Federal Aviation
Administration

Terminal Area Forecast-Modernization (TAF-M) Methodology

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TABLE OF CONTENTS

1. INTRODUCTION

The Terminal Area Forecast (TAF) is the official FAA forecast of aviation activity for U.S. airports. It contains active airports in the National Plan of Integrated Airport Systems (NPIAS) including FAA-towered airports, federal contract-towered airports, nonfederal towered airports, and non-towered airports. The TAF is comprised of TAF-M (Modernization) and TAF-L (Legacy). In 2015, TAF-M covered the forecasts of enplanements and commercial operations for the 223 airports with more than 100,000 enplanements in FY2014. TAF-L covered the forecasts for all other airports. The TAF-M model represents an enhancement in comparison to TAF-L by generating enplanement and commercial operation forecasts at the segment level.

2. MODELING ORIGIN AND DESTINATION (O&D) PASSENGER DEMAND FLOW

The origin and destination model applied in TAF-M provides insight into the *flow* of passengers from origin point i to destination point j, instead of only considering passenger count at a *static* specific location, as in TAF-L. The accounting of passengers via the flow takes into explicit account the network and is particularly helpful when there are multiple airports serving a single metropolitan area at both origin and destination locations. The O&D passenger demand forecast at the airport-pair level involves two steps: coefficient estimation and forecast generation with a dynamic log-log approximation process.

2.1 COEFFICIENT ESTIMATION IN STATA

A passenger demand model is used to obtain coefficient estimates based on the historical airline data (2000:Q1 to 2014:Q4; or 60 quarters at present; this sample is rolling as new data are added and updated):

$$\log(Passenger_{i-j,t}) = \beta_0 + \beta_1 \log(Fare_{i-j,t}) + \beta_2 \log(Route_{i-j,t}) + \beta_3 \log(Distance_{i-j}) + \beta_4 \log(Income\ Origin_{it}) + \beta_5 \log(Income\ Dest_{jt}) + a_{i-j} + u_{i-j,t} \quad (1)$$

where i-j indexes airport-pair between origin i and destination j and t indexes quarter. a_{i-j} is the airport-pair heterogeneity for a given airport-pair i-j, which can be understood as the unobserved airport-pair effect. The airport-pair unobserved effect contains things such as the underlying business model, managerial ability, or the cost structure, things that are roughly constant over time during the sample periods. The error $u_{i-j,t}$ is the idiosyncratic error. It represents unobserved factors that change over time and affect $\log(Passenger_{i-j,t})$.

$\log(Passenger_{i-j,t})$ is the log of sum of the O&D passengers flying on airport-pair i-j at quarter t. O&D passenger refers to the passengers in airline O&D survey ticket data (or, 10% sample) flying from an origination airport i to a destination airport j. There can be intermediate stops between airport i and airport j. Passengers on either non-stop flights or multiple-stop flights are included.

$\log(Fare_{i-j,t})$ is the log of the average market fares paid by the O&D passengers flying on airport-pair i-j at quarter t. Average fare is reported in the ticket portion of the O&D or 10% sample data.

$\log(Route_{i-j,t})$ is the log of the total number of routes provided by the airlines flying on airport-pair i-j at quarter t. For example, there are various ways to fly from DCA to RDU, such as, in addition to direct, from DCA to CLT to RDU or from DCA to ATL to RDU. We count the number of unique routes for each directional market and add up all the unique combinations serving a given i-j airport-pair at quarter t.

$\log(Distance_{i-j})$ is the log of non-stop market miles for airport-pair i-j. It does not vary with time.

$\log(Income\ Origin_{it})$ is the total real personal income (millions 2000$) at the MSA level for the origination beginning point on airport-pair i-j at quarter t. Similarly, $\log(Income\ Dest_{jt})$ is the total real personal income (millions 2000$) of the MSA associated with the destination airport, j.

Starting in the fall of 2015, we estimated equation (1) with correlated random effects (CRE). In contrast, equation (1) was estimated with OLS without intercept in the past. CRE is an econometric technique designed for panel data sets. It combines features in RE (random effects) and FE (fixed effects), both of which are well known panel data models in econometrics. CRE unifies RE and FE in that the RE estimates of the time-varying covariates are the FE estimates given that the average across time for a given airport-pair is included.

In empirical panel data literature, FE is often chosen over RE as RE imposes a strict assumption of zero correlation between the heterogeneity and all the covariates, which is rarely true in the empirical data. On the contrary, such correlation is allowed to be non-zero under the FE framework. However, FE model has an unfortunate property that the time-invariant variables are removed during the estimation, which can be problematic if the variable of interest does not vary with time. Furthermore, among the time varying variables, those with very little time series variation will not be accurately estimated with the FE approach.

Consequently, CRE is chosen to preserve the coefficient on the variable that stays constant over time like $Distance_{i-j}$, and to improve the accuracy of the coefficients on the variables that have very little time series variation such as $Income\ Origin_{it}$ and $Income\ Dest_{jt}$. The FE estimates of (β_4, β_5) in equation (1) seem grossly inflated due to the lack of time series variation. Under the CRE framework, we use the RE estimates to calculate $(\beta_3, \beta_4, \beta_5)$, while the FE estimates are used for the rest of the variables.

In the previous years, equation (1) was estimated separately for each quarter to better capture the seasonal effect. For each quarter, the estimation was further divided into thick and thin markets. Thick markets refer to airport-pairs with quarterly O&D passengers greater than 500 in the 10% survey. Airport-pairs with 500 or less O&D passengers quarterly in the 10% survey are defined as thin markets. Consequently we used to run eight regressions to estimate equation (1): four regressions for thick markets (one regression for each quarter) and four regressions for thin markets.

Starting in October 2015, we eliminated the distinction between thick and thin markets and opted for weighted regression approach. This removes the somewhat arbitrary assumption on the definitions of thick and thin routes. It also reduces total number of regressions from eight to four, one for each quarter. While we believe that elasticities like air fare differ between large and small routes, it is unclear to us whether income elasticity should be different based on the traffic volume of the routes. Therefore, we decide to apply the same model to all various sized routes.

However, because smaller routes significantly outnumbers larger routes in our sample, a regression without weights and without separate grouping in the data will generate coefficients that are more representative of the results for the smaller routes. Weights, measured by average O&D passengers at the airport-pair level, are added to properly scale the estimators so that data from heavily traveled routes will receive more attention during the estimation process.

At the end, a weighted CRE approach was used to estimate equation (1). The corresponding Stata code is *xtreg, pa corr(exchangeable) vce(robust)* with a frequency weight (*[fw=]*) option. The standard CRE estimation is done in Stata using *xtreg* with the *re* option, which implements the panel data random-effects model. However, *xtreg* with *re* option does not have the option to add weights. The population averaged panel data regression (*xtreg* with the *pa* option) with the correlation of u_{it} and u_{is} set to a constant is asymptotically equivalent to the random-effects estimator, and it allows the frequency weight option. Lastly, the option *vce(robust)* is added to calculate cluster robust standard errors.

