PROS O&D

Forecaster

Technical Document

Revision History

Product VERSION	DATE	PERSON	REASON FOR CHANGE
1.0	12/12/05	Stacy Parker	Draft Product document
1.1	1/5/06	Stacy Parker	Update
1.2	1/26/06	Stacy Parker	Update
1.3	1/30/06	Stacy Parker	Update based on SCI feedback
1.4	7/7/06	Stacy Parker	Added Influences section

References

List all documents that are referenced

Forecaster SRD

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TABLE OF CONTENTS

1. Overview

The Forecaster is a major component of the O&D system, which predicts expected traffic on every itinerary that is feasible based on the most current schedule of an Airline. Three types of forecasts are produced: booking, cancellation, and show-up forecasts, all at the Fare Class level. The O&D system maintains forecasts for all departure dates open for sale in the reservation system.

The O&D booking and cancellation forecasts are derived from the booking and cancellation transactions observed in the PNR data. The leg show-up forecasts are derived from the final pre-departure data and the post-departure data in the inventory records. The Forecaster supports seasonality, holidays, sponsorship, and user influences.

2. Bayesian Forecast Engine Overview

The PROS O&D system uses a Hierarchical Bayesian Forecast Engine to generate forecasts. As the name suggests, the forecast engine uses a Bayesian technique and also incorporates hierarchical modeling where changes can occur at different levels of detail.

The Forecast Engine accounts for the dynamic nature of observations (where changes can occur at different levels of detail), models covariate effects (including automated seasonality), utilizes transformations, and groups the booking period into data collection points (DCPs). All of these components are modeled jointly; they are integrated into a single forecasting process. Within PROS, the Hierarchical Bayesian Forecast Engine is used for forecasting purposes across a wide range of applications.

The forecasting model begins by establishing an initial estimate, or opinion, of how much demand is likely. The preliminary estimate (assuming no history) is usually based on initialization parameters, and serves as a foundation on which to base the forecast. Then, as actual observations are recorded, the process updates the initial estimate and provides a new estimate. This new estimate is continually revised and updated as new observations are collected and recorded.

Hierarchical Bayesian forecasts have the benefit of learning and identifying new trends from multiple levels of information not used by other techniques. A gross booking or cancellation rate forecast will be based primarily on its own DCP history. As shown in Figure 1, the majority of the DCP 5 forecast for the 29JAN departure date of a given ODPF will be based on historical DCP 5 observations. To a lesser extent, the following information will also be included in determining the forecast (based on weighting, high to low):

- That departure date’s own previous DCP history
- Observations from other DCPs (note the recent observations shown along the guillotine edge as well as earlier DCPs for future departures)
- Observations from other classes

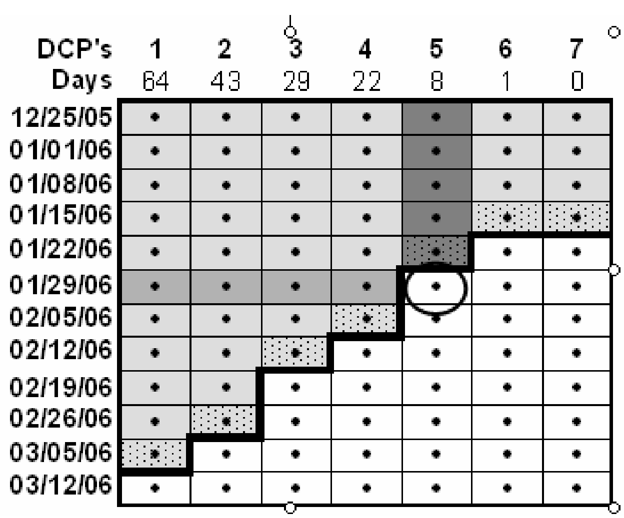


Figure 1

2.1 Gross Bookings & Cancellation Rate Forecasts

The PROS O&D system forecasts gross bookings and cancellation rates separately, rather than calculating "net bookings". This allows the system to treat the two demand patterns differently. Gross bookings are treated similarly to an additive effect (gross new bookings); while cancellations are treated similarly to a multiplicative effect (rates).

The observations for gross bookings and cancellation are obtained from the Data loaders which generate Booking and Cancellation transaction by comparing consecutive PNR images and applying several business rules.

Booking and cancellation rate models are based on the following dimensions:

- Online Origin (starting airport of the itinerary in the Airline revenue-controlled network)
- Online Destination (ending airport of the itinerary in the Airline revenue-controlled network)
- Trip Origin (starting airport of the itinerary, regardless of carrier)
- Trip Destination (ending airport of the itinerary, regardless of carrier)
- Path (routing)
- POS (point of sale)
- Day of Week
- Departure Time Window (time-of-day ranges)
- Travel Time Window (length of total journey in minutes)
- Passenger Type (group vs. individual)
- Fare Class

2.2 Data Collection Points

The PROS O&D system forecasts gross booking and cancellations for each DCP interval defined by two consecutive DCP.

