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AIRLINES' ENTRY DECISIONS UNDER SCHEDULE OPERATIONAL CONSTRAINTS

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INTRODUCTION

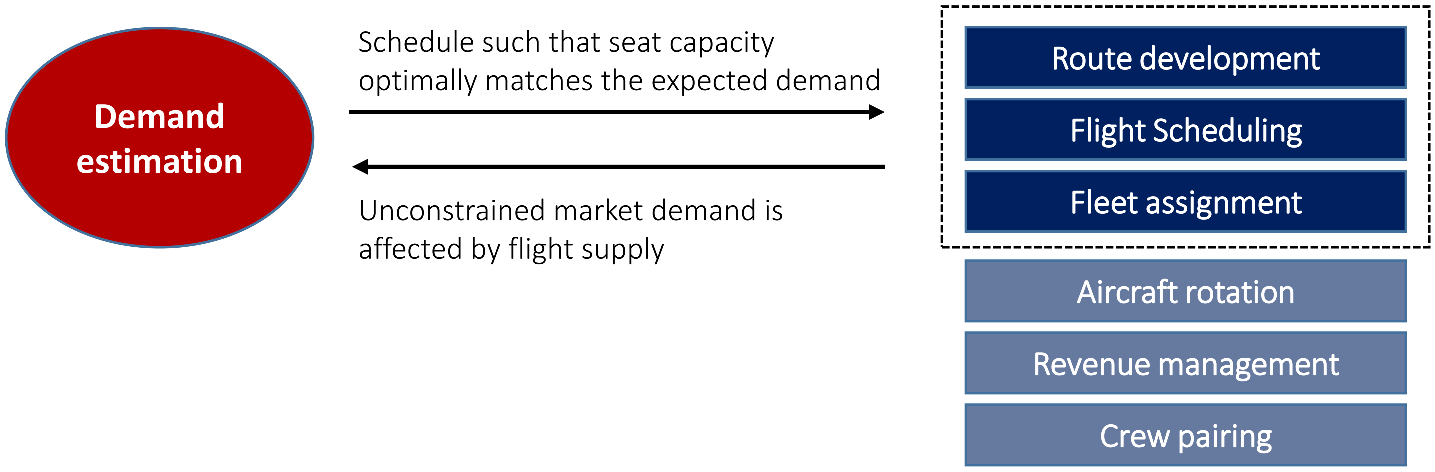
OBJECTIVE

The purpose of the papar is to develop an integrated fleet assignment and schedule planning model which directly accounts for air trip generation over city pairs as a tool to assist airlines' entry and/or re-fleeting decisions.

RATIONALE FOR THE STUDY

> the **interdependency between demand and supply** is a crucial element of airline schedule planning which is not fully taken into account by sequential airline planning schemes

> Schedule evaluation models used for demand estimation provided by private company (e.g. Sabre)



LITERATURE

- Scholars have been developing integrated models that simultaneously optimize the process of selecting flight legs to include in the schedule and assigning aircraft types to these legs.
- Common approaches involve the estimation of **unconstrained demand** in each market and differ in the estimation of passenger flow redistribution across available alternatives:
  - Models based on a **Spill and recapture** process (*Lohatepanont & Barnhart, 2004; Pita et al., 2012; Pita et al., 2014; Sherali et al., 2010, 2013*)
  - Models based on a **Discrete choice modelling** process (*Dong et al., 2016*)

- We contribute to the current literature in a twofold way:
  - **Demand estimation:** by explicitly assessing the impact of itinerary's connectivity and service level on additional demand generation.
  - **Airline planning**: we propose a new methodology to tackle the demand/supply interaction within schedule optimization models leveraging on the estimated impact of newly operated connections.

METODOLOGY

Demand estimation

Development of a **gravity model** (Grosche et al. (2007), Shen (2004), Hwang and Shiao (2011), Srinidhi (2009)) to explore the determinants of air travel demand over city-pairs

Modal split

Definition of a modal split rule to allocate passenger flows over itineraries.

Flight scheduling and fleet assignment

Development of a **Mixed Integer Linear Problem (MILP)** for the integrated flight scheduling and fleet assignment model, where potential demand for each market is estimated simultaneously within the model

DEMAND ESTIMATION: MODEL FORMULATION

- In order to estimate air passenger volume between *city-pairs*, we use the following **gravity model** formulation:

$$D_m = \frac{Pop_o Pop_d}{e^{I_m}} \quad (1)$$

- Which can be linearized through logarithms and estimated by OLS regression:

