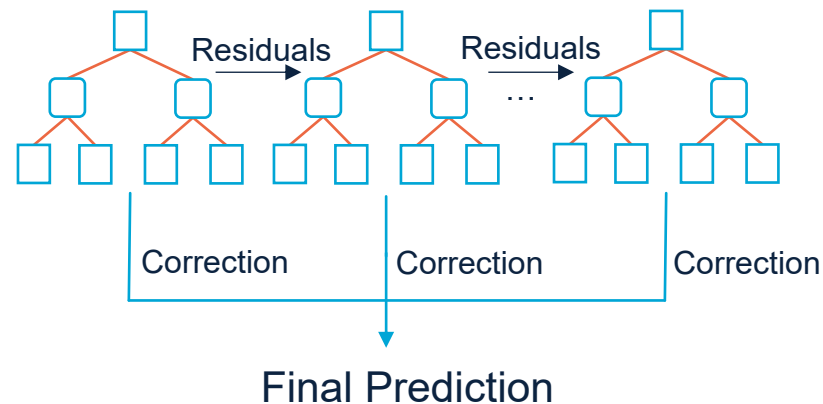
Model Framework

Input Features

- Flight Plan Features
 - City pair
 - Aircraft type
 - Aircraft weight
- Weather Features
 - Cloud ceiling/Visibility
 - Wind speed & direction
 - Wind gusts
- Route Effects
 - Mean/standard deviation historical trip duration
 - Mean/standard deviation historical trip duration deviation

Model

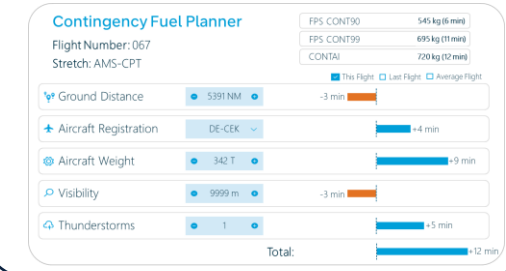
- Gradient Boosting Machine
- LightGBM implementation



Output

Quantile-Based Prediction of Required Contingency Fuel

Interpretability Metrics



03

Results

Machine Learning Metrics

- Quantile goodness-of-fit [5]:

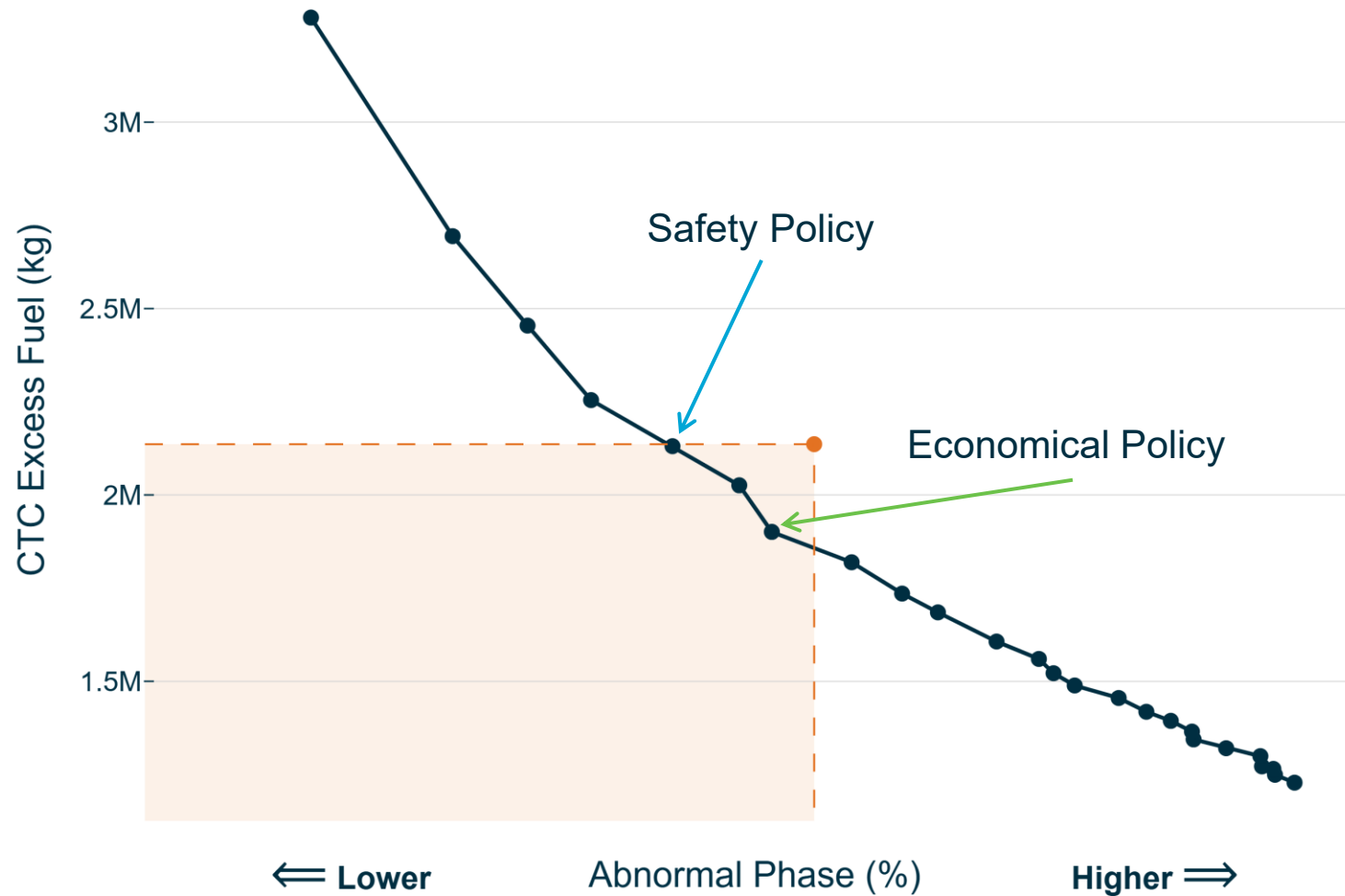
$$R_{\tau}^1 = 1 - \frac{\hat{V}(\tau)}{\tilde{V}(\tau)}$$