The selection of Data Collection Points refers to a segmentation of the booking period into intervals depending on the number of days prior to the departure date. The underlying assumption regarding DCPs is that the arrival rate of bookings will remain constant throughout the DCP. The process of grouping different days prior with the same arrival rate together improves the forecast model as it increases the number of observations used for estimating the unknown parameters (e.g. the mean and variance).

At installation time, the Airline specifies a set of Data Collection Points (DCPs). These DCPs are expressed as days prior to departure and represent capture points on the booking cycle of a departure date. Data is aggregated between the capture points and sent to the forecaster models as one unit. The PROS O&D system produces forecasts of Bookings and Cancellation rates for each DCP interval. Every night, a subset of future departure dates reaches one of their DCPs. The observations are aggregated for these departure dates and are sent to the appropriate booking and cancel forecast models on that night. By forecasting at the DCP level, the PROS O&D system utilizes the most recent DCP information to identify new trends. Observations from all completed DCPs are included in the forecast, so history is not limited only to departed flights.

2.3 Seasonality

Seasonality is automatically calculated and dynamically updated with each observation. This design captures seasonality and constantly reevaluates it with new data points, enabling the system to apply specific up-to-date seasonality to a large number of low-level entities.

The PROS O&D Forecaster uses "filters" to fit specific seasonal curves. The purpose of seasonality filters is to find smooth functions of time that reflect slow changes in booking behavior. The system will detect seasonality in booking, cancellation and show-up data and incorporate it into the forecast models. The system will do this by fitting a sine curve seasonality model to the observed data (see Figure 2). The parameters of the seasonality model will be updated after each new observation is received, prior to incorporating the observation into the forecasting model.

Seasonality is modeled as a covariate in the PROS O&D system. Along with each observation, a covariate variable indicating the seasonality factor of the observation is passed into the Forecaster. When requesting the forecast, the seasonality covariates for future dates are factored in to produce the forecast outputs.

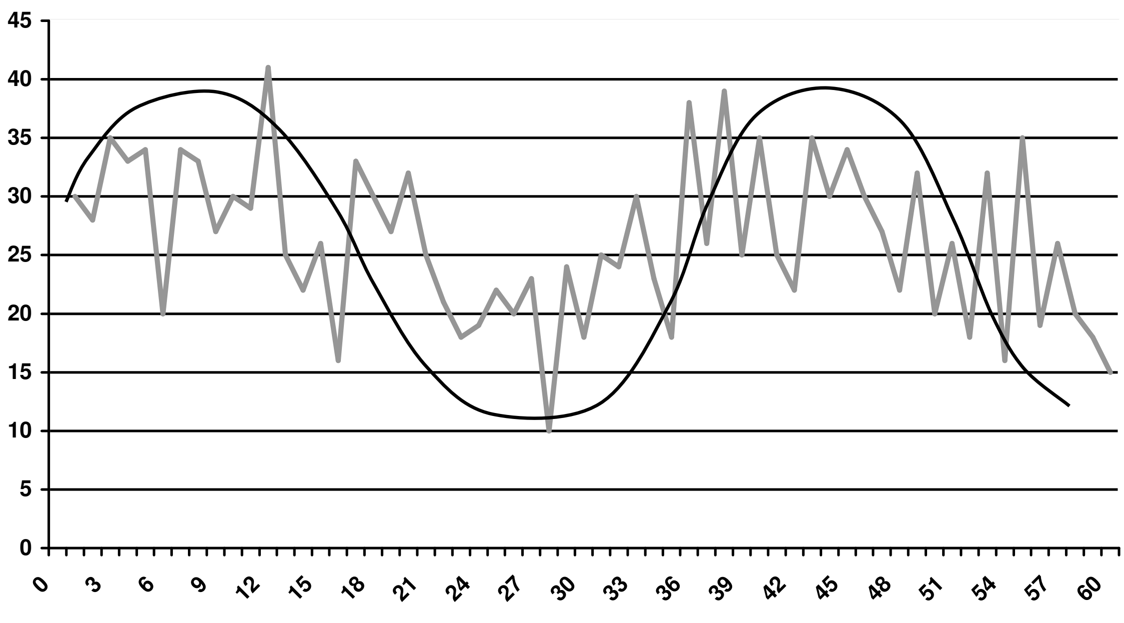


Figure 2

The seasonality covariate is implemented in the form of a sine wave. Given that the models are maintained at a Day of Week level, the covariate denotes seasonality associated with the week of the departure date. At installation time, the client specifies the frequency of the sine wave to be used for fitting to the seasonality curve.