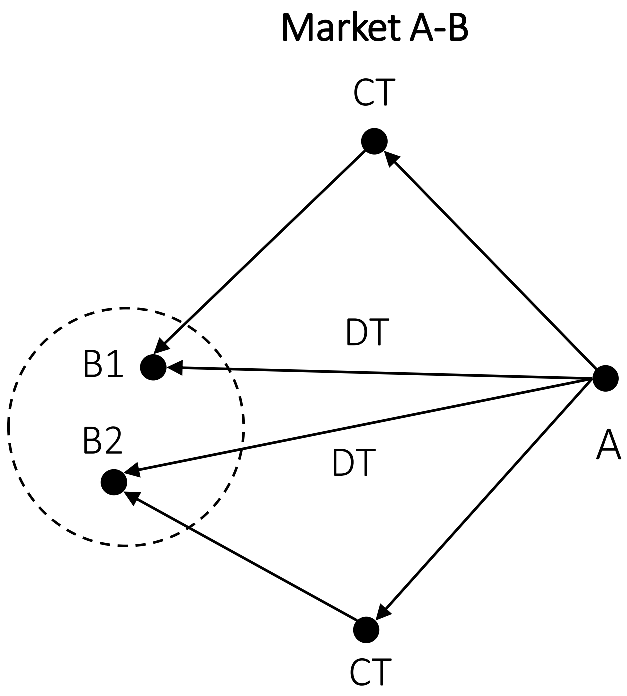
$$ln(D_m) = \beta_{const} + \beta_{Pop_o} ln(Pop_o) + \beta_{Pop_d} ln(Pop_d) + I_m + \varepsilon_m, \quad (2)$$

  - Pop_o: Population at origin
  - Pop_d: Population at destination
  - I_m: Impedance measure (I_m) as function of **distance** and **frequency** (Doganis, 2004) broken down by itinerary type *c*:

$$I_m = \beta_{dist} dist + \sum_{c \in itinerary\_type} \beta_c n_c \quad (3)$$

DEMAND ESTIMATION: CLUSTER ANALYSIS

- To capture the difference contribution to demand generation from itineraries with different characteristics, we perform a clustering analysis by **K-means** algorithm on two features:
  - the **routing factor (RF):** Total Flight Time (TFT) / Direct Flight Time (DT)
  - the **connectivity index (CI)**: Connecting Time (CT) / total travel time (TT)



Itinerary type		Routing factor	Connectivity index
Cluster 0	Nonstop flights	1	0
Cluster 1	Low RF – Low CI	1.50 (*0.22*)	0.33 (*0.07*)
Cluster 2	High RF – Low CI	2.38 (*0.30*)	0.32 (*0.08*)
Cluster 3	Low RF – High CI	1.50 (*0.58*)	0.58 (*0.07*)
Cluster 4	Low RF – High CI	2.28 (*0.30*)	0.57 (*0.07*)

DEMAND ESTIMATION: DESCRIPTIVE STATISTICS

- Data source: OAG, *SEDAC, Columbia University*
- EU top 100 airports by passenger traffic: 290,780 direct flights, 3,326,316 indirect flights
- Indirect itineraries: 1 hour ≤ CT ≤ 6 hours

Variables at market (city-pair) level		**Descriptive Statistics**			
		Mean	*Std. Dev.*	*Min*	*Max*
D	Average passenger flow (daily)	256.78	431.76	0.03	4,275
Pop(o)	Population at origin (within 20 km)	125,880	156,738	578	748,708
Pop(d)	Population at destination (within 20 km)	135,129	164,257	731	748,708
n_itineraries (0)	Average number of direct itineraries (daily)	3.06	4.68	0.03	52.57
n_itineraries (1)	Average number of indirect itineraries (daily) belonging to different clusters	10.72	13.01	0.00	158.00
n_itineraries (2)		5.01	7.98	0.00	76.53
n_itineraries (3)		12.73	17.40	0.00	224.60
n_itineraries(4)		6.92	14.53	0.00	254.63
Distance	Average distance	1,698	633	156	5,230

DEMAND ESTIMATION: MODEL RESULTS

- Coefficients have the expected sign and are statistically significant, except for type-4 itineraries
- Consistently, itineraries with lower routing factor and connectivity index have a greater impact on demand stimulation
- The non-significance of type 4 itineraries' coefficient denotes how low attractive connections (high RF – high CI) do not influence demand
- Distance has a negative impact on passenger flows, although its coefficient is fairly low (intra-EU flights)

Parameters	*Estimate*	*Std.dev*	
ln(Pop_o)	0.0896	(0.0142)	***
ln(Pop_d)	0.0834	(0.0152)	***
n_itineraries (0)	0.1450	(0.0039)	***
n_itineraries (1)	0.0150	(0.0022)	***
n_itineraries (2)	0.0067	(0.0033)	**
n_itineraries (3)	0.0044	(0.0016)	***
n_itineraries (4)	7.54e-04	(0.0018)	
distance	-5.03e-05	(2.70e-05)	*
constant	2.370	(0.2580)	***

