Conditional Sell-up Rate Estimation and Demand Forecasting in Unrestricted Fare Structures

Tim Yuxuan Lu

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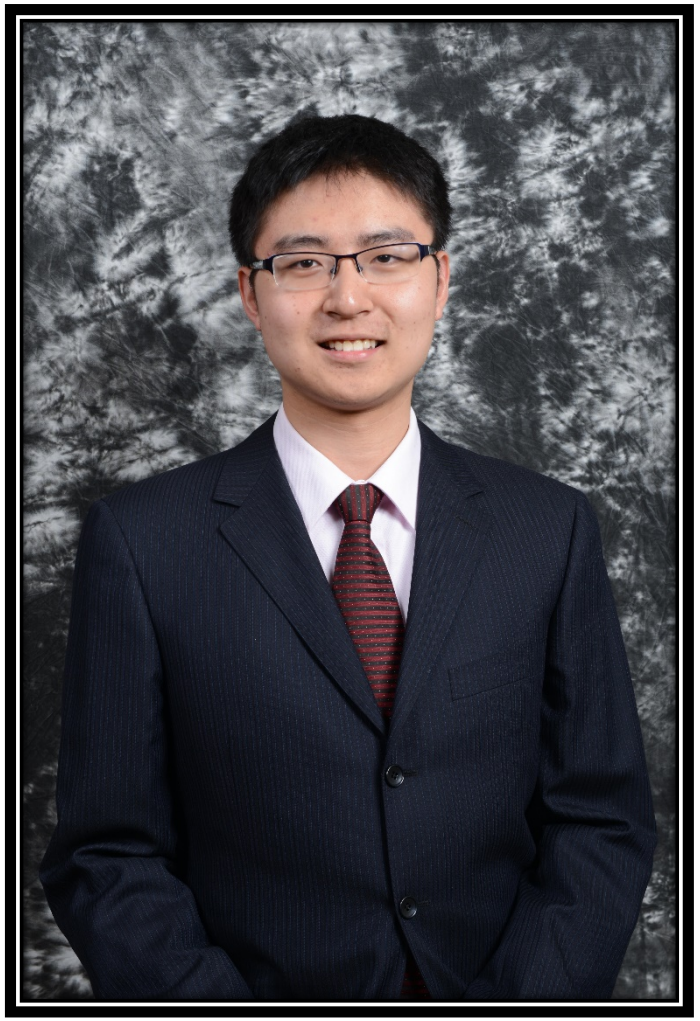
Bio



- Tim (Yuxuan) Lu is a Ph.D. candidate at Massachusetts Institute of Technology advised by Dr. Peter Belobaba with a primary research focus on airline revenue management. He has been contributing to various research projects under the Passenger Origin Destination Simulators (PODS) consortium. In 2019, he completed his Master's thesis, *Impacts of Ancillary Services on Airline Revenue Management*, introduced the recent trends of airline ancillary services and studies their impacts on airline revenue management.

- Currently, his research focus is on airline passenger willingness-to-pay estimations. His secondary research focus is on airline operations research, where he is conducting research, assisting in teaching MIT courses, and tabulating MIT's Airline Data Project.

Price-Demand Forecasting and Sell-up Estimation in Unrestricted Fare Structure: Is Q-Forecast Good Enough?

PODS
MIT International Center for Air Transportation

Scope: fully unrestricted fare structures with no APs and no restrictions

In markets with such fare structures, passengers *always* choose the *lowest available* option *across airlines*

Existing solution: WTP-based Q-forecast Methodology

- **Converting** an airline's bookings at higher fare classes **into basefare-equivalent demand (Q-demand)** according to an assumed sell-up rate (FRAT5), and then **partition Q-equivalent demand back to fare class forecast** using the same assumed sell-up rate (Hopperstad & Belobaba, 2004)

Step 1

Conversion of historical BKs to equivalent Q-DEM

(made-up data)

FCL	Fare	Hist. BKs
1	$412.85	2.00
2	$293.84	5.00
3	$179.01	10.00
4	$153.03	20.00
5	$127.05	40.00
6	$101.06	63.00