A 52 week filter denotes that one seasonality cycle (one peak and one valley) is observed throughout the year. A 26-week filter indicates two seasonality cycles (two peaks and two valleys) during the year. Both filters can be used simultaneously, and may better fit the historical data. With new observations, parameters such as amplitude and the phase of the sine wave are updated at the individual model level based on a best fit of the observations for the model with the sine wave.

2.4 Unconstraining

If demand is impeded by closed availability, then observations must be unconstrained to account for the "true demand" given no booking constraints. Booking history will be unconstrained prior to being fed to the forecasting models. Unconstraining accounts for the effects of bookings that could not be accepted and therefore do not appear in the input data.

Booking history will be unconstrained at the ODPF/DCP level, based on the availability of the itineraries that contribute to that path. Bookings will be unconstrained each time a new observation for a DCP is complete. The system will use the fares and bid prices in effect at that time to do the unconstraining.

2.4.1 Determining Posted Probability at the ODPF level

Different itineraries contribute to each ODPF. For a given ODPF, some itineraries may be available for sale, while others are not. The customer choice algorithm assigns appropriate values to the various itineraries, resulting in a posted probability at the ODPF level.

If an ODPF has multiple ODIFs associated with it, a weighted average based on the customer choice algorithm is used to derive the probability that the ODFP was closed. In the following example, assume 2 itineraries contribute to the path LHR JFK MIA:

- LHR JFK MIA (earliest available connection to MIA in JFK)
- LHR JFK MIA (later connection to MIA in JFK)

ODIF	Posted Status	Travel Time	Customer Choice Weight
LHR JFK MIA (1st connection)	1 (closed)	9 hrs	0.8
LHR JFK MIA (2nd connection)	0 (open)	12 hrs	0.2
		posted probability	**0.8**

Figure 4

The first itinerary was posted (closed), so its weight, based on the customer choice algorithm, adds to the posted probability for the ODPF. However, the second itinerary was not closed, so it does not contribute to the posted probability of the ODPF. The resulting posted probability for the ODPF is 80%.

2.4.2 The Mixed Estimator model

Unconstraining starts with the latest forecast distribution [mean and variance], and incorporates two methods within the Mixed Estimator model. The Maximum Likelihood Estimator (MLE) is the most likely demand given that it was constrained. It is the maximum of either the constrained demand or the forecast mean. The MLE is more stable and conservative and works well for low demand cases.

The Logistic Estimator (LE) is the average demand given that it was constrained. It is the expected demand given that it was at least as big as the constrained demand, so it is always greater than or equal to both the constrained demand and the forecast mean. The LE works better for high demand cases

Unconstrained demand is the expected demand conditional on the demand being greater than or equal to the constrained demand. As a simple example, suppose that the forecast distribution was as follows:

Demand	Probability
0	0.25
1	0.25
2	0.25
3	0.25

Figure 3

Based on Figure 3, there is an equal probability associated with demand of 0, 1, 2, or 3. The average demand is (0+1+2+3)/4 = 1.5.

Suppose that the demand was constrained at 1.

The MLE would be 1.5 (the maximum of the average and the constrained demand).

The LE is the average given that the demand is at least 1, or (1+2+3)/3 = 2.

The MLE and LE are then weighted depending on the forecast mean to determine the unconstrained value.

2.5 Holidays & Special Events

PROS O&D forecasts holidays and special events separately. Holidays affect travel around the same time period every year. Special events take place at smaller location levels, such as cities, and the places and times for special events can change every year. A single special event record for a year can include multiple locations and times.

Holidays are modeled in the system as a multiplicative effect on the normal observation pattern for an ODPF/DCP. The holiday model functions in conjunction with the regular forecasting model. Incoming observations for the Holiday period are normalized before insertion into the "regular" forecast models. The estimate of the holiday effect is computed by the ratio of the observed mean for the ODPF/DCP relative to the unconstrained holiday observation. This multiplicative effect is tracked and updated using Bayesian methodology as the observations for the Holiday trickle in. When the forecast is requested for the Holiday period, the Holiday model multiplier effect calculated from the observations is reapplied to the output.

Holiday models can be built in the system at a configurable level of detail. If the client airline wishes to track the holiday effect at the lowest ODPF/DCP level then the system can be configured at install time to do that. However, data at the ODPF/DCP level is too sparse for the holiday model to have any meaningful multipliers. Typically Holiday models are built at a higher level in the hierarchy. This hierarchy is independent of the level at which the Holiday is defined by the user. Once the level of the holiday model is specified, each user request is expanded into entities whose holiday effect must be tracked independently in the system.