Observations	2,962
R-squared	0.563

MODAL SPLIT: ESTIMATION OF ITINERARY DEMAND (1/2)

> Let α be the weighted current provision of air transport services in market m

$$\alpha = \sum_{c \in itinerary\_type} \hat{\beta}_c \bar{n}_c \tag{4}$$

> Let γ represent the following constant for market m:

$$\gamma = e^{\hat{\beta}_{const}} \overline{Pop_d}^{\hat{\beta}_{Pop_d}} \overline{Pop_d}^{\hat{\beta}_{Pop_d}} e^{\hat{\beta}_{dist} dist} \tag{5}$$

> The expected market demand following the introduction of $n_c, c \in itinerary\_types$ new itineraries in market m can be written as follows:

$$\hat{D}' = \gamma e^{\alpha + \sum_{c \in itinerary\_type} \hat{\beta}_c n_c} \tag{6}$$

ASS1: Itineraries with same characteristics get the same market share

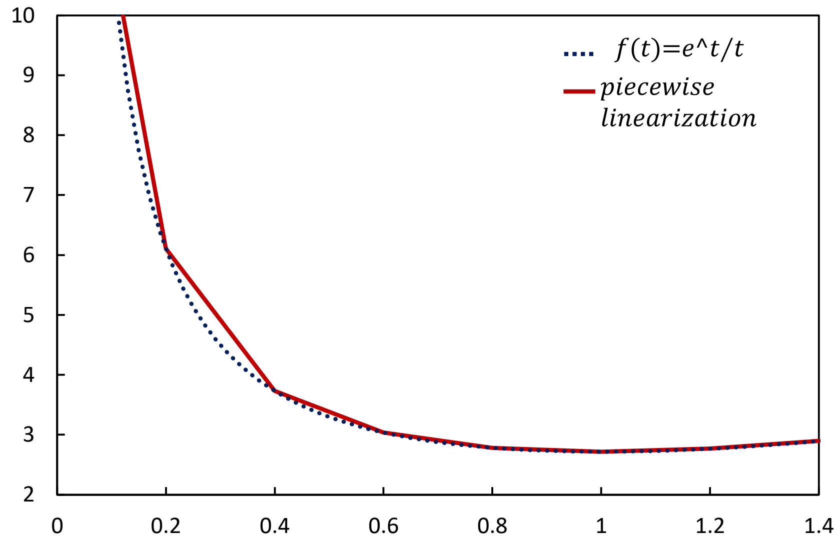
ASS2: Potential demand on itinerary-type c is proportional to estimated beta coefficients from previous regression

MODAL SPLIT: ESTIMATION OF ITINERARY DEMAND (2/2)

- Holding the assumptions true and setting $t = \alpha + \sum_{c \in itinerary\_type} \hat{\beta}_c n_c$ the demand for each itinerary type c in market can be estimated as follows:

$$d'_c = \gamma \frac{e^t}{t} \beta_c \qquad (7)$$

- Which is a univariate function that can be directly entered into our MILP by means of **piecewise linearization**.



OPTIMIZATION MODEL: NOTATION

SETS

$N = set\ of\ activity\ nodes, indexed\ by\ n$

$M = set\ of\ markets, indexed\ by\ m$

$I = set\ of\ itineraries, indexed\ by\ i$

$F = set\ of\ flight\ arcs, indexed\ by\ f$

$F^m \subset F = set\ of\ mandatory\ flight\ arcs$

$F^o \subset F = set\ of\ optional\ flight\ arcs$

$G = set\ of\ ground\ arcs, indexed\ by\ g$

$CL_f = set\ of\ flight\ arcs\ crossing\ the\ count\ line$

$CL_g = set\ of\ ground\ arcs\ crossing\ the\ count\ line$

$AT = set\ of\ fleet\ types$

$F_n^{in} = set\ of\ flight\ arcs\ arriving\ at\ activity\ node\ n$

$F_n^{out} = set\ of\ flight\ arcs\ departing\ from\ activity\ node\ n$

$G_n^{in} = set\ of\ ground\ arcs\ arriving\ at\ activity\ node\ n$

$G_n^{out} = set\ of\ ground\ arcs\ departing\ from\ activity\ node\ n$

$I_m = set\ of\ itineraries\ in\ market\ m$

$F_i = set\ of\ flight\ arcs\ in\ itinerary\ i$

$I_f = set\ of\ itineraries\ featuring\ flight\ arc\ f$

PARAMETERS

$fleet_a = fleet\ size\ by\ aircraft\ type$

$cap_a = passenger\ capacity\ by\ aircraft\ type$

$N_i = number\ of\ flight\ legs\ in\ itinerary\ i$

$\beta_i = beta\ coefficient\ for\ itinerary\ i$

$\alpha_m = current\ weighted\ air\ service\ provision\ in\ market\ m$

$\gamma_m = market\ m's\ constant$

$c_f^{pax} = variable\ cost\ per\ pax\ (landing\ fees, etc)$

$c_f^{fix} = fixed\ cost\ (airport\ fees, etc)$

$c_a^{op} = flight\ costs\ per\ hour\ of\ flight\ for\ an\ aircraft\ of\ type\ a$