FRAT5 = 1.6

psup
0.0283
0.1104
0.4102
0.5521
0.7430
1.0000

Q-EQ BKs
20.00
45.29
24.38
36.23
53.84
63.00
Total:242.74

$$psup = \exp\left(\frac{\ln(0.5)}{FRAT5 - 1} * \left(\frac{F}{F_Q} - 1\right)\right)$$

Step 2

Partitioning Q-EQ Demand to FCL Forecast

FRAT5 = 1.6

Partition
0.0283
0.0821
0.2998
0.1419
0.1909
0.2570

FCL Q-FCAST
6.87
19.92
72.78
34.43
46.34
62.39

$$partition_F = psup_F - psup_{F-1}$$

Introduction to Simulations

- All simulations are performed using Passenger Origin Destination Simulator **(PODS) network A2TWO**, which is a **small network with symmetric schedules**
  - Symmetric unrestricted fare structure
  - On average, 35% of the passengers generated are business passengers with higher budgets and smaller price sensitivities
  - 16 Time Frames/Data Collection Points/Re-optimization Points in booking horizon

Flight Schedule

AAA — **BBB**

Airline 1	AAA-BBB	2.5h	17:00-19:30	Nonstop	130 Seats
Airline 2	AAA-BBB	2.5h	17:00-19:30	Nonstop	130 Seats

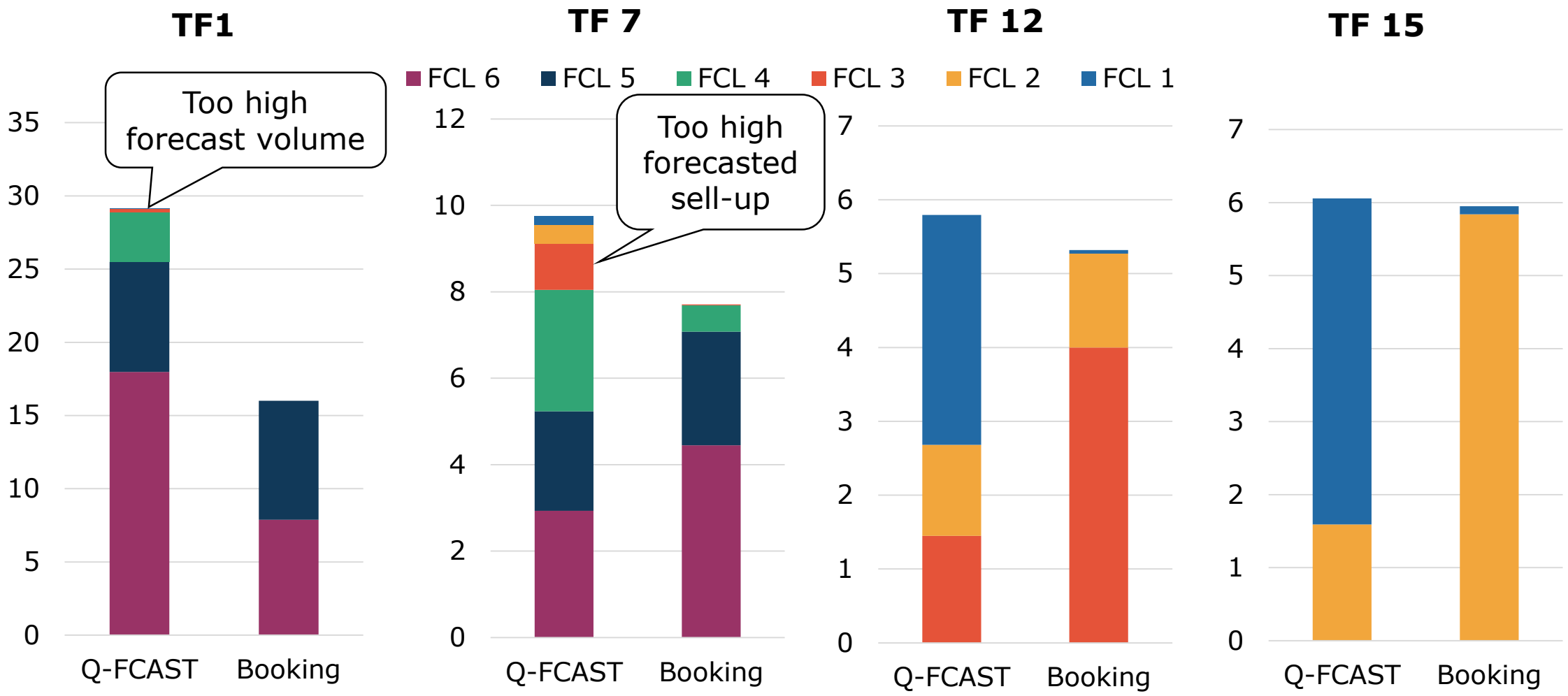
- Both airlines use the **same RM settings** that are reasonably good
  - Q-forecast with full fare adjustment (QFFA1.0)
  - ProBP and EM detruncator
  - A moderate sell-up estimation curve (FRAT5 C), giving airlines reasonable fare class mixes and load factors (~79.3%), and the highest revenues among other PODS FRAT5 curves