2.5.1 Demand & Cancellation Rate Forecasts

In the Demand module, you can create HSE rules for the following forecast types:

- Bookings
- Cancellations
- Bookings/Cancellations Group

Bookings/Cancellations Group HSE rules apply the same set of rules to the bookings and cancellations forecasts for a forecast entity. For Demand HSE rules, you should almost always use Bookings/Cancellations Group HSE rules instead of separate Bookings and Cancellations rules.

Holiday and Special Event rules for demand forecasts use the following dimension patterns:

- Online Origin
- Online Destination
- Point of Sale
- Compartment or Class

2.5.2 Show Up Rate Forecasts

In the Show Up module, Holidays and Special Events rules apply uniquely to show-up forecasts. Holiday and Special Event rules for show-up forecasts use the following dimension patterns:

- Leg Origin
- Leg Destination

3. Forecaster Inputs

Figure 3 shows those inputs required to create ODIF Forecasts in the O&D system:

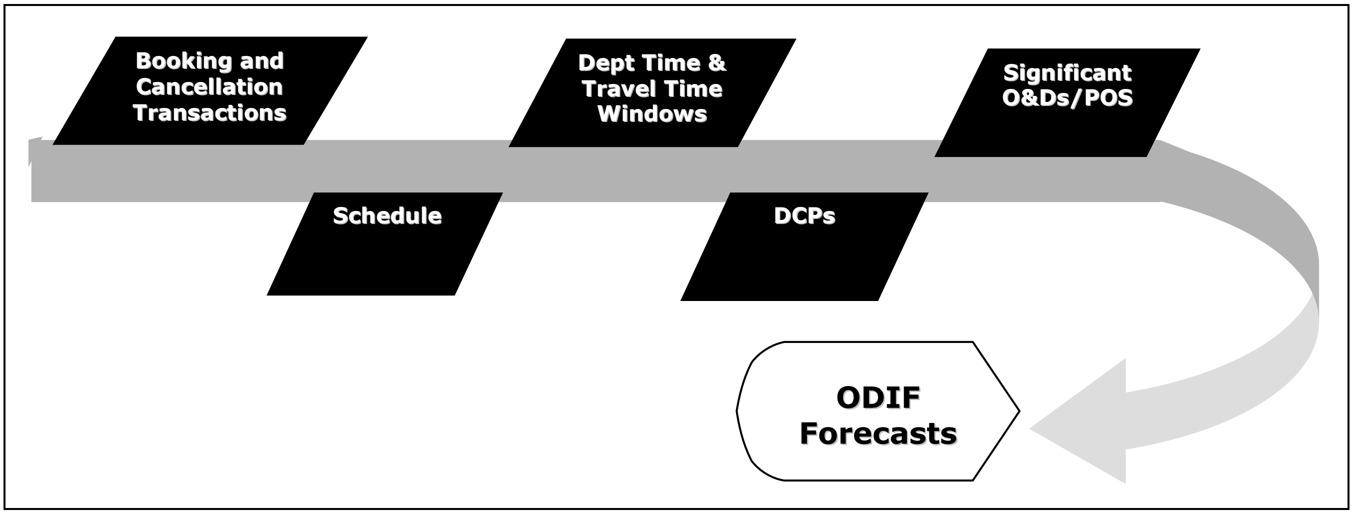


Figure 5

3.1 Booking & Cancellation Transactions

Booking and cancellation transactions having the same online O&D, trip O&D, POS, fare class, path, departure time window, travel time window, & passenger type are aggregated into DCP ranges. These ODI booking and cancellation transactions are inputs to the Forecaster, report data, and dashboards.

The booking and cancellation transactions must be associated with a future departure date, based on the departure date of the first online leg. The transaction date denotes the time of the booking or cancellation, and the transaction date and time are passed in the PNR file to O&D.

3.2 Open for Sale Schedule & Inventory

The open-for-sale schedule provides flight arrival and departure time information. It is used as an input to a connection builder function that generates the list of flight origin and destination itineraries (ODIs) that are currently open for sale.

Inventory data provides information needed for show-up forecasting, such as physical capacities, capacity restrictions and class inventory maps required for network optimization. The inventory data source is an airline's RES system, as well as other offline sources that include group and post-departure information.

Inventory data is loaded nightly and includes flight itinerary, inventory map, booking counts and authorization levels. After a flight departs, additional post-departure information is passed with this data.

3.3 Departure Time Windows & Travel Time Windows

Departure time windows (i.e. time-of-day ranges) are used to alleviate or lessen the impact on the forecast models due to flight number changes and departure time changes.

Departure time windows are path-based. They are created by the system, based on parameters determined by the carrier. Departure time windows follow the first online leg, and ranges must cover all applicable times.