2.2 DYNAMIC LOG-LOG APPROXIMATION IN SQL

It is well known that the first-order derivative of the dependent variable with respect to covariates in (1) represents elasticity, or percentage change in dependent variable with respect to changes in independent variables. Thus, a dynamic equation, developed from log-log approximation may be used to forecast future O&D passengers as follows:

$$Passenger_{i-j,t+1}$$
$$= Passenger_{i-j,t}$$
$$* \left(1 + \hat{\beta}_1 \left(\frac{Fare_{i-j,t+1}}{Fare_{i-j,t}} - 1\right) + \hat{\beta}_2 \left(\frac{Route_{i-j,t+1}}{Route_{i-j,t}} - 1\right)\right.$$
$$+ \hat{\beta}_3 \left(\frac{Distance_{i-j,t+1}}{Distance_{i-j,t}} - 1\right) + \hat{\beta}_4 \left(\frac{Income\ Origin_{i,t+1}}{Income\ Origin_{i,t}} - 1\right)$$
$$\left.+ \hat{\beta}_5 \left(\frac{Income\ Dest_{j,t+1}}{Income\ Dest_{j,t}} - 1\right)\right) \quad (2)$$

All variables in (2) are in their original form rather than the logarithm form. Equation (2) can be derived from (1) through the following transformation (i.e., a Cobb-Douglas type transformation). The transformation is demonstrated with only one covariate, x_{it}, on the right hand side:

$$\log y_{it} = \alpha + \beta \log x_{it} + a_i + u_{it}$$

$$\rightarrow \frac{d \log y_{it}}{d y_{it}} * dy_{it} = \beta \frac{d \log x_{it}}{d x_{it}} * dx_{it} + \frac{da_i}{da_i} * da_i + \frac{du_{it}}{du_{it}} * du_{it}$$

$$\rightarrow \frac{1}{y_{it}} * dy_{it} = \beta \frac{1}{x_{it}} * dx_{it} + da_i + du_{it}$$

$$\rightarrow \frac{\Delta y_{it}}{y_{it}} = \beta \frac{\Delta x_{it}}{x_{it}} + \Delta a_i + \Delta u_{it}$$

$$\rightarrow \frac{y_{i,t+1} - y_{it}}{y_{it}} = \beta \left(\frac{x_{i,t+1}}{x_{it}} - 1\right) + (u_{i,t+1} - u_{it})\ given\ that\ \Delta a_i = 0$$

$$\rightarrow y_{i,t+1} - y_{it} = y_{it} * \left[\beta \left(\frac{x_{i,t+1}}{x_{it}} - 1\right) + u_{i,t+1} - u_{it}\right]$$

$$\rightarrow y_{i,t+1} = y_{it} \left[1 + \beta \left(\frac{x_{i,t+1}}{x_{it}} - 1\right) + u_{i,t+1} - u_{it}\right]$$

$$\rightarrow \hat{y}_{i,t+1} = y_{it} \left[1 + \hat{\beta} \left(\frac{x_{i,t+1}}{x_{it}} - 1\right)\right]\ assuming\ E(u_{it}|x_i) = 0$$

Because we do not have forecast values on the time-varying covariates in equation (2) other than $Income\ Origin_{it}$ and $Income\ Dest_{jt}$, $\left(\frac{Fare_{i-j,t+1}}{Fare_{i-j,t}} - 1\right) = 0$ and $\left(\frac{Route_{i-j,t+1}}{Route_{i-j,t}} - 1\right) = 0$ for all t in the forecast years given that $Fare_{i-j,t} = Fare_{i-j,t+1}$ and $Route_{i-j,t} = Route_{i-j,t+1}$ for all t in the future. Additionally, $\left(\frac{Distance_{i-j,t+1}}{Distance_{i-j,t}} - 1\right) = 0$ in the forecast periods as well because distance at any given airport-pair i-j stays constant at all t.

Consequently, the effective dynamic equation used to forecast future passenger demand becomes:

$$Passenger_{i-j,t+1} = Passenger_{i-j,t} * \left(1 + \hat{\beta}_4 \left(\frac{Income\ Origin_{i,t+1}}{Income\ Origin_{i,t}} - 1\right) + \hat{\beta}_5 \left(\frac{Income\ Dest_{j,t+1}}{Income\ Dest_{j,t}} - 1\right)\right) \quad (3)$$

One can alternatively understand this as $Fare_{i-j,t}$ is held constant at the nominal level observed at the last period, i.e., the latest quarter for which information is available; while number of routes between i and j at quarter t,

$Route_{i-j,t}$, is constant at the last observed period as well. Constant fare and a fixed network at the observed quarter are features of the forecasting passengers. Notice, however, both $Fare_{i-j,t}$ and $Route_{i-j,t}$ will change as the $t=1$ changes to $t=2$, 3 and 4 as route pairs and fares are often season dependent.

Estimated coefficients that were used to generate 2015 TAF-M forecasts are given in Table 1. Quarter column represents four quarters for which data have been aggregated. The rest of the columns display fare, route frequencies, distance, origin income and destination income elasticities, respectively. All estimated coefficients are significant and have the right signs and magnitudes [see for example, Bhadra and Kee (2008); "Structure and Dynamics of the Core US Air Travel Markets: An Empirical Analysis of Domestic Passenger Demand", *Journal of Air Transport Management*, Vol. 14(2008), pp. 27-39].

Table 1: Weighted CRE Estimates of Parameters or Elasticities by Quarter

Quarter	Fare Elasticity	RouteFreq Elasticity	Distance Elasticity	OriginIncome Elasticity	DestIncome Elasticity
1	-0.682	0.541	-0.505	0.331	0.331
2	-0.748	0.542	-0.570	0.342	0.338
3	-0.794	0.537	-0.558	0.348	0.348
4	-0.755	0.519	-0.553	0.336	0.335

Based on equation (3), to generate passenger demand forecast for Q1 from 2015:Q1 through 2040:Q1 for a given airport-pair i-j, we start with generating 2015:Q1 forecast based on 2014:Q1 historical data:

$$Passenger_{i-j,2015:Q1}$$
$$= Passenger_{i-j,2014:Q1}$$
$$* \left(1 + \hat{\beta}_4 \left(\frac{Income\ Origin_{i,2015:Q1}}{Income\ Origin_{i,2014:Q1}} - 1\right) + \hat{\beta}_5 \left(\frac{Income\ Dest_{j,2015:Q1}}{Income\ Dest_{j,2014:Q1}} - 1\right)\right)$$

where $\hat{\beta}_s$ are taken from Table 1. Percentage change in incomes, for origin and destination, can be calculated from the forecasts of incomes for MSAs from Global Insight.