Fare Class	Fare	AP	Restrictions
1	$500	--	--
2	$390	--	--
3	$295	--	--
4	$200	--	--
5	$160	--	--
6	$125	--	--

Motivation: Significant Deviations from Q-Forecasts to Actual Bookings with Fully Unrestricted Fare Structures

Airline 1 Q-Forecast vs. Bookings at Various TF/DCPs

Unrestricted A2TWO; Symmetric RM: QFFA KI 1.00 FRAT5C/EMSRb/EM detruncator



Price-Demand Forecasting and Sell-up Estimation in Unrestricted Fare Structure: Is Q-Forecast Good Enough?

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Assumptions of Q-forecast that could undermine its accuracy

1. Lack of competition-awareness: passengers buy across airlines for cheaper tickets. Existence of competitors offering higher or lower fares affects an airline's booking

2. Assuming input sell-up rates will be actual sell-up rates. However, passengers buy down facing cheaper alternatives.

3. Assuming the same sell-up rate for every departure date, regardless of demand level and actual fare classes offered

The 3 assumptions listed on the above can be cause by the lacking of…

Conditionality:

In unrestricted fare structures, bookings are strongly correlated with the lowest fare classes offered, so should forecasts. Forecasts in unrestricted fare structures should take conditionality into account.

Plans for today: Examine weaknesses of Q-forecast and propose Conditional Forecast (C-FCAST)

I will first show evidences of the potential weaknesses of the Q-forecast, and then propose the philosophy of a conditional forecaster and show results of a simple conditional forecast proof-of-concept

Defining Conditionality and Testing for Its Impacts

- What exactly is conditionality? We call a set of availabilities of all fare classes offered by an airline a ***Booking Policy***, or ***Policy***, often denoted as π, for example,

Policy π_a: $\{Y, B, M, Q, E\}$: All FCL open:	Y	B	M	Q	E
Policy π_b: $\{Y, B\}$: only FCL Y and B open:	Y	B	~~M~~	~~Q~~	~~E~~
Policy π_c: $\{\emptyset\}$: complete closure of path:	~~Y~~	~~B~~	~~M~~	~~Q~~	~~E~~

