ABSTRACT

With all the published research on hotel Revenue Management (RM), a framework to guide a comprehensive hotel RM is rare in the extant literature. This research proposes a complete revenue opportunity framework for applying a traditional revenue management model for controlling room inventories for hotels. We propose and describe the framework and the model in this paper. The finished research will use archived data from a major hotel chain and apply the framework for generating controls for managing hotel room inventories to maximize revenue.

Keywords: Revenue Management, Hotels, Forecasting, Forecast monitoring, Room allocation, Hotel Management Analytics

INTRODUCTION

Revenue Management (RM) is the process of selling the right type of capacity to the right customer, at the right price, at the right time (Smith, Leimkuhler, & Darrow, 1992). The process involves rationally pricing and controlling reservations of perishable assets across market segments to maximize revenue (Cross, 1997; Baker & Murthy, 2005). A number of service firms reported significant increases in profitability due to RM. American Airlines reported approximately a 4-5% increase (1.4 billion USD over three years) in revenue (Smith et al., 1992; Cook, 1998).

While airlines industry benefited from RM, the hotel industry has not seized the revenue opportunity from the existing RM models because of the proprietary nature of the models. The hotel industry was one of the early adopters of RM practices, based on initiatives in the airline industry (McGill and van Ryzin, 1999). Goldman et al. (2002) published a few stochastic models and techniques for hotel revenue management for accepting reservations for stays in a hotel. Vinod (2004) describes various RM techniques for controlling hotel rooms. Aslani et al. (2013) address the multiple night stay in hotel revenue management using a decomposition model. Ferguson and Smith (2014) more recently chronicled the changes in practices and responsibilities of the hotel revenue managers.
With all these efforts on hotel RM, a comprehensive approach is still missing in published literature. A comprehensive approach consists of all component models – revenue opportunity model, forecast model, and optimization model in the least. All component models need be tested on real data before publication. As this approach is missing in various published literature on RM for hotel industries scholars only find piece by piece information. The first step then is to apply a comprehensive approach to real data and publish revenue opportunity achieved by the collection of component models.

The contribution from the research applies to both academics and industry. In the academic world the researchers can use the results as benchmark to compare the results from their own models. In absence of one set of complete controls ROM performance cannot be compared. Research scholars have proposed many complex models. The question remains—Do they work? This leads to another conclusion that the model must be implementable. RM analysts (RMA) don’t have the necessary skill to understand the complex models. Therefore, the research needs to connect RM practitioners.

Kimes (2010) states that an effective futuristic hotel revenue management will involve moving RM to a separate department and making sure that revenue managers have the necessary analytical and communications skills to be able to work across departments. In addition, it is likely that many RM functions will become more centralized and that a hybrid centralized/decentralized organizational model will develop. The research proposed here wishes to fill in the chasm between practice and proposed models for an effective futuristic hotel management. The research will use archived data from a hotel chain for five hotels and apply the RM models and concepts described in this paper in booking hotel rooms.

**LITERATURE REVIEW**

**Revenue Management Framework**

This research proposes and extends traditional RM models utilized by the airlines for hotel industry. The RM in airlines consists mainly of two types of methods – forecasting of passenger demand and optimized allocations of seats in each flight. The proposed project extends the same concepts for hotel RM. The next sections explain the airlines RM process in a nutshell.

**Demand Forecasting and Forecast Accuracy**

An airlines passenger demand forecasting predicts the number of rooms expected to fly on each combination of itinerary and fare category (Colville, 1996). A major airline can have thousands of unique fare categories or products because, on a very fundamental level, values to variables (such as city-pairs, number of stops, advance purchase requirements, Saturday restrictions, time of day [red-eye flights, etc.], sale fares, competitor pricing, and other market conditions) give rise to thousands of unique fare products. At the most detailed level, one distinct fare product is known in the airline industry as fare basis code (FBC). However, in handling the seatmix problem, to avoid computational complexity and time consuming reservation decision making, airlines do not deal with the thousands of unique FBCs. Instead, airlines cluster these FBCs into a more manageable number of classes, called buckets, in each cabin based on the fare product’s economic value. From the airline’s point of view, due to differences in attributes of itinerary such as origin and destination, time of the day, and so on, passengers in the same fare class on the same flight are not equally valuable. Revenue management (RM) generates forecasts and seat availability numbers at bucket levels. We extend the similar concepts for
hotel revenue management. Hotels will have similar products like special rooms, general rooms, suites, etc.