Travel time windows allow multiple itineraries in a single departure time window to be forecasted separately (e.g. longer connections, stopover traffic, etc.). Travel time windows must be defined by path and by departure time window, and cannot overlap (by path). Travel time windows must also be contiguous, covering the entire range of time from 1-9999 (in minutes).

For example, assume the ODP LHR-JFK-MIA contains two possible itineraries. The departure time window, based on the first online leg (LHR-JFK), is 0800-1000. However, passengers can connect to a JFK-MIA leg departing at 1200 or 1800. A default travel time window setting of 1-9999 will forecast both itineraries in the same path, and will use the customer choice algorithm to disaggregate the forecast to the ODIF level. By defining two travel time windows (e.g. 1-1000, 1001-9999), separate forecasts will be created for each itinerary in the LHR-JFK-MIA ODP.

3.4 Data Collection Points (DCPs)

The O&D system forecasts a booking and cancellation rate for each DCP interval. See section 2.2 for additional information.

3.5 Significant O&Ds/POS

"Significant" O&Ds and POS are those O&Ds and POS deemed important to the network. Significance is determined based on a set of business rules utilizing booking and cancellation transaction data, and typically involves the number of non-directional net-bookings for a given period. Other O&Ds may be added to the list for strategic business reasons (e.g. sales/revenue impact). The list is updated periodically and thus reflects dynamic changes in markets and networks.

Significant O&Ds/POS are created in order to have a manageable subset of data to produce fare forecasts and demand forecasts. This allows the analysts to focus on the O&D/POS that are most likely to be traveled. Both Fare Valuation and the Demand Forecaster use the same list of significant O&Ds/POS.

4. Forecaster Steps

The PROS O&D Forecaster forecasts future bookings and cancellations by DCP for every itinerary and departure date open for sale in the reservations system. It also forecasts show-ups for every future leg departure. The Forecast Engine runs three principal processes:

- Build observations
- Update models
- Request forecasts

The Forecaster Engine bases its forecasts on PNR booking and cancellation transactions, post-departure inventory data, and schedules. In addition to significant O&D/POS, the Demand Forecaster creates forecast models for non-significant online O&Ds that have the "other" identifiers, where *** represents "other" trip O&Ds, and ** represents "other" points of sale. "Other" trip O&Ds and points of sale are aggregations of all non-significant trip O&Ds and points of sale for individual ODPF/time windows.

To complete the forecasting process, Origin Destination Itinerary Fare Class (ODIF) booking and cancellation transactions, post-departure inventory data and the current open-for-sale schedule are required. User-provided information, such as significant O&Ds, influences, holiday and special event definitions, as well as the forecast schedule, is also required.

4.1 Build Observations

4.1.1 Booking and Cancellation Observations

The O&D Data Loader post-processing logic generates ODIF booking and cancellation transactions. Every night the O&D System receives a download of all new PNRs created in the reservation system as well as changes made to existing PNRs in the system. The Observation Builder aggregates these transactions occurring between two DCPs and assigns the summed transaction amounts to the latter DCP.

The booking and cancel transactions are created at the ODIF level. An ODIF represents a unique itinerary in the Airline's network and consists of the following data elements:

- Online Origin - Starting airport of the itinerary in the Airline revenue controlled network
- Online Destination - Ending airport of the itinerary in the Airline revenue controlled network
- Trip Origin - Starting airport of the itinerary
- Trip Destination - Ending airport of the itinerary
- POS - Country where the PNR was booked
- Class - Booking Class of the passenger
- Pax Type - Type of passenger on the itinerary, typically used to distinguish Individual and Group traffic
- Itinerary - Online portion of the itinerary including operating and marketing flight numbers, flight numbers, arrival and departure time

Every night, the booking and cancellation transactions for DCPs that have just completed are retrieved. The Observation Builder then determines all viable ODIs, calculates all nonzero and zero ODIF/Date/DCP observations, discards any non-posted zero observations, and aggregates these observations to the non-flight-specific Origin Destination Path Fare

Class (ODPF) level. Transactions that represent a book-and-cancel or a cancel-and-rebook within 24 hours are ignored (based on the client-configurable churn parameter setting). The remaining transactions are aggregated to the ODPF level and sent to the Forecaster.

Due to changes in the schedule, it is not always possible to find an exact match for observed ODIF with the ODIF entities feasible for future departure dates. To eliminate this issue forecaster modes are created at the ODPF level.

An ODPF has the same data elements as the ODIF. The online itinerary field in the ODIF is replaced by three elements: the online airport path, the departure time window associated with the itinerary from the first online airport, and the travel time (in minutes) of the online journey. In the observation building process, all ODIF observations belonging to the same ODPF are aggregated and passed as one number to the Forecaster models.