- At the same time, airlines can have different policies

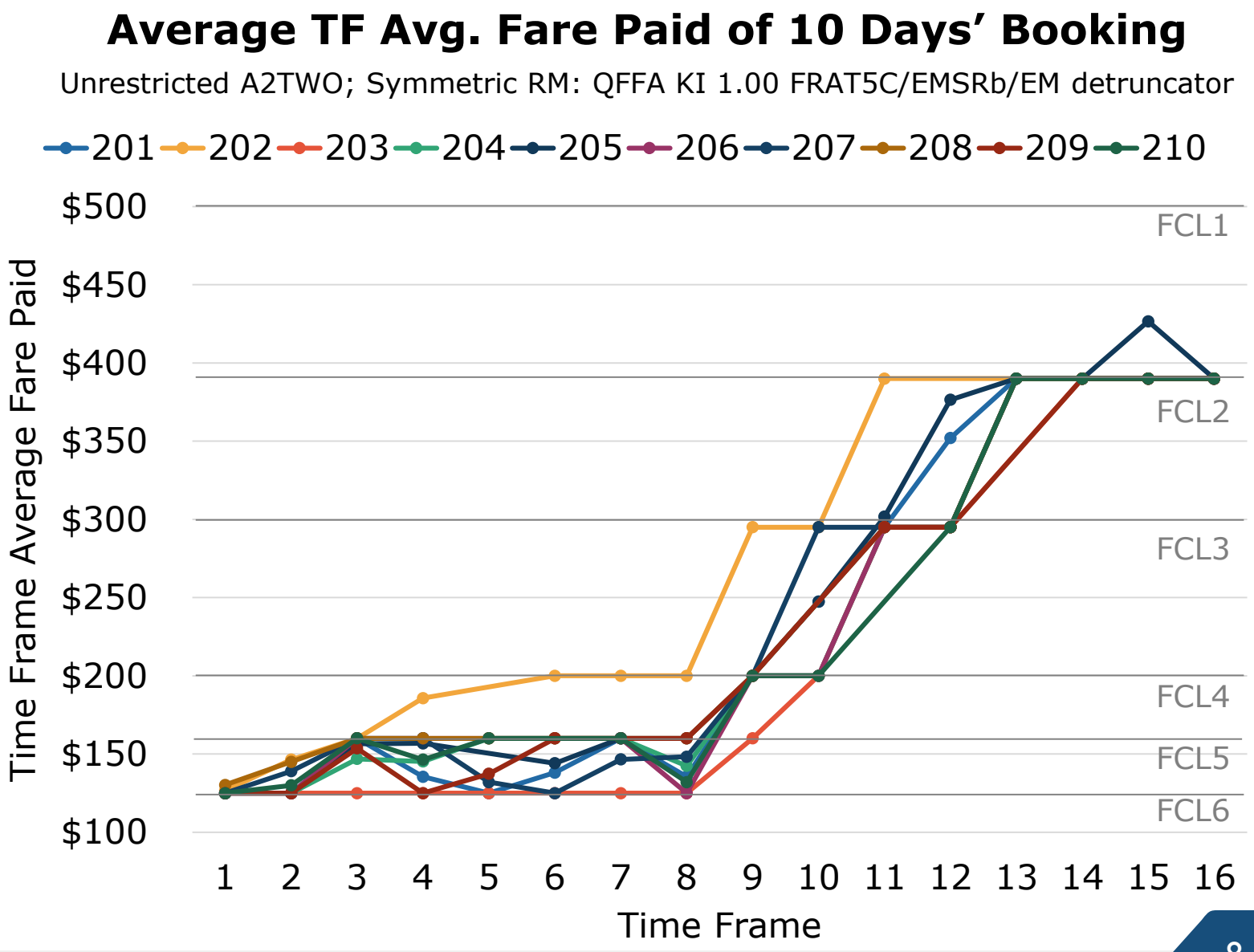
AL1 Policy π^1: $\{Y, B, M\}$:	Y	B	M	~~Q~~	~~E~~

AL2 Policy π^2: $\{Y, B\}$:	Y	B	~~M~~	~~Q~~	~~E~~

- Our analysis shows the cause of Q-forecasts' biases is the partition step rather than the conversion step
  - Q-forecast partition Q-equivalent demand by the input sell-up rate, regardless of actual policy offered. As a result, it partitions Q-equivalent demand/forecast to higher fare classes that often see no bookings

Demand Fluctuation and Policy Variation Across Departures Also Undermines Q-Forecast's Accuracy

- Q-forecast assumes a **pre-determined** and **static** sell-up rate, regardless of policy variations and demand fluctuations
- In real-world, average fare paid and the inferred price elasticity can differ significantly by day
- In our simulation, the average fare paid can differ by $100 in the first 10 days into the simulation
- Even if the estimates are accurate, lack of conditionality undermines Q-forecast's disaggregate-level accuracy