Similarly, the 2016:Q1 forecast for a given airport-pair i-j can be generated based on the 2015:Q1 forecast:

$$Passenger_{i-j,2016:Q1}$$
$$= Passenger_{i-j,2015:Q1}$$
$$* \left(1 + \hat{\beta}_4 \left(\frac{Income\ Origin_{i,2016:Q1}}{Income\ Origin_{i,2015:Q1}} - 1\right) + \hat{\beta}_5 \left(\frac{Income\ Dest_{j,2016:Q1}}{Income\ Dest_{j,2015:Q1}} - 1\right)\right)$$

The iteration process continues until 2040:Q1 or any point for which forecasts of origin and destination incomes are available:

$$Passenger_{i-j,2040:Q1}$$
$$= Pass_{i-j,2039:Q1} * \left(1 + \hat{\beta}_4 \left(\frac{Income\ Origin_{i,2040:Q1}}{Income\ Origin_{i,2039:Q1}} - 1\right) + \hat{\beta}_5 \left(\frac{Income\ Dest_{j,2040:Q1}}{Income\ Dest_{j,2039:Q1}} - 1\right)\right)$$

The same process is repeated for Q2, Q3, and Q4 individually. $\hat{\beta}_4$ and $\hat{\beta}_5$ are estimates based on historical data from 2000 through 2014 or 60 quarters' of data, at present. The values of $\hat{\beta}_4$ and $\hat{\beta}_5$ that go into equation (3) vary depending on the quarter in question.

Once passengers in a given airport pair *i-j* have been estimated and forecasted, there are multiple itineraries that can take the passenger from origin point *i* to destination point *j*. With the growing number of connections, segments, and market routes, it is imperative to consider the route that the passengers take in determining the impact of the passenger demand for the entire NAS network.

In TAF-L, only the static point of a specific airport location was considered, and as such the NAS network impact was not observed or considered in the forecast. The modeling of passenger demand by origin and destination and assignment of route to the passenger demand are detailed in Section 3.

3. ASSIGNING O&D PASSENGERS TO ROUTES

3.1 PROCESS OVERVIEW

Assignment of passengers flow between *i-j* to various routes (i.e., *i-j; i-k-j; i-k-l-j,* etc.) within the NAS is necessary to obtain segment or route-level forecasts. This is accomplished using an assignment algorithm where the number of passengers (say, between *i* and *j*) is distributed across various routes (direct or *i-j*; or indirect possibilities such as *i-k-j* (2-coupon or segments); or *i-k-l-j* (3-coupon or segments), etc.) are based on the historical information available for the same quarter last year. This ensures that the entire network is taken into consideration during route assignment.

3.2 THE ASSIGNMENT PROCESS

3.2.1 ROUTING PASSENGERS IN A METROPOLITAN PAIR

The assignment process begins by selecting an origin and a destination metropolitan area (i.e., MSAs). Once the areas are finalized for the assignment, the next step is to determine the number of routes that have been flown between the two metropolitan areas in the same quarter of the last observed year. The number of routes will include both non-stop (*i-j*) and multi-stop routes (or indirect routes). Once the number of routes is identified, historical data is overlaid to determine the number of passengers flying each specific route.

The historical coupon data is pulled from the same quarter of the prior year to in order to minimize the impact of seasonality on route evolutions. Percent distribution of passengers by route is then applied to the passenger origin-destination demand forecast to arrive at the number of passengers expected to travel each specific route segment.

Take, for example, the case of 100 passengers that are projected to fly between Austin (in this case, origin *i*) and Chicago (in this case, destination *j*) MSAs. Our first task is to identify valid routes that were flown between the pairs at present (i.e., same quarter last year or the reference point). Notice that the option of multiple airports within a single MSA, Chicago with two airports ORD and MDW in this example, is treated as part of the observed "route" choice. Choice of airport in a multi-airport MSA is a research area that APO is presently exploring.

We allocate passengers among existing route segments according to the current percentage distribution for that O&D market. Thus, 25% is observed to fly direct between AUS and MDW; while 45% takes AUS-DFW to ORD; and the remaining 30% takes AUS-ATL-MDW.
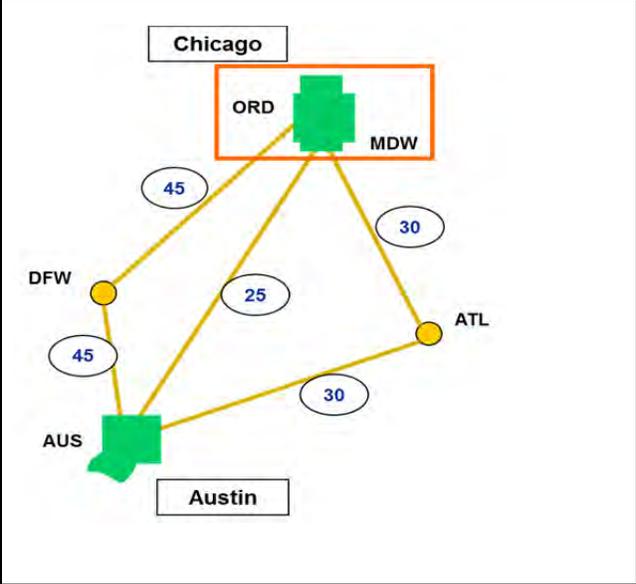

We currently do not attempt to predict new routes and keep these observed routes constant going forward. Evolution of new routes in the NAS is a research area that APO is exploring together with researchers in the community [for an application of route choice in limited context, see Bhadra and Hogan (2008): "Choice of Route Networks: A Qualitative Choice Model for Over-Land and Over-Water Routes", *Journal of Aircraft*, Vol. 45(1), January-February 2008, pp. 56-63].

3.2.2 EXPANSIONS TO NAS

The concept described above is then applied to an additional pair, say, for example, Austin to Minneapolis, of metropolitan markets to determine the passenger demand by route segment.