$ftime_f = flight\ time\ for\ flight\ arc\ f$

$fare_i = price\ of\ itinerary\ i$

VARIABLES

$x_{a,f} \in 0,1$	$= 1\ aircraft\ type\ a\ is\ assigned\ to\ flight\ arc\ f$ $= 0\ aircraft\ type\ a\ is\ not\ assigned\ to\ flight\ arc\ f$
$y_{a,f} \in N^+$	$the\ flow\ value\ of\ aircraft\ type\ a\ though\ ground\ arc\ g$
$k_i \in 0,1$	$= 1\ itinerary\ i\ is\ operated$ $= 0\ itinerary\ i\ is\ not\ operated$
$t_m \in R^+$	$the\ weighted\ air\ service\ provision\ in\ market\ m$
$d_m \in R^+$	$f(t_m) for\ market\ m\ such\ that\ d_m \gamma_m \beta_i\ gives\ expected\ demand\ for\ itinerary\ i\ in\ market\ m$
$q_i \in N^+$	$the\ flow\ of\ passengers\ accommodated\ on\ itinerary\ i$

OPTIMIZATION MODEL: MODEL FORMULATION

Max

$$\sum_{i\in I} q_i\, fare_i - \sum_{a\in AT}\sum_{f\in F} x_{a,f}\, c_f^{pax} - \sum_{f\in F} c_f^{pax} \sum_{i\in I_f} q_i - \sum_{a\in AT} c_a^{op} \sum_{f\in F} x_{a,f}\, ftime_f$$

Subject to:

(1) Flow balance

$$\sum_{f\in F_n^{in}} x_{a,f} + \sum_{g\in G_n^{in}} y_{a,g} = \sum_{f\in F_n^{out}} x_{a,f} + \sum_{G\in G_n^{out}} y_{a,g}\,, \qquad \forall\, n\in N, \forall\, a \in AT$$

(2) Schedule repeatability

$$\sum_{n\in SL}\sum_{f\in F_n^{out}} x_{a,f} + \sum_{n\in SL}\sum_{g\in G_n^{out}} y_{a,g} = fleet_a, \qquad \forall\, a\in AT$$

(3) Fleet availability

$$\sum_{f\in CL_f} x_{a,f} + \sum_{g\in CL_g} y_{a,g} \le fleet_a, \qquad \forall\, a\in AT$$

(4)-(5) Mandatory/ optional flight legs

$$\sum_{a\in AT} x_{a,f} = 1, \qquad \forall\, f\in F^o$$

$$\sum_{a\in AT} x_{a,f} \le 1, \qquad \forall\, f\in F^m$$

6)-(7) Itinerary status constraints

$$k_i - \sum_{a\in AT} x_{a,f} \le 0, \qquad \forall\, f\in F_i,\ \forall\, i\in I$$

$$k_i - \sum_{a\in AT}\sum_{f\in FA_i} x_{a,f} \ge 1 - N_i, \quad \forall\, i\in I$$

(8)-(9) market demand

$$t_m = \alpha_m + \sum_{i\in I_m} \beta_i k_i, \quad \forall\, m\in M$$

$$d_m = \frac{e^{t_m}}{t_m}, \quad \forall\, m\in M$$

(10)-(11) passengers per itinerary

$$q_i \le \gamma_m d_m \beta_i, \quad \forall\, i\in I$$

$$q_i \le M_{big} k_i, \quad \forall\, i\in I$$

(12) aircraft capacity

$$\sum_{i\in I_f} q_i \le \sum_{a\in AT} x_{a,f}\, cap_a\,, \quad \forall\, f\in F$$

CONCLUSIONS & FUTURE DEVELOPMENTS

- Computational complexity for large-scale problem due to the high number of binary variables
  - Develop *specialized algorithms* to solve larger instances or add additional elements to the model formulation
  - Adopt an *iterative process*
- Consider additional features to be included in the clustering process to better distinguish itinerary types (prices, timetable differentiation)
- Improve the gravity model formulation:
  - Include variables describing the general economic activity and geographical characteristics of city-pairs to better deal with city-pairs where poorly air service is currently established
  - Distinguish among Intercontinental flights and LCCs vs FSCs
  - Test for other functional forms and tackle causality issues

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