- Comparison to currently implement SCF model:

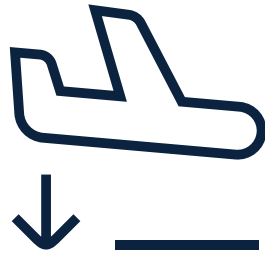
Quantile/Model	Goodness-of-Fit	Coverage
97.8	0.249	0.967
SCF90	-0.533	0.967
98.8	0.292	0.980
SCF95	-0.231	0.978
99.8	0.298	0.995
SCF99	0.196	0.994

Flight type segmentation shows **decreased performance** for longer **intercontinental** flights compared to regional flights.

Business Key Performance Indicators



Operational & Environmental Impact



Safety Policy

- 22.2% reduction in ABNPH



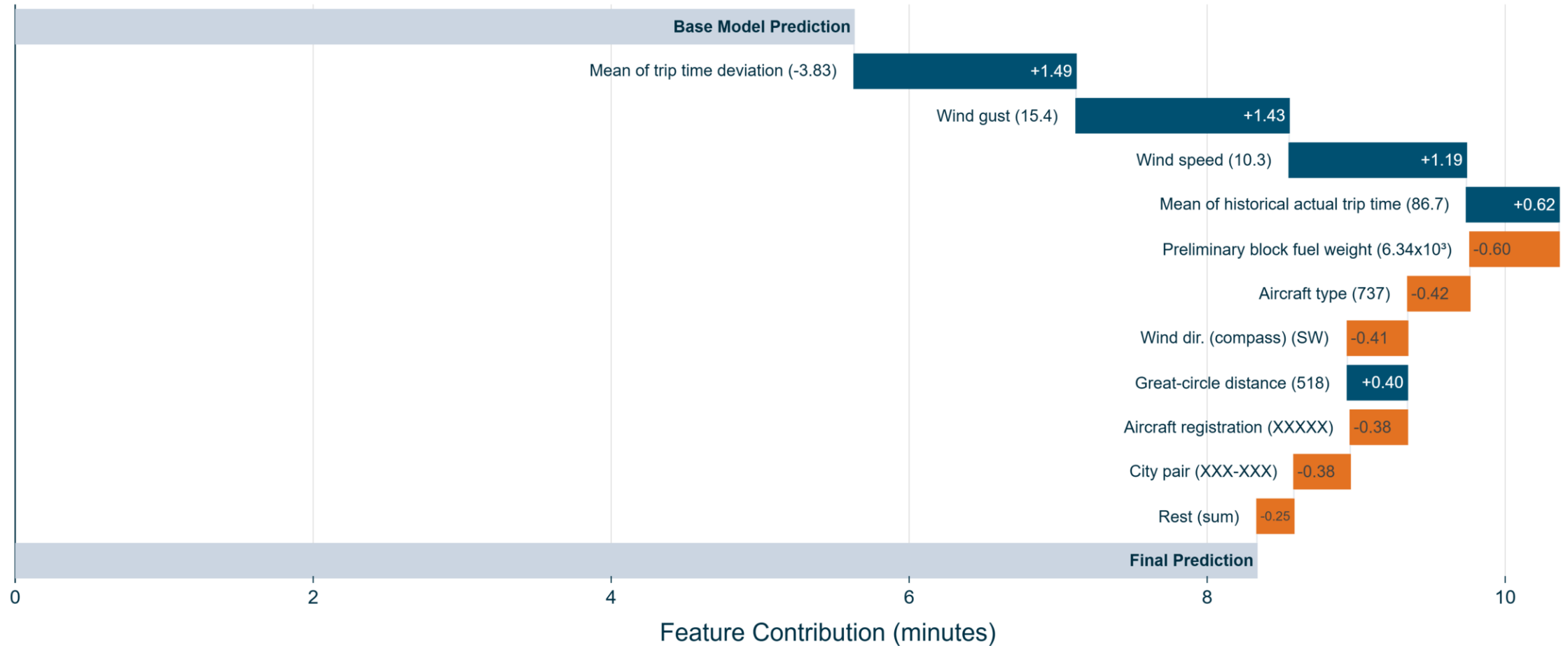
Economical Policy

- 235,364 kg fuel reduction
- 743t CO₂ reduction

04

Explainability Framework

Explaining Individual Model Predictions



Decision Support Tool

Contingency Fuel Planner

Flight Number: 067
Stretch: AMS-CPT

FPS CONT90545 kg (6 min)

FPS CONT99695 kg (11 min)

CONTAL720 kg (12 min)

☒ This Flight☐ Last Flight☐ Average Flight

📍

Ground Distance

⬅️

5391 NM

➡️

-3 min

✈️

Aircraft Registration

DE-CEK

▼

+4 min

⚙️

Aircraft Weight

⬅️

342 T

➡️

+9 min

🔍

Visibility

⬅️

9999 m

➡️

-3 min

⚡

Thunderstorms

⬅️

1

➡️

+5 min

Total:

+12 min

05

Conclusion

Discussion

Comparison with Current SCF Model



- **Main value** from **decreasing discretionary fuel** usage, through **transparent, data-driven reasoning**.

Operational Considerations



- Model relies on **flight-plan inputs**, creating a **feedback loop** within the planning system.

Limitations



- Uses **single quantile** for all flights.
