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Forecasting for Hotel Revenue Management: Testing Aggregation Against Disaggregation

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Abstract

[Excerpt] A successful yield-management strategy is predicated on effective control of customer demand. Businesses have two interrelated strategic levers with which to accomplish this, namely, pricing and duration of customer use. Prices can be fixed (one price for the same service for all customers for all times) or variable (different prices for different times or for different customer segments) and duration can be predictable or unpredictable.

Variable pricing to control demand is conceptually a straightforward process. It can take the form of discount prices at off-peak hours for all customers (such as low weekday rates for movies) or it can be in the form of price discounts for certain classes of customers (such as senior discounts at restaurants).

Keywords

hotel industry, revenue management, yield management, aggregation, disaggregation

Disciplines

Hospitality Administration and Management

Comments

Forecasting for Hotel Revenue Management

Testing Aggregation Against Disaggregation

BY LAWRENCE R. WEATHERFORD, SHERYL E. KIMES, AND DARREN A. SCOTT

A successful yield-management strategy is predicated on effective control of customer demand. Businesses have two interrelated strategic levers with which to accomplish this, namely, pricing and duration of customer use.[1] Prices can be fixed (one price for the same service for all customers for all times) or variable (different prices for different times or for different customer segments) and duration can be predictable or unpredictable.

Variable pricing to control demand is conceptually a straightforward process. It can take the form of discount prices at off-peak hours for all customers (such as low weekday rates for movies) or it can be in the form of price discounts for certain classes of customers (such as senior discounts at restaurants).

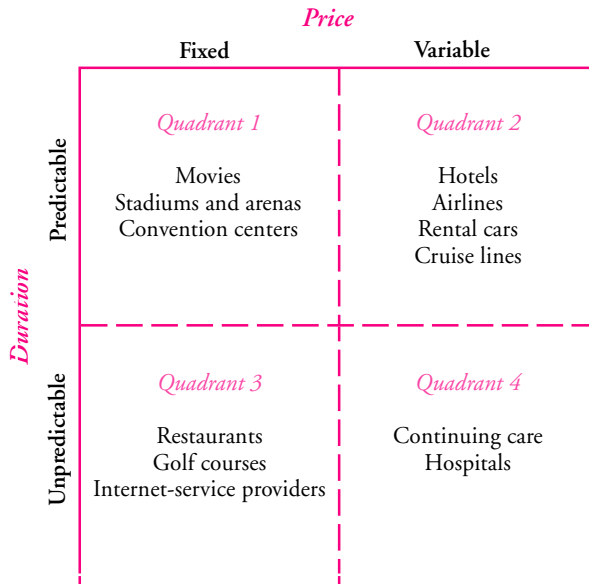Duration control is more complicated to manage, but at the same time represents an area that can improve the effec-tiveness of revenue management. By implementing duration controls that help managers predict the length of service, companies maximize overall revenue across all time periods rather than just during high-demand periods.

Different industries use different combinations of variable pricing and duration control, as shown in Exhibit 1 (overleaf). Industries traditionally associated with revenue management (hotel, airline, rental car, and cruise line) tend to use variable pricing for services with a specified or predictable duration (Quadrant 2). Movie theaters, performing-arts centers, stadiums and arenas, and convention centers generally charge a fixed price for a service of predictable duration (Quadrant 1), while restaurants and golf courses use a fixed price but suffer relatively unpredictable customer duration (Quadrant 3). Many health-care industries charge variable prices (e.g., Medicare or private pay) but do not know the duration of patient

EXHIBIT 1

A Typology of Revenue Management

Price

	Fixed	Variable
Predictable	*Quadrant 1* Movies Stadiums and arenas Convention centers	*Quadrant 2* Hotels Airlines Rental cars Cruise lines
Unpredictable	*Quadrant 3* Restaurants Golf courses Internet-service providers	*Quadrant 4* Continuing care Hospitals

Duration

This diagram was previously used in: Sheryl E. Kimes, "Revenue Management on the Links: Applying Yield Management to the Golf-course Industry," *Cornell Hotel and Restaurant Administration Quarterly,* Vol. 41, No. 1 (February 2000), p. 127.

tion, hotels forecast demand by length of stay (LOS) for different rate categories (RC); airlines try to forecast demand by origin–destination city pairs; and rental-car companies predict demand by rate category and length of keep. As the key driver of any revenue-management system, the forecast is the focus of our research.