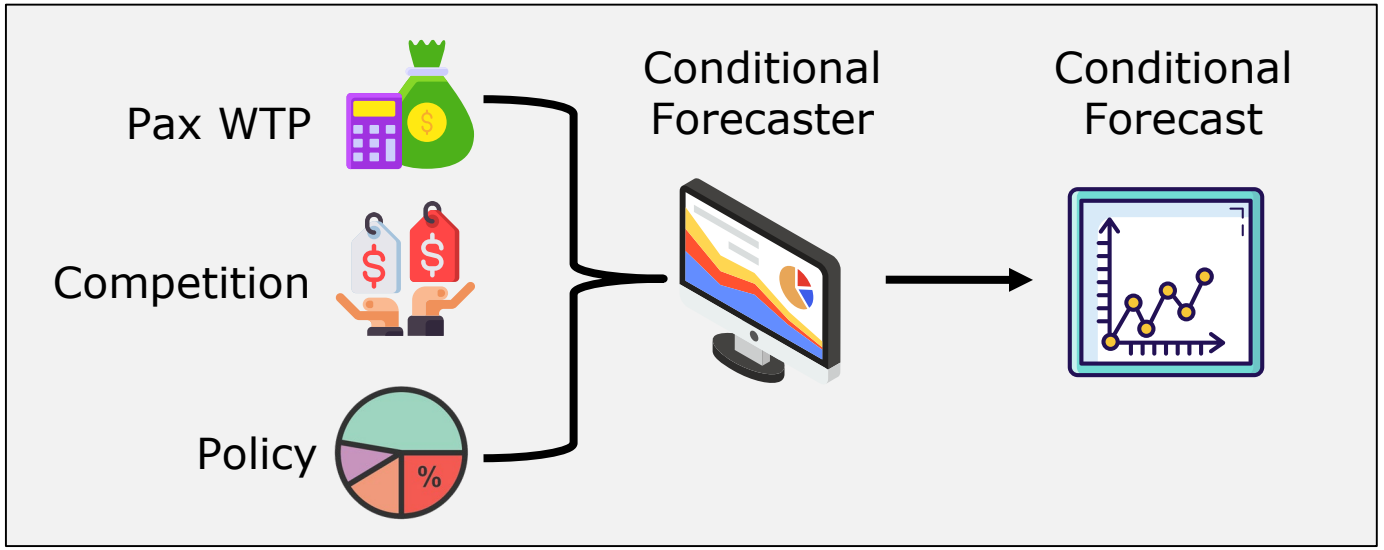
Conditional Forecast Can Help Improve the Weaknesses of Q-Forecast

- We can see that the weaknesses of Q-forecasts lie in its lack of conditionality:

Assuming sell-up independent of daily demand variabilities

Ignoring policies (sell-up/competition)

- In the following slides, I will explain the philosophy of conditional forecast, and how it can take additional but necessary information into account
  - I will also show a some preliminary results from my proof-of-concept experiment, which shows promising accuracy improvements over Q-forecast

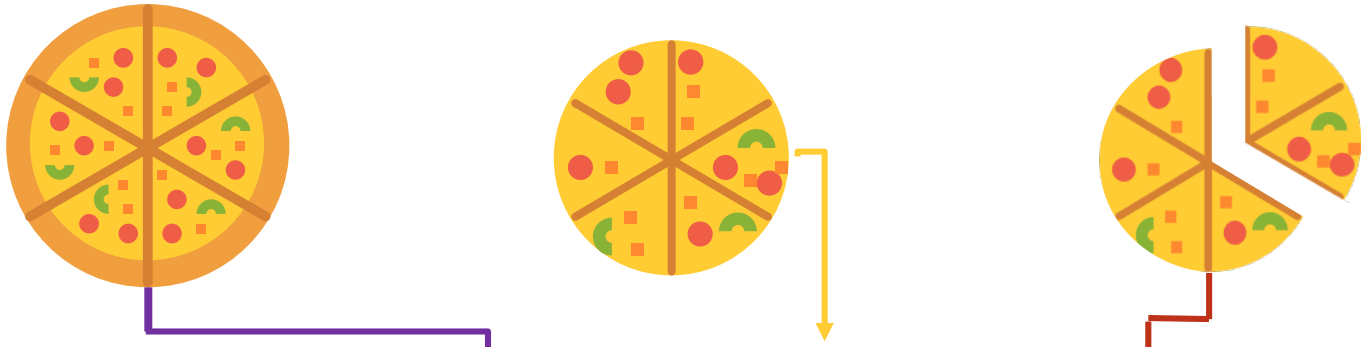


Conditional Forecasts in Unrestricted Environments: Dividing the Pizza

Entire pizza
=
Total market demand

"Tasty" pizza
=
Total affording pax

"Our" pizza
=
Pax book with "us" in a FCL



$$C\text{-FCAST}_A(FCL) = \sum_t \widehat{\lambda_t} \cdot e^{-\frac{\ln(0.5)*(f-f_Q)}{(\widehat{F5X}-1)*f_Q}} \cdot \gamma_{MS|\widehat{\pi^*}} \cdot L_{\min(\widehat{\pi^*})=FCL}$$