- **Weaker performance** on long-haul flights due to **higher uncertainty** in input data.

Recommendations



- Develop **adaptive quantile selection** strategies.
- Explore **region-specific** models.

Conclusion



Quantile-regression LightGBM **improves** over current inhouse model.



Provides a **fleet-wide** model applicable to regional and intercontinental routes.



Introduces **explainable outputs** to support pilot and dispatcher adoption.



References

- [1] Megan S Ryerson, Mark Hansen, Lu Hao, and Michael Seelhorst. Landing on empty: estimating the benefits from reducing fuel uplift in US Civil Aviation. *Environmental Research Letters*, 10(9):094002, September 2015.
- [2] Lei Kang and Mark Hansen. Improving airline fuel efficiency via fuel burn prediction and uncertainty estimation. *Transportation Research Part C: Emerging Technologies*, 97:128–146, December 2018.
- [3] Lei Kang and Mark Hansen. Quantile Regression–Based Estimation of Dynamic Statistical Contingency Fuel. *Transportation Science*, 55(1):257–273, January 2021.
- [4] X. Zhu and L. Li, “Flight time prediction for fuel loading decisions with a deep learning approach,” *Transportation Research Part C: Emerging Technologies*, vol. 128, p. 103179, July 2021.
- [5] Koenker and J. A. F. Machado, “Goodness of Fit and Related Inference Processes for Quantile Regression”, *Journal of the American Statistical Association*, vol. 94, pp. 1296–1310, Dec. 1999.

**Thank you for your
interest & attention!**

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