THEORETICAL DEVELOPMENT/MODEL

A Generalized Framework of RM Forecasting for Hotels

Usually, forecasts for a room reservation can be made on the basis of unconstrained demand (an estimate of true demand) during a set of time interval periods for a group of similar room products. If a room product is open for sale, the observed booking for the product during the period is equal to unconstrained booking.

We assume that a typical room product stays for about 50 weeks (350 days) prior to the check-in date in the reservation system. The 350-day span comprises a set of control time intervals. Usually, at the end of each interval, RM updates reservation and other controls for all future dates. The total time can consist of 50 weeks of equal seven-day intervals. However, intervals do not have to be of equal length. Historical room bookings used in forecasting demand for a room product come from both past and future check-in dates. Days left (DL) to check-in date is then (d-fd) where fd is the date when the forecast is made. The final forecast for a specific product for a specific d for a hotel will be the sum of the bookings on hand up to fd and forecast for remaining bookings to come from fd to d. The forecast for the remaining bookings to come is the sum of the incremental booking forecasts for all time intervals from fd to d. We assume day-of-week seasonality since Monday bookings look like Monday bookings for all dates falling on Mondays and so on.

Let us say that each set of time intervals is indexed by a set i Є I. For example, the set {0, 7, and 14} would index two periods that correspond to intervals DL = 7 to DL = 0 and DL = 14 to DL = 7. The final forecast for DL = 14 will be the sum of the bookings on hand up to DL = 14 from DL = 350 and the forecasts for remaining incremental bookings from DL = 14 to DL = 7 and DL = 7 to 0. RM analysts determine the set of check-in dates to be used in the computation of the forecasts for the interval i, such as:

\[ d_i \in D(I) \quad \text{iff} \quad (d_i - \text{Min DL in interval } i) < (fd - 1) \]  

and

\[ d_i \geq \text{maximum of } (d_i \in D(I)) - 7*N \]

The constraint (1) above ensures that all the bookings data for the interval i forecast have been collected. Constraint (2) ensures that historical incremental bookings are used from the most recent similar check-in-dates. The parameter N is multiplied by 7 in constraint (2) to accommodate day-of-the-week (DOW) seasonality. A value of N = 8 spans over approximately the most recent two months’ similar check-in-dates.

The unadjusted room demand forecast for interval i, DOW w, booking product b, check-in-date d, and forecasting date fd is:

\[ UIF_{i,w,b,d,fd} = \frac{\sum_{n=\text{dl} \in D(1)} M_n \ast IB_{i,w,b,d,fd,n}}{\sum_{n=\text{dl} \in D(1)} M_n} \]
where \( M_n = \text{smoothing weights} = F(a, n), \) \( a = \text{revenue management analyst (RMA) chosen smoothing parameter}, \) \( n = 1, \ldots, N, \) and \( IB \) is incremental bookings for interval \( i \) of similar flight departures.

\[
\text{Unadjusted final forecast for } w, b, d, \text{ and } fd \text{ is:}
\]

\[
UFF_{w,b,d,fd} = BH_{w,b,d,fd} + \sum_{i} UIF_{i,w,b,d,fd}
\]

where \( BH_{w,b,d,fd} \) is current bookings on hand up to \( fd \) in booking product \( b \) for date \( d \), day-of-week \( w \).