(equation adapted from Thomas et al. (2018))

- $\widehat{\lambda_t}$: forecast volume/total passenger
- $\widehat{F_{5_X}}$: maximum WTP estimate (exponential)
- γ: estimates of fare class market share, given policy estimations
- $\widehat{\pi^*}$: a usual/actual observed BK policy, which can be revised in-line like forecast
- $L_{\min(\widehat{\pi^*})=FCL}$: a indicator of percent time that a fare class is the lowest open FCL

Defining Conditional Sell-up Rate *(psup)* in Unrestricted Environment

- Define airline A's conditional sell-up rate to fare f as: *

$$\begin{aligned} c\text{-}psup_{A,f} &= \mathbf{P}(p \text{ choose A and pay } f) \\ &= \mathbf{P}(p \text{ afford } f) \cdot \mathbf{P}(p \text{ paid } f \mid p \text{ afford } f) \cdot \mathbf{P}(p \text{ choose } A \mid p \text{ paid } f \cap \text{ afford } f) \end{aligned}$$

  - $\mathbf{P}(p \text{ afford } f)$ captures the budget constraints of the passengers
  - $\mathbf{P}(p \text{ paid } f \mid p \text{ afford } f)$ captures the influences from other available fare classes
  - $\mathbf{P}(p \text{ choose } A \mid p \text{ paid } f \cap \text{ afford } f)$ captures the demand shared with competitors
- In <u>fully unrestricted fare structures,</u> passengers only buy the lowest available fare f_L in the market (including from competitors)

$$\mathbf{P}(p \text{ paid } f \mid p \text{ afford } f) = \begin{cases} 1, & if\ f = f_L \\ 0, & if\ f \neq f_L \end{cases}$$

- That is to say, in fully unrestricted environments

$$c\text{-}psup_{A,f} = \begin{cases} \mathbf{P}(p \text{ afford } f_L) \cdot (Market\ Share \mid \{\pi^1, \dots, \pi^n\}), & for\ f = f_L \\ 0, & for\ f \neq f_L \end{cases}$$

*The equation above assumes independence between terms, and there are arguments both ways

Convergence Between Sell-up Rate Estimation and Forecast in Unrestricted Fare Structure

- In an unrestricted fare structure and a given time interval t with a constant lowest fare f_L, Airline A has a conditional forecast of

$$c\text{-}forecast_{A,FCL,t} = \begin{cases} \text{TOT DEM}_t \cdot \mathbf{P}(p \text{ afford } f_L) \cdot (MS_A | \{\pi^1, \dots, \pi^n\}), & for\ f = f_L \\ 0, & for\ f \neq f_L \end{cases}$$

- Remember on the last slide, we derived

$$c\text{-}psup_{A,f,t} = \begin{cases} \mathbf{P}(p \text{ afford } f_L) \cdot (MS_A | \{\pi^1, \dots, \pi^n\}), & for\ f = f_L \\ 0, & for\ f \neq f_L \end{cases}$$