The assignment process continues until the entire NAS is mapped and passengers are distributed across all routes within the NAS. The assignment process is accomplished using SQL, as manual calculation is not feasible for the over 35,000 O&D market pairs, and numerous routes often exceeding hundreds of thousands, serving the primary O&D markets in the NAS.
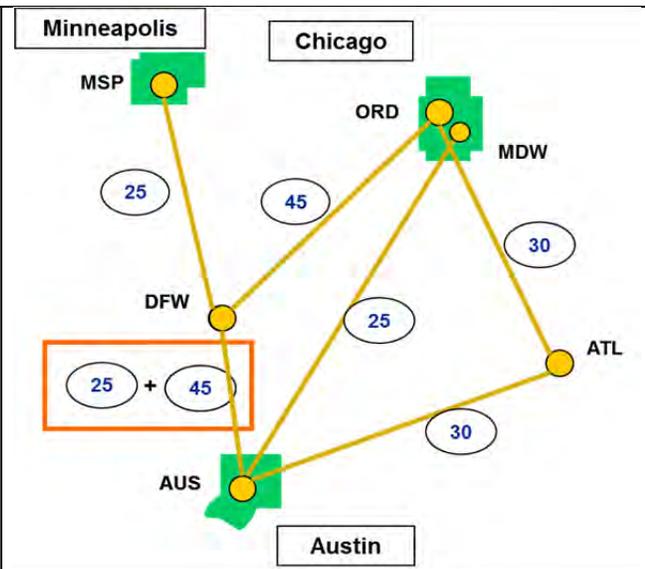
Upon completing this process for all MSAs and associated routes, we compare and adjust routed passengers with T100 segment passengers (Form 41), a database where commercial airlines report all passengers that flew routed segments. The database also provides invaluable information regarding types of aircraft that were used to fly these passengers in the segments. This information is mined and used to allocate and project aircraft departures in the routed segment which we describe in the following section.

9

4. DETERMINING AIRCRAFT DEPARTURES AND OPERATIONS

After determining the distribution of passengers across various routes within the NAS, it is important to determine the type of aircraft that is flown on each specific route, as it will help determine the number of departures (and operations) on the specific route.

4.1 PROCESS OVERVIEW

Generally speaking, determining number of aircraft departures on a specific route segment requires the information of the following variables. They include, but are not limited to:

- Number of passengers in segments
- Performance limits of A/C
- Distance between segments
- Operating costs per mile
- Type of airport in both ends of the segments

Notice that from the section described above, we have information about number of routed passengers, both history and forecast, distance, and types of airport (i.e., large, medium and small hub in the NAS). Performance limits of aircraft are determined by the types of aircraft while operating costs vary by types of aircraft and airlines and available from Form 41. At present, there are over 90 distinct aircraft types in the system. Because modeling over 90 distinct types of aircraft is complex and computationally infeasible, the types are aggregated to reduce these complexities. This narrows down the number of distinct aircraft types to be used for modeling to a manageable level. Examples of the aircraft type groupings that can be used include seat type, number of engines, aircraft range, and other definitions of missions. At present, we use classification according to seats as specified by AEE and is defined in Table 2.

Table 2: Seat Class Definition

| Aircraft ID Class	Aircraft Seat Class	Min Seats	Max Seats
1	0	0	0
2	19	1	19
3	1	20	50
4	2	51	100
5	3	101	150
6	4	151	210
7	5	211	300
8	6	301	400
9	7	401	500
10	8	501	600
11	9	601	650
12	999	651	999999999

Groupings other than seats have been tried and tested in the past as well [see, for example, Bhadra (2005); "Choice of Aircraft Fleets in the US Domestic Scheduled Air Transportation System: Findings from a Multinomial Logit Analysis", *Journal of the Transportation Research Forum*, Vol. 44(3), Fall, 2005, pp. 143-162].

4.2 SHORT-RUN ASSIGNMENT OF AIRCRAFT TO ROUTES

Oftentimes, airlines' choice of aircraft fleet, particularly in the short run of 4-5 years, is somewhat rigid. This is so because once the airlines have aircraft in their fleet inventory and/or orders are firm, the choices to fly them are fixed due to both network and financial commitment. Of course, there are some limited flexibility that may still be available to airlines through arrangement with other airlines and/or leasing companies, but generally speaking, inventory and firm orders in the book generally guide airlines' choice of routes and markets. Given that, we assume that aircraft serving the segments of the NAS within the first 5 years (or 20 quarters) of the forecast is same as they have been observed in the past. In other words, aircraft that have flown a particular segment will continue to do so in the first 5 years (or 20 quarters) of the forecast and there will be no change. We assign the same aircraft as observed in the last year of the same quarter on a particular segment and continue for 20 quarters. Beyond that, aircraft choice can be modeled as described next.

4.3 LONG-RUN ASSIGNMENT: APPLYING THE ECONOMETRIC MODEL

The multinomial choice model [described in Bhadra (2005) in detail] is applied to the aircraft choices to arrive at departure forecasts for the years following the first five years of the forecast. Without going into technical detail, figure below illustrates the process of forecasting aircraft operations. Using routed passengers, performance limits, distance and types of airports, number of departures between two segment pairs are determined. The result of applying multinomial choice model is the number of aircraft that can be flown on a particular route or segment based on the passenger demand is described in below.

| Types of aircraft departures associated with segments result from the multinomial choice models where aircraft types are aggregated according to number of seats. Once that assignment is complete, we now can determine number of departures between two segments, for example, LAX to ORD where four aircraft (with 51-100 seats) are required. Similarly, two aircraft (with 21-50 seats) are needed to fly non-stop between ORD to DCA. This process continues until all segments have been exhausted.	

Since performance limits, distance and types of airports do not change over time, therefore, numbers of departure are driven primarily by routed passengers and seasons (i.e., different quarters). These counts, multiplied by 2, provide us the number of operations accounting for both landings (i.e., arrivals) and take-offs (i.e., departures).

5. SUMMARY OF TAF-M PROCESS IN THE DOMESTIC NAS

The TAF-M process, as described above, can be summarized in the diagram on the right side of the panel: first, we estimate and forecast O&D passenger demand between airport-pairs, *i-j* and seasonality (i.e., quarters 1 through 4) across samples (at present, 2000-2014); second, using those forecasts and combining them with observed routes, we determine segment or routed passenger flows by airport pairs.

Finally, using those routed passengers and combining them with performance limits of types of aircraft, distance and types of airports, we estimate and forecast departures and operations by types of aircraft for the years beyond year five into the forecast. For short-run, we assign the observed aircraft into the routes.
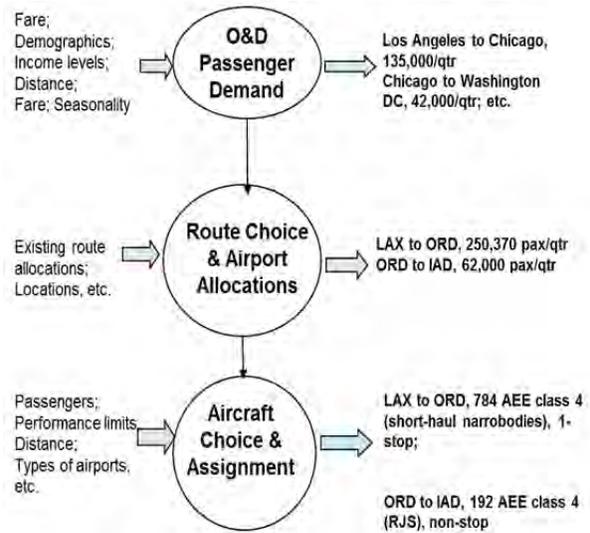
This network and aircraft-integrated process is carried through all segments of the commercial service airports within the United States in order to forecast passengers and departures. When these segments are aggregated at the level of origin airports, they produce passenger and operation activities at the airport, equivalent to TAF-L from before. Aggregation of segments at the destination level airports may provide landing activities but that is not presently done. This is what is known as Terminal Area Forecast-Modernized (TAF-M) version.