**METHOD WITH ILLUSTRATION**

**Accuracy Measurement Levels**

Let us say, for example, the forecast date \( fd \) is Oct 16, 2006, Monday, for a check-in-date in 14 days on Oct 30, 2006. The RM forecasts for two incremental intervals: 14-7 and 7-0. If RMAs choose the value of \( N = 8 \), historical bookings from eight most recent check-in-dates (Oct 23, Oct 16, Oct 9, Oct 2, Sep 25, Sep 18, Sep 11, and Sep 4, all in 2006) will be used for 14-7 incremental forecast. The incremental forecast for the interval 7-0 is generated from historical bookings from eight most recent check-in-dates: Oct 16, Oct 9, Oct 2, Sep 25, Sep 18, Sep 11, Sep 4, Aug 28 in 2006. The system computes final forecasts by adding the incremental forecasts of intervals 14-7 and 7-0 with bookings on hand up to Oct 16, 2006 all the way from DL = 350.

This research adopts the concept of *critical booking threshold* (CBT) from Mukhopadhyay et al. (2007) for measuring forecast accuracy. Monitoring forecast accuracies based on products could sometimes involve low demand numbers, because some of the high revenue products may not observe any bookings at all in many flights. Percentage forecast error for these products will be high even if there is only one room difference between the actual value and the forecasted value. Therefore, it is better to evaluate forecast accuracy in terms of the sum of the bookings in a product and all higher-valued products above. The calculation for the thresholds starts with calculating the cumulative percent of bookings for each \( b \). Let us assume that that there are 16 (an arbitrarily chosen number for the purpose of illustration) \( b s \) in a hotel, \( Y_1 \) through \( Y_{16} \), with \( Y_1 \) being the highest-revenue-yielding \( b \) and \( Y_{10} \) the lowest. Table 1 illustrates an example of CBT. The total or cumulative bookings for a hotel at a specific \( d \) are accumulated at the product level from \( Y_1 \) to \( Y_{10} \). Using these bookings for a hotel, the cumulative percent of bookings in each \( b \) is calculated.

Next, we select the products with the top percentiles in terms of revenue to be measured. We define the booking top percentile thresholds as 10%, 25%, 50%, 75%, 90%, and 100% of hotel bookings. The percentile levels may vary from hotel to hotel depending on RMA experience. The booking type selected is the first product that is greater than or equal to the percentile to be measured (fifth column in Table 1). This also means that when a product spans two thresholds, it will be selected for both.
### Table 1: Example of CBT

<table>
<thead>
<tr>
<th>Products</th>
<th>Bookings</th>
<th>Cumulative Bookings</th>
<th>Cumulative Percentage</th>
<th>Thresholds</th>
<th>Sum CBT Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y1</td>
<td>5</td>
<td>5</td>
<td>8</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>Y2</td>
<td>2</td>
<td>7</td>
<td>12</td>
<td>10%</td>
<td>7</td>
</tr>
<tr>
<td>Y3</td>
<td>2</td>
<td>9</td>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y4</td>
<td>2</td>
<td>11</td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y5</td>
<td>0</td>
<td>11</td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y6</td>
<td>5</td>
<td>16</td>
<td>27</td>
<td>25%</td>
<td>16</td>
</tr>
<tr>
<td>Y7</td>
<td>5</td>
<td>21</td>
<td>35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y8</td>
<td>5</td>
<td>26</td>
<td>43</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y9</td>
<td>5</td>
<td>31</td>
<td>52</td>
<td>50%</td>
<td>31</td>
</tr>
<tr>
<td>Y10</td>
<td>5</td>
<td>36</td>
<td>60</td>
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</tr>
<tr>
<td>Y11</td>
<td>5</td>
<td>41</td>
<td>68</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y12</td>
<td>5</td>
<td>46</td>
<td>77</td>
<td>75%</td>
<td>46</td>
</tr>
<tr>
<td>Y13</td>
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<td>48</td>
<td>80</td>
<td></td>
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</tr>
<tr>
<td>Y14</td>
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<td>50</td>
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<td></td>
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<tr>
<td>Y15</td>
<td>5</td>
<td>55</td>
<td>92</td>
<td>90%</td>
<td>55</td>
</tr>
<tr>
<td>Y16</td>
<td>5</td>
<td>60</td>
<td>100</td>
<td>100%</td>
<td>60</td>
</tr>
</tbody>
</table>

### ANALYTICAL RESULTS

#### Forecast Accuracy Measures

We propose to measure mean absolute error (RMSE) and average error (BIAS) for all forecasts at the CBT levels. **Bias** shows whether, on the average, forecasts were under or over the actual unconstrained room demand. **RMSE** shows how much, on average, the forecasts were off the truth.