- Therefore, we can say that in an unrestricted fare structure

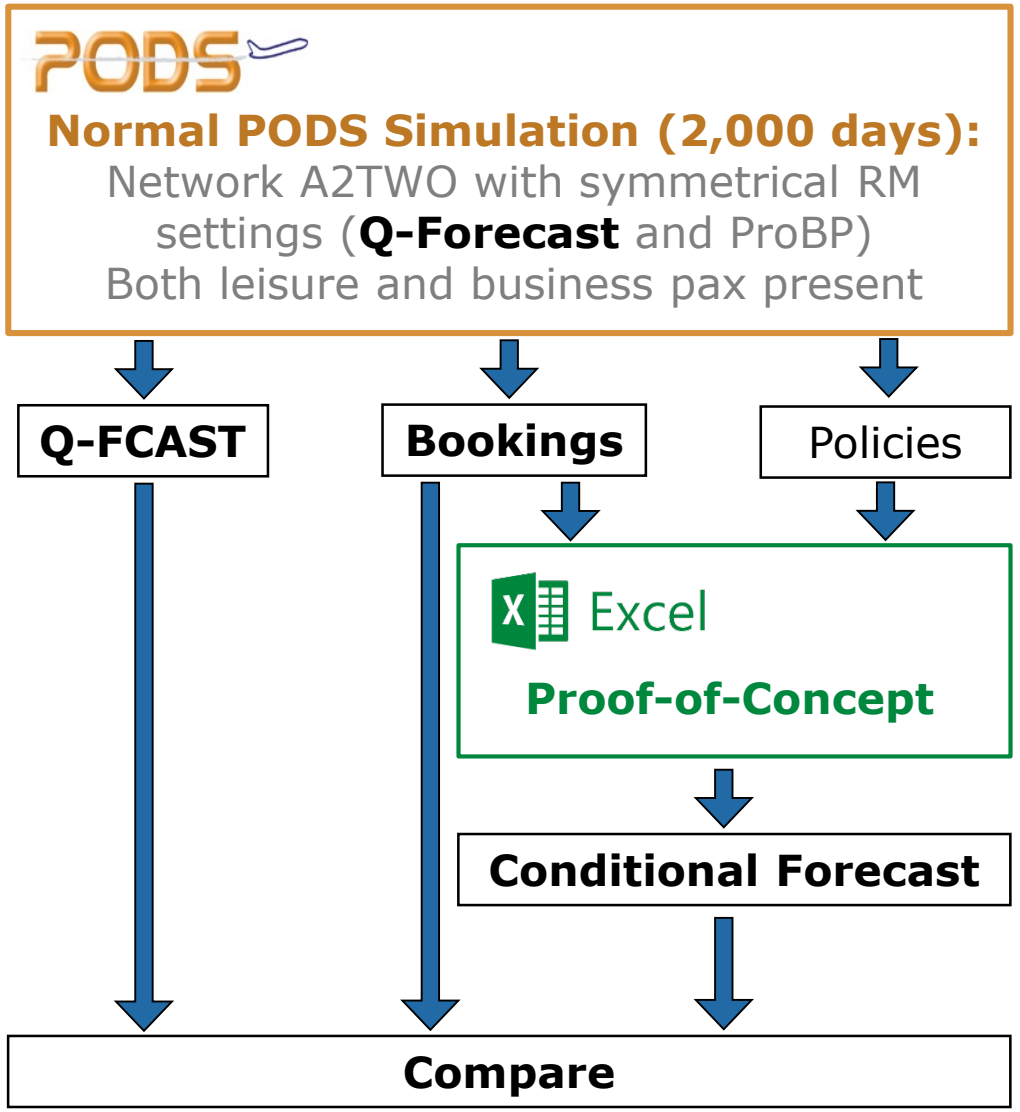
$$c\text{-}forecast_{A,f,t} = c\text{-}psup_{A,f,t} \cdot \text{Total Demand}_t$$

or

$$c\text{-}psup_{A,f,t} = \frac{c\text{-}forecast_{A,f,t}}{\text{Total Demand}_t}$$

- As demonstrated, generating conditional forecasts would not only be a necessary step but also a nice by-product of estimating sell-up in unrestricted fare structures

Proof-of-concept Set-up and Assumptions



- In this early-stage proof-of-concept, I made assumptions to test this conditional forecast concept