6. ADDITIONAL DETAILS

Once we have output from the TAF-M process described above, we process it for a few more steps before it can become ready for FAA's official terminal area forecast. In Section 6, we briefly describe these processes as they are stand-alone pieces for most part.

6.1 TREATMENT OF DOMESTIC CARGO

Within the domestic NAS, cargo departures account for approximately a little less than 5%. In some airports, for example, MEM (Memphis, TN) and SDF (Louisville, KY), their numbers are higher; but in many of the commercial airports, cargo operations are fairly large.

As the panel on the right shows that although MEM far surpassed, by a magnitude of 8 on average, annual cargo departures in other large airports are significant as well. Ranging somewhere between 1000-6500 annual departures, these airports facilitate air cargo transportation that has been growing quite substantially over the last two decades.

From TAF-M process, we can easily identify these departures. For departures that are associated with zero passengers are identified, by the DOT, as cargo departures. Based on the estimate and forecast of departures demand described above in TAF-M process above, we account for cargo departures for which associated passengers is zero.

Air Freight Departures at OEP 35 Airports in 2011
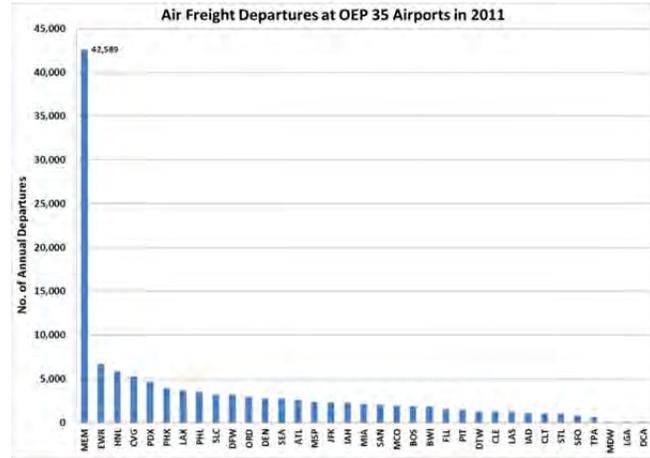
We report these departures, by both segment routes and aggregated at the airport, as cargo departures. Multiplying these departures by two yields cargo operations at a particular airport.

6.2 ESTIMATION AND FORECAST OF INTERNATIONAL PASSENGER AND CARGO

Originally developed by the MITRE Corporation, estimation and forecast of international passenger, departures and cargo departures are presently done outside the integrated TAF-M. In order to undertake this step, we first process T100International segment data by all carriers. At present, data covering the period of 2000-2014 are used. T100 international segment data provide the number of passengers and other details by flown segments.

Passengers in many international segments are relatively low. For this reason, we define thick segments or markets in international module as sum of passengers in the last 4 quarters >= 10,000. Thin segments/markets are defined as those that have passengers less than 10,000 as sum in the last 4 quarters. Like in case of domestic markets, there are many thin international segments. On average, thin international markets/segments number around 4.500 while thick markets/segments are around 2,000. While numbering over double the number of thick markets, thin markets account for less than 10% of total international passengers. Thick markets, on the other hand, carry over 90% of all international passengers. To put it differently, , thick segments accounting for only 1/3rd of total number of segments account for over 90% of passengers while 2/3rd of total segments are relatively thin and account for only 10% of passengers.

Segment passengers, both thick and thin, are modeled and forecasted using ESM procedure researched, tested and developed by the MITRE Corporation. Time series specification using Winters' method in SAS is the procedure by which international passengers are estimated and forecasted by segment pairs. Assuming segment load factors and average seat factors (i.e., fixed aircraft type) being fixed at the observed levels, departures are then calculated using passenger forecasts. Both passenger and departures, and operations, in turn, then added onto the main TAF-M databases.

6.3 REALLOCATION OF AIRCRAFT BY TYPES

It is evident from the aircraft orders, both delivered and those in order book, that the US, in particular and the world in general, is at a point of another evolution in aircraft fleet. Aircraft that were introduced in 1990s to facilitate the evolution and expansion of hub-and-spoke network are beginning to go out of circulation. Generally speaking, these are smaller jets and are of types of ERJ135, ERJ145 and CRJ100, CRJ200, etc. These are being gradually replaced by larger variants of ERJ170/190s, and CRJ700/900s.

One shortcoming of TAF-M is that it is not capable of predicting the evolution of new aircraft in the system. Both during the short-run (i.e., less than 5 years) and in the long-run, aircraft we assigned as per last observed in the segment as in the case of former or aircraft is assigned via estimation based on history data as in the case of the latter. In either cases, new aircraft that had never been observed before cannot be assigned during the forecast periods.

In order to bridge the gap between what aircraft has been assigned in the TAF-M and what is anticipated, we formulate algorithms that reflect these reallocations of aircraft. Aircraft that are assigned or modeled to be of smaller sizes (i.e., earlier generation) are to be replaced, irrespective of the types of segments in the NAS, by newer and larger aircraft (i.e., next generation). Thus, for example, an older version of ERJ145, typically with 50 seats, will be replaced by 0.71 of ERJ170 with a typical seat configuration of 70. This is explained in detail in Section 7.

Combined with the assumption of fixed (and observed) load factors in segments, this would result in recalculation of seats available in that segment. Recalculated seats combined with fixed load factor would result in reduced number of departures and operations. It will also lead to recalculation of passengers in the segment. We impose these reallocations on a macro basis. When macro algorithms are carried through taking into account types of aircraft and their substitutions, seats, departures, and passengers from TAF-M are recalculated and aggregated at the segment levels. These numbers are then put forward as the final output of the TAF-M. These recalculated numbers are what reported in the final TAF-M.

6.4 CALIBRATION TO SHORT-TERM PASSENGER AND OPERATIONS USING AIRLINE SCHEDULE

By the time TAF-M is put into use, typically in the beginning of the calendar year (i.e., 2016 for the present cycle), a year is already past (2015) from the time actual data were available (i.e., 2000-2014). Furthermore, a lot is already known, from airlines' schedule data, for about half of the year of 2016 in addition to the past year, 2015. In other words, by the time forecast data are finalized and ready for public use, a further need arises to calibrate it with what is known already (i.e, 2015-2016 first half).