#### Probabilistic Room Inventory Model at Product Level

The room booking of hotel management problem is probabilistic because there is uncertainty about the ultimate number of booking requests for rooms on a future day. There will be stochastic variation in demand around the expected values among similar flights sampled consistently over a homogeneous period of time similar to airline seat bookings assumed in a past research (Belobaba, 1987).

Past analyses have generally assumed a Gaussian (normal) distribution of total demand in transportation industry. Means and variances depend on the hotel being studied and on the nature of its bookings. We assume Gaussian distribution for demand density. Demand densities for different products are not correlated significantly and the numbers of requests for various products during different periods before flight departure are not correlated.

#### Number of rooms to Protect for higher revenue room product from the Lower revenue room product

This section explains the model that decides how many rooms to protect from the current product to the next lower one. This is called the protection level (PL) of the current product. **PL** for the current product is:
PL = Demand Forecast for the current product + Risk Factor due to Forecast Accuracy

Risk Factor due to Forecast Accuracy

Depending on the forecast accuracy of the demand RMA add or subtract a few rooms from the forecasted number to compute the PL. We assume that PL is the ideal expected demand level of the current product at which the expected revenue by protecting a room (marginal room number) for the current product from the next lower level product is equal to the marginal revenue (revenue of the current product minus the revenue of the next lower valued product). Therefore,

\[
P(Z < PL) \times R1 = R1 - R2
\]

(5)

Where \(R1\) = Revenue from the current higher valued room product, \(R2\) = revenue from the next lower valued product, and \(Z\) is the standardized score of demand of the current product.

\[
Z^* \text{ (critical value of } Z \text{ at the margin of ideal } PL \text{ value)} = (PL − DF)/\sigma_d
\]

(6)

Where \(DF\) is the demand forecast for the current product and \(\sigma_d\) = standard deviation. From equation 5,

\[
P(Z^*) = (R1-R2)/R1 = 1 - (R2/R1) = 1 - \text{Revenue Ratio (RR)}
\]

(7)

and

\[
Z^* = \text{Norm Inverse of (1-RR)}
\]

(8)

Substituting the value of \(Z^*\) in equation 6, we get

\[
\text{Norm Inverse of (1-RR)} = (PL − DF)/\sigma_d
\]

(9)

and

\[
PL = DF + \sigma_d \times \text{Norm Inverse of (1-RR)}
\]

(10)

Where the second part of the right hand side of equation 10 is denoted as the “risk factor.” The risk factor associates with forecast accuracy. The risk factor in equation 10 will go up with decreased differential revenue between the higher valued current product and the next lower-valued product. In that case, protecting too many rooms for the higher valued product will cost the hotel with unoccupied room inventories. On the contrary, the risk in protecting fewer rooms for the current product will cost the hotel in achieving suboptimal total revenue.

**EMPIRICAL APPLICATION**

The research will use published masked revenue management data from five hotels from a major hotel chain in USA. Currently all the data have been downloaded and we are in the process of cleansing the data for correctness.

**CONCLUSION AND CONTRIBUTION**

Recently RM models have been of quite interest to service industry as well as to the academic community. This research, therefore, will generate a lot of interests to academic as well as
business community. The main contribution lies in the first time application and extension of traditional RM to many service industries.
In the past researchers have proposed a few models in isolation. This research aims at applying traditional revenue management on a real world hotel data. The model generated controls can be compared with existing controls. The differential in controls will generate new data for future researchers.

REFERENCES