All forecasts for bookings and cancels are for unconstrained demand i.e., the demand expected for an ODIF assuming there are no booking controls on any part of the itinerary. To make a forecast for unconstrained demand, the unconstrained history must be used as well. However, the observed PNR bookings may not reflect the true demand for an itinerary if that itinerary was closed for sale. To estimate the true historical demand, the observed ODIF bookings must be unconstrained. The Observation Builder adds a flag to each itinerary to indicate whether or not the itinerary was open or closed for sale at the end of the DCP interval.

4.1.2 Show-up Observations

The Observation Builder generates leg class show-up observations based on final bookings and post-departure inventory data. The post-departure passengers out value is adjusted for denied boardings, standbys, and upgrades/downgrades into/out of booking classes to create a standardized passengers out value known as the adjusted out. Final pre-departure booking and post-departure adjusted out inventory data is sent to the Forecaster as show-up observations.

4.2 Update Models

After sending new observations to the PROS Forecast Engine, the next step is to update the forecast models. At every DCP, the Forecaster updates forecast model parameters for all forecast entities based on new observations loaded for departed dates. Only observations for a complete DCP period will be incorporated into the models. All parameters related to the model will be updated in this step, including model coefficients, model error and seasonality factors for the auto-seasonality feature. When complete, the base model parameters are saved for all departed dates.

4.2.1 Unconstraining Posted Booking Observations

Bookings can be limited by capacity and sales factors, whereby true demand is greater than or equal to the number of bookings accepted. Since true ODI demand is not observed when the ODI is not available for sale, scaling of the observed ODI demand is required to estimate the true unconstrained demand. The Forecaster unconstrains observed bookings in the closed-for-sale O&D itineraries to estimate the true demand, using a proprietary unconstraining algorithm. If unconstraining were not done, forecasts would be artificially limited and inaccurate forecasts would result.

The system will only perform unconstraining at each DCP for significant ODPFs which have historical data. Unconstraining is further described in Section 2.4.

4.2.2 Accounting for Seasonality and Holiday Effects

As observations are received, the Forecaster analyzes these observations for seasonality and holiday effects. Seasonality reflects patterns in booking demand that vary from one season to the next during a year. The Forecaster models automatically take care of seasonality effects in the input data. The seasonal pattern is automatically computed and stored with every forecaster observation when it comes in. When forecasts are made for future dates, the Forecaster automatically takes the seasonal pattern of the future date into account. This is done by means of covariates.

Holidays are calendar periods defined by users that identify measurable increases or decreases in passenger demand from their normal levels. At the time an observation is added, a check is made whether the observation is associated with a holiday period. The observation is normalized for the effects of the holiday prior to being sent to the Forecaster. If the forecast output is for a holiday period, the effect of the holiday period is automatically added back to the forecasts.

4.3 Request Forecasts

PROS O&D requests forecasts for ODIF dates and leg-class dates according to a request schedule. PROS O&D produces separate forecasts for bookings and cancellations on all future DCPs of the requested ODPF/Date. ODPF-level forecasts are disaggregated to ODIFs based on open schedules, minimum connection times, and the customer preference logic. Cancellation and show-up forecasts are rate forecasts, so they are not disaggregated. For cancellation rates, the rate at the ODIF level is equal to the rate at the ODPF level.

4.3.1 Request Forecast Schedule

Booking and cancellation rate forecasts are generated for a scheduled set of future departure dates, and the data is converted to ODIFs. Show-up rate forecasts are generated for future flight leg departures. The request forecast schedule is based on a list of Day Prior values. A day-of-week pattern (e.g. request forecasts for all future Mondays) is recommended for efficiency in requesting forecasts.

When making future forecasts, the holiday effects are superimposed on the forecasts made by the base model. During forecast generation, the Forecaster applies any O&D and show-up influences that were entered by users.

4.3.2 Map Forecasts to the Current Open-For-Sale Schedule

Mapping forecasts to the open-for-sale schedule is required because the Optimizer requires forecasts for the current schedule at the itinerary level of detail. Booking and cancellation rate forecasts are generated at the path and time-of-day level. These forecasts are then disaggregated to specific itineraries contained the Airline’s open-for-sale schedule. The disaggregation is made on the basis of the total trip times of each ODIF associated with the ODPF. The booking and cancel rate forecasts are at a DCP level. Once specific itinerary booking and cancellation rates are calculated, the Forecaster calculates O&D itinerary demand-to-come and cancellations-to-come.

Similarly, show-up forecasts are first generated at the path and time-of-day level and then applied to the specific flights in the Airline’s open-for-sale schedule.