Forecast accuracy has a significant effect on revenue generated from revenue-management systems. In his study of airline forecasting, Lee found that a 10-percent improvement in forecast accuracy on high-demand flights resulted in an increase in revenue of 1.5 to 3.0 percent.[2]

Finding the best approach. Most major hotel chains use linear-programming-based models that require detailed forecasts by day of arrival, length of stay, and rate category.[3] Hotels arrive at these detailed forecasts in several ways (see Exhibit 2). Some hotel chains forecast overall arrivals and then develop detailed LOS and RC forecasts by applying historical probability distributions to the arrivals forecast. (The accompanying sidebar on page 57 discusses how one derives those probability distributions.) Others forecast arrivals by RC or LOS and then apply the appropriate probability distribution to derive the detailed forecasts. Finally, some chains develop detailed arrivals forecasts by RC and LOS together. The question we wanted to answer is, which is the best approach?

Airlines have a problem similar to the length-of-stay issue with origin–destination forecasting.[4] Airline revenue management has traditionally been based on individual legs of an overall trip,[5]

use (Quadrant 4). There is no fixed demarcation point between any pair of quadrants, and so an industry may lie partially in one quadrant and partially in another, as in the case of a restaurant with an early bird menu and a late-dinner menu.

Predicting Customer Arrivals

Successful revenue-management applications are generally found in industries where managers can make a reasonable prediction regarding customers' duration of use (Quadrant 2). Such predictability enables managers to make clear delineations among their services (usually by time of use) and to generate maximum revenue from those services through variations in pricing.

Forecasting is key. Accurate forecasting is one of the ways to increase the predictability of duration of use. In hotels, duration is defined as length of stay; in airlines, as time in flight (known as origin–destination); and in rental cars, as length of keep. To help increase the predictability of dura-

[2]A.O. Lee, "Airline Reservations Forecasting: Probabilistic and Statistical Models of the Booking Process," Massachusetts Institute of Technology Ph.D. Thesis, 1990.

[3]See: L.R. Weatherford, "Length-of-stay Heuristics: Do They Really Make a Difference?," *Cornell Hotel and Restaurant Administration Quarterly,* Vol. 36, No. 6 (December 1995), pp. 47–56; C. Hensdill, "The Culture of Revenue Management," *Hotels,* March 1998, pp. 83–86; and T.K. Baker and D.A. Collier, "A Comparative Revenue Analysis of Hotel Yield-management Heuristics," *Decision Sciences,* Vol. 30, No. 1 (1999), pp. 239–264.

[4]See: E.L. Williamson, "Airline Network Seat Control," Massachusetts Institute of Technology Ph.D. Thesis, 1992; and B. Vinod, "Origin-and-Destination Yield Management," in *Handbook of Airline Economics*, ed. D. Jenkins (New York: McGraw-Hill, 1995).

[5]P.P. Belobaba, "Air-travel Demand and Airline-seat Inventory Management," Massachusetts Institute of Technology Ph.D. Thesis, 1987.

and forecasts for origin–destination pairs have not usually been attempted. Recent research has shown that origin–destination revenue management can result in revenue increases of 1 to 3 percent over leg-based approaches.[6] Origin–destination forecasting in the airline industry is difficult because of the large number of origin–destination city pairs. Some airlines have tried to circumvent this problem by using virtual nesting,[7] but virtual nesting (which is beyond the scope of this article) does not provide the same level of detail as origin–destination forecasting.

Aggregation level is obviously not the only issue that must be addressed with hotel revenue-management forecasting. Managers must also consider the type of forecasting method, what to forecast (arrivals or room-nights), the type of data (constrained or unconstrained),[8] the number of periods to include in the forecast, which data to use, the treatment of outliers, and the measurement of accuracy (see Exhibit 3).[9]

Previous research has shown that exponential smoothing and the classical-pickup method produce the most accurate forecasts of six methods that were tested. Studies also demonstrated that the amount of data used (i.e., completed stay-nights versus all data) does not affect accuracy to any great degree.[10] Our research addressed the second issue, which is the level of aggregation.