Notice, however, with a lag of 2-3 quarters, primary data corresponding to TAF-M (i.e., O&D) are not readily available from the DOT and only partial information for the period known from T100 data which have a slightly faster publication (with one quarter lag). Therefore, we need to combine available T100 data with airline schedule data in order to update the first part of the forecast (i.e., 6 quarters). We account for this and calibrate the forecasts, for core 30 airports at present, by the available T100 and airline schedule data. Oftentimes, adjustments are minor but we make sure that trends in the forecasts correspond to what we observe from the newer data from T100 and available airline schedule.

6.5 CALIBRATION TO OPSNET DATA

Although the entire process is exercised using DOT data and the airline data that are available from schedule, we need to calibrate the final data by the FAA's official count. Known as OPSNET, this is the repository of the Agency's accounting of departures and take-offs as counted by the controllers and now more mechanically (known as CountOps).

In order to carry out these calibrations for departures, we take the latest observed numbers from CountOps and calculate the ratios that translate them onto TAF-M generated actual data for the corresponding periods. At that point, we also compare the rates of growth for departures between these two data sources. Once we have established these correspondences for departures at the airport levels for which CountOps are available, we allow the TAF-M generated growth rates (for the forecast periods) to drive the actual CountOps departure data into forecasts. In other words, CountOps generated actuals are driven by TAF-M generated departures growth rates during the forecast periods. Data related to passengers and other details remain unaltered.

6.6 TREATMENT OF EXCEPTION AIRPORTS

Once we generated these forecasts and compared them against the actuals and published forecasts from last year's TAF, we output these forecasts at the FAA's final forecasts for most airports. Some airports require additional

treatments and they can be categorized, at present, into two: (a) constrained airports; and (b) demand scenarios affected by additional forces or supply-induced demand.

It is evident from the discussion above that TAF-M and the additional steps that we outlined above represent demand for aviation activities that are unconstrained. In other words, no constraints in airports are taken into account. In reality, however, there are a couple of airports in the NAS, La Guardia (LGA) and Reagan National (DCA), which are restricted by slots. These may change in the future but at present, these are the only two airports for which slots are binding; i.e., slot restricts the unconstrained forecasts sometimes in the future. In order to take these slot restrictions and their impact on departures and, in turn, on the passengers, we further calibrate forecast data. Depending upon the time at which these slots restrict departures, we calibrate both departure mixes and passengers to arrive at the final forecasts for these two airports. LGA and DCA are the only two airports with (a) in place requiring some further calibration.   In TAF-M, demand is estimated and forecasted using the history data. History of activities at airports for which restrictions have been in place will necessarily undermine the actual potential. The case of Dallas Love (DAL) airport is a case in point. As the Wright Amendment expired in Oct, 2014, DAL experienced a surge of airlines scheduling new departures that have not been seen and/or supported by the past passenger flows. These are supply-induced demand that are, generally speaking, results of the removal of restrictions. Airlines scheduling new flights from DAL represent a mix of many factors: passenger traffic at DAL; competitive factors between DAL and DFW and airlines' anticipation of spill-overs from DFW and so on. Supply side factors, i.e., airport competition, tend to influence many of these decisions and resultant passenger traffic often far surpasses the historical trends. In order to account for these surges, particularly in the short run, we calibrate forecast output of DAL to reflect this new reality of (b).

6.7 SUMMARY OF TAF-M PROCESS IN THE DOMESTIC NAS AND BEYOND

The process map in the right hand panel thus concludes the entire forecasting process. In addition to the processes outlined and discussed in Sections 2, 3, and 4, now we add domestic cargo, international passengers, departures and cargo into TAF-M as add-ons onto main TAF-M database.

Two further calibrations are performed in the forecast data: first, by short-run airlines schedule and T100 data to account for the changes we observed (from T100) or sure to observe (from airline schedules) during the first 6 quarters; and second, by Agency's OPSNET or CountOps data. Finally, two algorithms, one taking into account effect of slot restrictions and the other taking into account supply-induced demand, are applied to LGA, DCA; and DAL respectively.
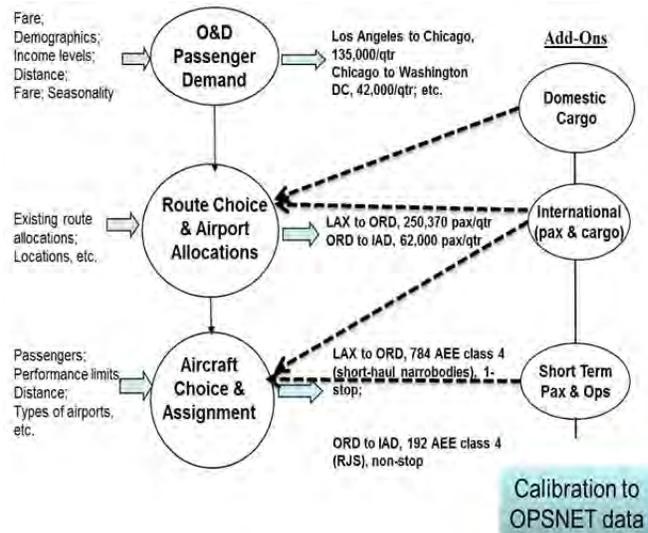
## 7. AIRCRAFT REALLOCATION ROUTINE IN TAF-M

This section describes the aircraft reallocation process, outlined in Section 6.3 (Reallocation of Aircraft by Type), in greater details. Section 7.1 explains the main concept that guides the reallocation process. Section 7.2 lays out the substitution rate calculation. Section 7.3 lists the aircrafts that are being replaced and the aircrafts that are replacing

with. Since the aircraft reallocation process is done at the airport level, Section 7.4 shows an example of the reallocation algorithms at the Lafayette Regional Airport. Section 7.5 completes the example.

7.1 ED GREENSLET'S AND FAA'S PROJECTIONS OF REGIONAL JETS (RJS)

The main idea of substitution of smaller RJs ($\leq$ 50 seats) comes from Ed Greenslet's, and subsequently, FAA's forecast of fleet. Ed's study titled "*Fleet Forecast – 2012 through 2033*" provides the basic foundation of what has been implemented in TAF-M. In Section 7, we will describe the steps that integrate Ed/FAA's analysis of RJs (i.e., stock of RJ aircraft and projections) into TAF-M (i.e., flow of departures by airports).