4.3.3 Process Forecast

The Process Forecast task applies influences to demand forecasts, updates the FLTCLSFRC table with show-up forecast data, and blends booking and cancellation forecasts.

4.3.3.1 Application of Influences

Application of influences involves looking up any user-specified influences (additive, multiplicative, minimums, maximums, overrides, and demand mapping) and making the appropriate adjustments to the forecasts. Both the influenced and the non-influenced forecasts for each DCP will be kept.

4.3.3.2 Blending Process

A blending of forecasts is required since the input to the optimizer is net demand-to-come, rather than bookings and cancellations. The booking and cancellation rate forecasts are combined to achieve the net demand-to-come forecast as well as a booking curve forecast, both of which are necessary for the optimizer to perform its duties.

To forecast net bookings to come for each DCP, the blending process incorporates:

- Forecasted demand at each DCP (absolute number)
- Expected cancellation at each DCP (rate/percent)
- Bookings on hand

Net demand is calculated through a process that blends demand and cancellation rate by DCP and moves across all future DCPs.

Example using 3 DCPs:

- Net bookings at DCP 1 = 10
- Forecasted new bookings at DCP 2 = 5 and at DCP 3 = 10
- Forecasted cancellation rates at DCP 2 = 0.1 (10%) and DCP 3 = 0.2 (20%)

Where N(i) is forecasted demand, X(i) the forecasted new bookings at DCP i, R(i) the forecasted cancellation rate at DCP i.

Forecasted net bookings at DCP 2:

$$N(2) = [\ N(1) + X(2)\ ] * [\ 1 - R(2)\ ]$$

$$= [\ 10 + 5\ ] * [\ 1 - 0.1\ ] = 13.5$$

Forecasted net bookings at DCP 3:

$$N(3) = [\ N(2) + X(3)] * [\ 1 - R(3)\ ]$$

$$= [\ 13.5 + 10\ ] * [\ 1 - 0.2\ ] = 18.8$$

5. Forecast Influences

This section will discuss the following influences:

- Multiplicative Adjustments
- Additive Adjustments
- Sponsorship
- Demand Mapping

5.1 Multiplicative Adjustments

Purpose: Increase or decrease demand for a specific period when changes to volume, timing, and/or composition of traffic are anticipated but the event is not yet anticipated by the Forecast

Such changes may result from:

Competitive changes

Economic conditions

Political circumstances

Other

5.2 Additive Adjustments

5.3 Sponsorship

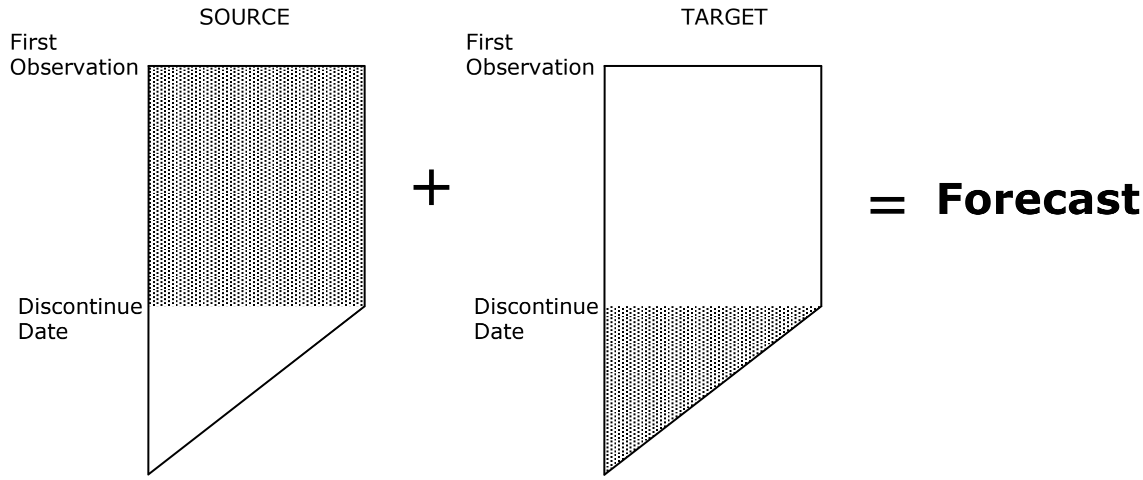
Sponsorship assists users in managing the business issues that arise from new entities such as O&Ds, DOW, time of day windows, or fare classes. Without intervention from the analysts, these new entities would build their own models and history; in the meantime, forecast accuracy could be lessened due to initially sporadic observations.

Any time a new market, day of week, or time of day window is loaded (typically during a schedule change), existing entities must be identified to provide proxy forecasts for the new entities until they have enough history to generate a reasonable or reliable forecast. These existing "source" markets are thus used to sponsor new "target" markets.