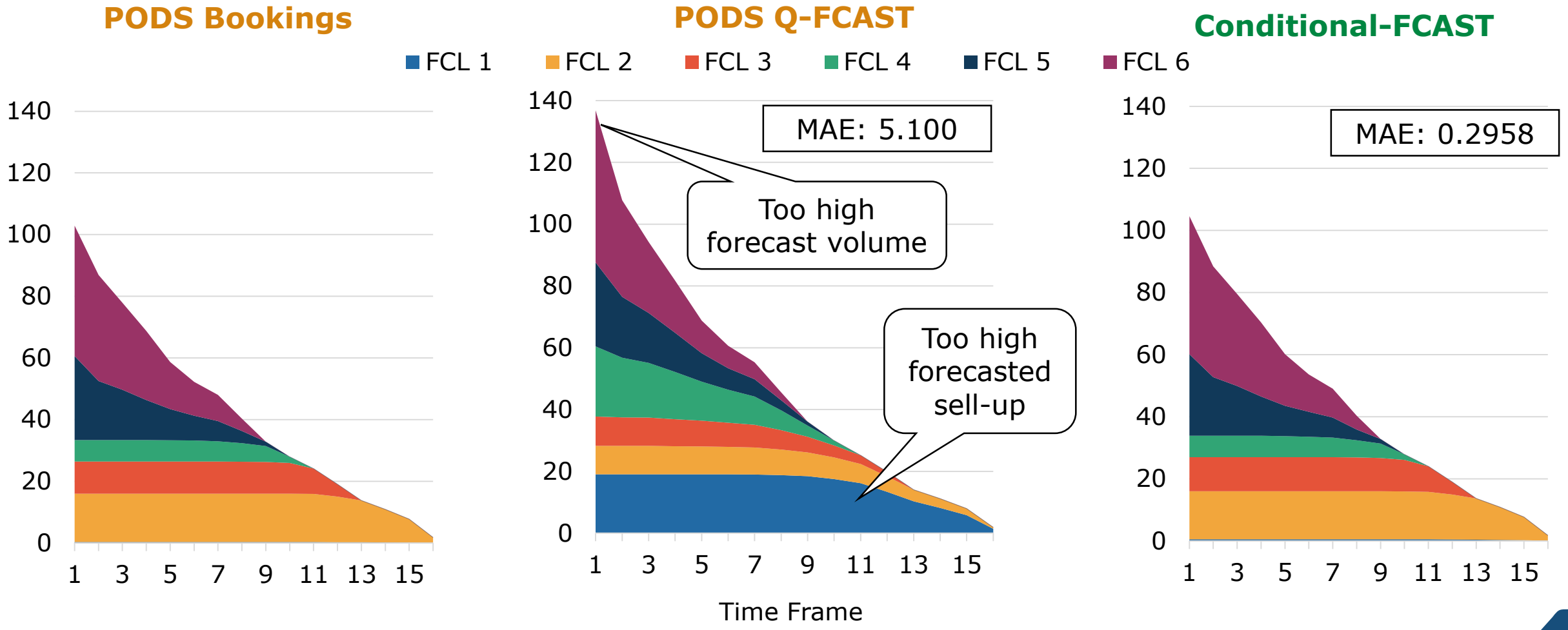
- Assumptions
  - The conditional forecaster has not been implemented and did not influence the results: conditional forecasts are calculated using *ex-post* information on past bookings and policies simulated with Q-forecast with a revenue-maximizing sell-up estimate curve (FRAT5C).
  - I used the *ex-post* knowledge of true WTP distributions of pax booked
  - A tiny and highly symmetric network A2TWO was used

Proof-of-concept Result: Conditional Forecast Shows Significant Accuracy Improvements

AL1's PODS Q-FCAST and Bookings, and Excel Proof-of Concept C-FCAST

(in Bookings/demand-to-Come Format)

Unrestricted A2TWO; Symmetric RM: QFFA KI 1.00 FRAT5C/ProBP/EM detruncator



Summary and Future Works

Summary of Findings

Identified weaknesses of Q-Forecast algorithm

- Conditionality
- Ignore demand fluctuations

Introduced the philosophy of conditional forecast

Demand + Budget + Policy + Competition → **Accuracy**

On-going Works

- Benefits of segmentation (C-FCAST)
  Weakness of lacking seg. (Q-FCAST)
- Policy statistics and prediction
- Demand level estimation
- Integration to RM

Future Works

Technical Problems

- Finalizing algorithms
- Simulation integration

Revenue realization

Business Problems

- Data availability and accuracy
- Computing resources
- Customization

Thank you!

Questions?

lutim@mit.edu

References

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