Ed's analysis of substitution of 50-seaters by 70&above (including 90-seaters) can be summarized in the following figure:
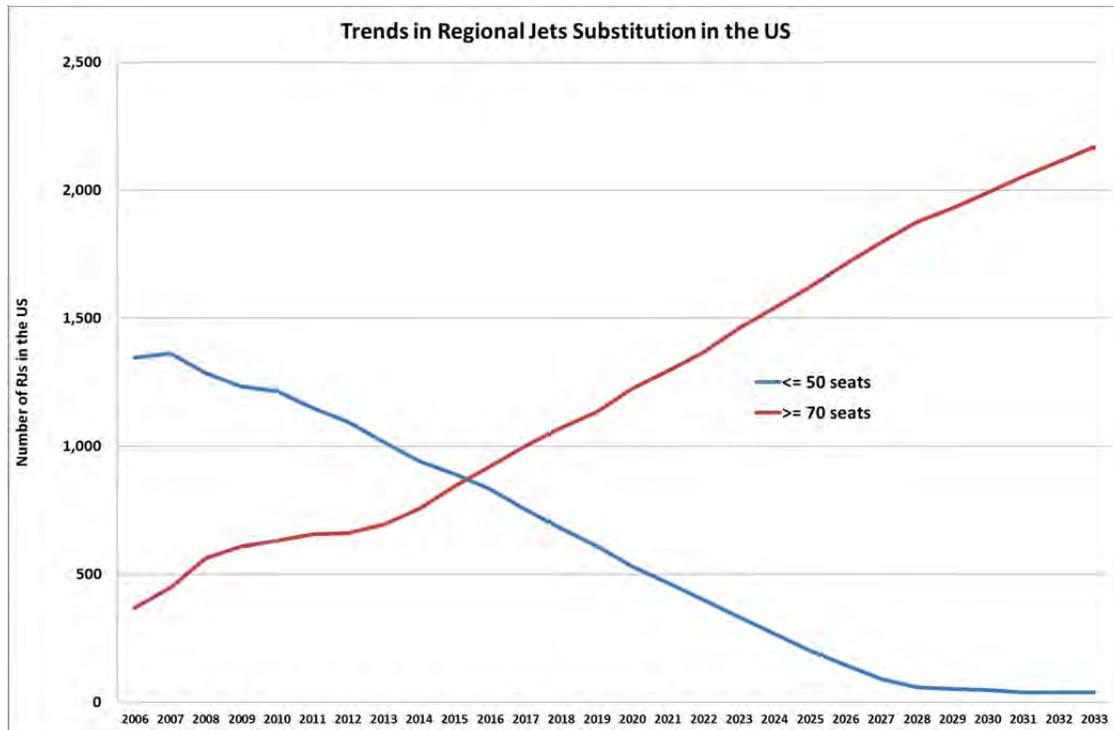
Notice that the stock of smaller RJs has been going down and accelerates this trend around 2014-2016. The substitution into larger RJs is almost completed by 2028-2029. Beyond that point, it is safe to assume that RJs with 70-seats and above are driven primarily by passengers.

7.2 FROM STOCKS OF RJS TO RATES OF SUBSTITUTION IN DEPARTURES

Assuming fixed value/s of rates of utilization (i.e., in terms of hours and number of departures within an hour), the above stocks of aircraft can be translated into flow of departures. This substitution is captured by the following parameterization (i.e., essentially assumption) within the TAF-M:

16

Substitution between Smaller and Larger RJs
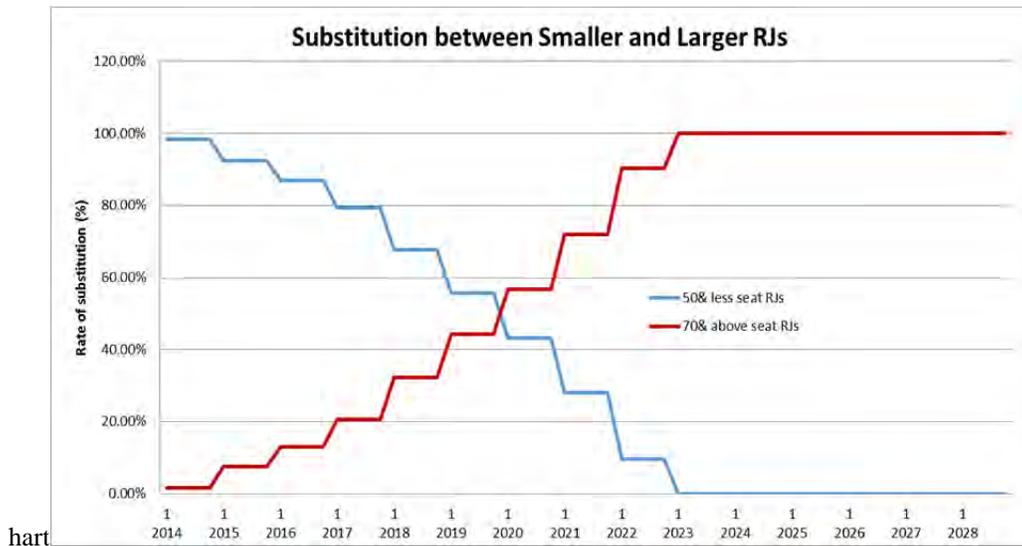
The above parameterization is an excel file that we control at the macro level in order to slow down the substitution or accelerate it given Ed's forecast and FAA's annual national updates. In the present run of TAF-M, the above parameterization is in place where substitution begins slowly in 2015 and completed by 2023. The steps signify quarterly rates which do not change within a particular year (horizontal axis); it changes only annually. By construction, this parameterization was to follow the overall trend of the first graph. Table 3 summarizes the parameterization.

Table 3: Parameterization Schedule

Forecast ID	Year	Percent of 70-seat and above RJs	Year	Percent of 70-seat and above RJs
111	2015	7.5%	2028	100%
111	2016	13.0%	2029	100%
111	2017	20.7%	2030	100%
111	2018	32.2%	2031	100%
111	2019	44.3%	2032	100%
111	2020	56.7%	2033	100%
111	2021	71.9%	2034	100%
111	2022	90.4%	2035	100%
111	2023	100%	2036	100%
111	2024	100%	2037	100%
111	2025	100%	2038	100%
111	2026	100%	2039	100%
111	2027	100%	2040	100%
111	2023	100%	2036	100%

7.3 REPLACEMENT OF SMALLER RJS BY NEWER, LARGER RJS

The replacement routine is applied to a specific group of RJs. At present, there are 7 types of RJs that are replaced by 4 larger counterparts (identified by DOT-specified 3-letter numeric). Table 4 lays out the guide for the RJ replacement.