In O&D, sponsorship provides a starting "baseline" estimate of bookings (or cancels or show-ups) based on a similar forecast entity. That estimate then goes through the standard Bayesian updating process as more data comes in. The result is that the effect of the sponsorship decays exponentially over time, much like the need for influences decay. This implies that there is no hard cut-over from using the sponsoring entity and not using it, but rather a gradual transfer that happens within the natural Bayesian update process.

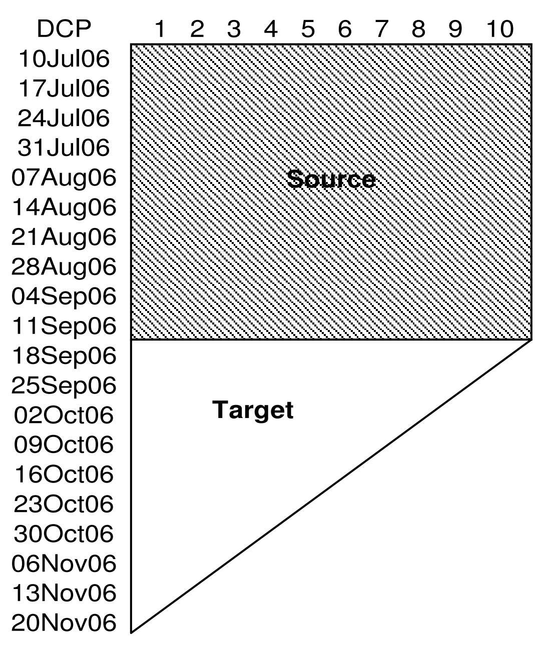
5.3.1 Discontinue Date

Sponsorship goes into effect during the next nightly forecasting process after a sponsorship record is created, and remains in effect until the Discontinue Date for the record has been reached. The Discontinue Date determines the point at which the target entity stops using the source entity's forecasting model and begins updating its model using its own observations.



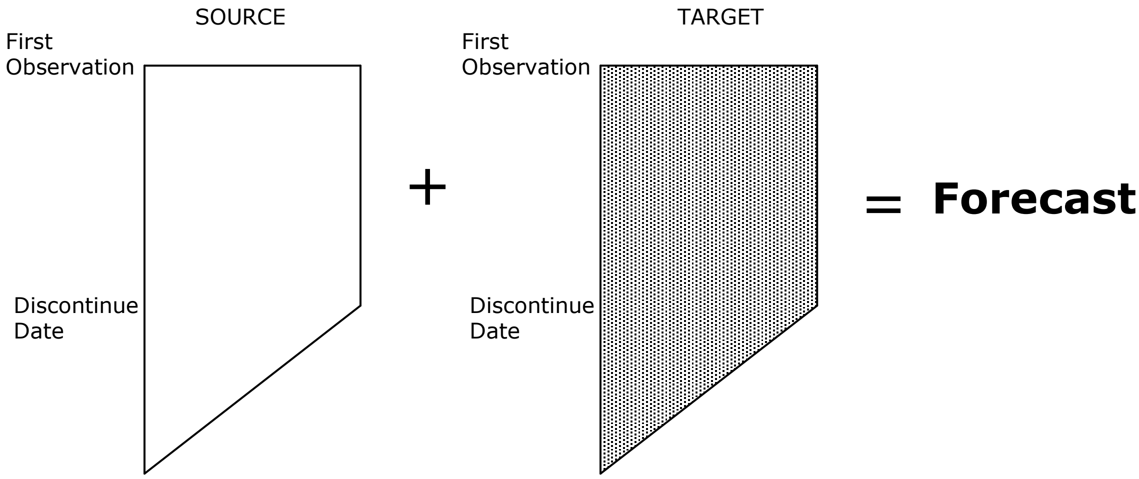
5.3.1.1 Example

Assume a new sponsorship record has been defined with a discontinue date of September 18, 2006. Prior to that date, the new entity's forecast will be based on the source model. After that date, the target's own observations will be used to update the model.



5.3.2 Sponsorship Threshold

If 26 weeks pass from the date of the first observation and the discontinue date hasn't been crossed, the target model will go live and will use its own data (even if there are zeros/gaps) and ignore the source data. NOTE: zeros do NOT count as observations (i.e. zero observations won't initiate the 26-week countdown)



5.4 Demand Mapping

- Purpose: Allows movement/mapping of demand from one entity to another
    - Demand Mapping can be used to move (cut/paste) a percentage of demand
        - From one class to another
        - From one point of sale to another
        - From one day of week to another
    - e.g. manage RBD re-structuring

- Movement of demand does not affect the base forecast model