Table 4: Aircraft Replacement List

		Replacement of A/C					Replaced with A/C				
					seats						seats
461,464 with 673	461	EMB-120 E	EMBRAER	EMBRAER	EMB-120	30	673	EMBRAER	EMBRAER	EMBRAER	ERJ-175	86
	461	EMB-120 E	EMBRAER	EMBRAER	EMB-120	30	673	EMBRAER	EMBRAER	EMBRAER	ERJ-175	86
	464	EMBRAER	EMBRAER	EMBRAER	EMB-110	30					
	464	EMBRAER	EMBRAER	EMBRAER	EMB-110	30					
674,675, 676 with 677	674	EMBRAER	EMBRAER	EMBRAER	EMB-135	37	677	EMBRAER	EMBRAER	EMBRAER	EMB-17	88
	674	EMBRAER	EMBRAER	EMBRAER	EMB-135	37	677	EMBRAER	EMBRAER	EMBRAER	EMB-17	88
	675	EMBRAER	EMBRAER	EMBRAER	EMB-145	50					
	675	EMBRAER	EMBRAER	EMBRAER	EMB-145	50					
	676	EMBRAER	EMBRAER	EMBRAER	EMB-140	44					
	676	EMBRAER	EMBRAER	EMBRAER	EMB-140	44					
629 with 631	629	RJ-200ER/	BOMBARD	CANADAII	CRJ-2/4	50	631	CANADAII	CANADAII	CANADAII	RJ-700	70
	629	RJ-200ER/	BOMBARD	CANADAII	CRJ-2/4	50	631	CANADAII	CANADAII	CANADAII	RJ-700	70
628 with 638	628	CANADAII	CANADAII	CANADAII	RJ100/ER	56	638	CANADAII	BOMBARD	CANADAII	CRJ-900	86
	628	CANADAII	CANADAII	CANADAII	RJ100/ER	56	638	CANADAII	BOMBARD	CANADAII	CRJ-900	86

First important thing to notice in Table 4 is that all smaller RJs, i.e., "replacement of A/C" are replaced larger RJs by using Ed's assumptions (i.e., "Replaced with A/C"). Notice also that although aircraft type 628 is above the 50-seat cut-off range, we decided to put it together with the 50-seat and lower as they too are expected to go out of service. The above (rate of) substitution along with the types of A/Cs are imposed at the level of airport (and not at segment level) and form the macro statement defining aircraft reallocation routine in TAF-M.

An important assumption for the reallocation process is that the passengers originating from any airport remain unchanged before and after the reallocation. If we further assume that load factor stays the same, the assumption implies that the capacity (available seats) remains the same. This is reasonable because the passenger growth driven by the market demand is already accounted for during the O&D passenger forecast stage (Section 1). Reallocation only changes the fleet mix so that the newly acquired 70 seat RJs, combined with the reduced fleet in the 50 seat RJs, can continue serving the same number of passengers.

7.4 AN EXAMPLE: THE CASE OF LAFAYETTE REGIONAL AIRPORT (LFT)

The example below, focusing on airport LFT in 2015:Q1, demonstrates in details the reallocation algorithm. Year 2015 is the first year during the forecast periods for Forecast ID 111, the most current forecast.

forecastid	year	quarter	origin	aircrafttype	Dep	Pax	Seat
111	2015	1	LFT	674	413.9	12,298.1	15,313.6

The table shows that departures performed is projected to be 413.9 operations for aircraft type 674 (Embraer 135), carrying 12,298.1 passengers with a total seat count of 15,313.6. In reality, the numbers should be integers. We keep the decimal points here to maintain a consistent level of precision.

7.5 INCORPORATING REALLOCATION

The reallocation routine proceeds in the following order: identification of the substitution rate, calculation of the remaining operations that will be performed by the smaller RJs, calculation of the additional operations that will be performed by the newer, larger RJs, and finally consolidating all records.

7.5.1. IDENTIFY THE SUBSTITUTION RATE

Based on Table 4, we learn that aircraft 674 at LFT will be replaced by 677. The rate of substitution is 7.5% in 2015 based on Table 3. We then conclude that only 92.5% of the 674 departures will be performed and the rest 7.5% will be replaced by 677.

7.5.2 CALCULATE THE REMAINING OPERATIONS THAT WILL BE PERFORMED BY THE 50-SEAT RJS

With the substitution rate of 7.5%, we can calculate how many departures, passengers, and seats will still be carried out by 674:

Remaining 674 departures
$= Original\ 674\ departures \times (1 - substitution\ rate)$
$= 413.9 \times (1 - 7.5\%)$
$= 382.8$

Remaining 674 passengers
$= Original\ 674\ passengers \times (1 - substitution\ rate)$
$= 12,298.1 \times (1 - 7.5\%)$
$= 11,375.7$

Remaining 674 seats
$= Original\ 674\ seats \times (1 - substitution\ rate)$
$= 15,313.6 \times (1 - 7.5\%)$
$= 14,165.1$

forecastid	year	quarter	origin	aircrafttype	Remainder_Dep	Remainder_Pax	Remainder_Seat
111	2015	1	LFT	674	382.8	11,375.7	14,165.1

7.5.3 CALCULATE THE ADDITIONAL OPERATIONS THAT WILL BE PERFORMED BY THE 70-SEAT RJS

Based on the assumption that the total passengers and seats remain constant before and after the aircraft reallocation, the addition of 677 passengers and seats should be equivalent to the reduction of 674 passengers and seats.

Addition of the 677 passengers
$= Reduction\ of\ the\ 674\ passengers$

$= 12{,}298.1 \times 7.5\%$

$= 922.4$

Addition of the 677 seats

$= Reduction\ of\ the\ 674\ seats$

$= 15{,}313.6 \times 7.5\%$

$= 1{,}148.5$

Addition of the 677 departures

$= Addition\ of\ the\ 677\ seats/maximum\ seat\ capacity\ of\ the\ 677\ aircraft\ (88\ seats)$

$= 1{,}148.5/88$

$= 13.1$

forecastid	year	quarter	origin	aircrafttype	Added_Dep	Added_Pax	Added_Seat
111	2015	1	LFT	677	13.1	922.4	1,148.5

7.5.4 CONSOLIDATE THE RECORDS

After consolidating the records between aircrafts 647 and 677, there are now two records for airport LFT at 2015:Q1

forecastid	year	quarter	origin	aircrafttype	Dep	Pax	Seat
111	2015	1	LFT	674	382.8	11,375.7	14,165.1
111	2015	1	LFT	677	13.1	922.4	1,148.5

Chances are there might been existing 677 operations for airport LFT in 2015:Q1. It is not the case in this particular example. However, if there were existing 677 operations, we would need to re-calculate 7.5.2 and 7.5.3 so that the final output table is grouped by year, quarter, origin, and aircraft type.

To compare the pre-reallocation with the post-reallocation numbers, the table below shows that the number of 674 operations in 2015:Q1 at LFT is 413.9 before reallocation and 382.8 afterwards. On the other hand, the number of 677 operations at LFT is 0 versus 13.1 after reallocation.

forecastid	year	quarter	origin	aircrafttype	Dep	Pax	Seat	Dep_recalc	Pax_recalc	Seat_recalc
111	2015	1	LFT	674	413.9	12,298.1	15,313.6	382.8	11,375.7	14,165.1
111	2015	1	LFT	677	0.0	0.0	0.0	13.1	922.4	1,148.5