Forecast Aggregation and Disaggregation

Forecast disaggregation has been extensively studied in the marketing and economics literature. In marketing, researchers are interested in pre-

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[6]S. Adyanthaya, "Bottom-line Implications of O&D Revenue Management," *Airline Economics*, September–October 1998.

[7]B.C. Smith, J.F. Leimkuhler, and R.M. Darrow, "Yield Management at American Airlines," *Interfaces*, Vol. 22, No. 1 (1992), pp. 8–31.
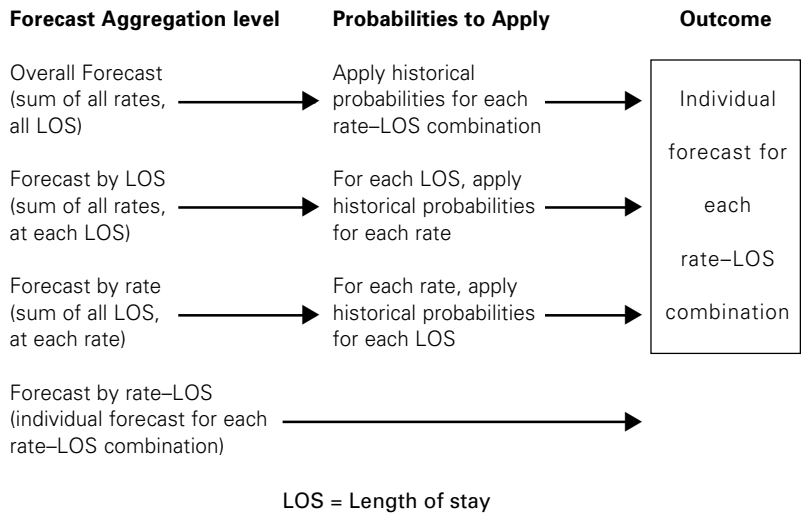
[8]For a full discussion of constrained and unconstrained demand, see: E. Orkin, "Wishful Thinking and Rocket Science: The Essential Matter of Calculating Unconstrained Demand for Revenue Management," *Cornell Hotel and Restaurant Administration Quarterly,* Vol. 39, No. 4 (August 1998), pp. 15–19.

[9]A full discussion of the issues can be found in: S.E. Kimes and L.R. Weatherford, "Forecasting Methods for Hotel Revenue Management: An Evaluation," *International Journal of Forecasting* (in review, 1999–2001).

[10]*Ibid.*

Forecast-aggregation levels

Forecast Aggregation level	Probabilities to Apply	Outcome
Overall Forecast (sum of all rates, all LOS) ⟶	Apply historical probabilities for each rate–LOS combination ⟶	Individual forecast for each rate–LOS combination
Forecast by LOS (sum of all rates, at each LOS) ⟶	For each LOS, apply historical probabilities for each rate ⟶	
Forecast by rate (sum of all LOS, at each rate) ⟶	For each rate, apply historical probabilities for each LOS ⟶	
Forecast by rate–LOS (individual forecast for each rate–LOS combination) ⟶		

LOS = Length of stay

Glossary

With the *classical pickup* method, the expected number of reservations to be picked up between a given day and the day of arrival is added to the current number of reservations on hand for that day. The expected pickup is usually determined by averaging the pickup over the previous four to eight periods.*

Exponential smoothing is a commonly used forecasting method in which the previous forecast is adjusted by a weighted average of previous forecast error.

A *random-walk forecast* simply uses the demand from the previous period as the forecast for the current period. For example, if a hotel had 120 arrivals for last Tuesday, the random-walk forecast for next Tuesday would be 120 arrivals.

A *reading day* is when the number of reservations on hand for a particular arrival day is updated. Typically, updates occur only every week or two when the arrival date is far off, but occur daily in the week before arrival.

*See: E. L'Heureux, "A New Twist in Forecasting Short-term Passenger Pickup," *Proceedings of the 26th Annual AGIFORS Symposium* (1986).

Revenue-management forecasting choices

1. **What to forecast**
   A. Arrivals
   B. Room-nights

2. **Level of aggregation**
   A. Fully aggregated
   B. Aggregated by rate category with length-of-stay probability distributions
   C. Aggregated by length of stay with rate-category probability distributions
   D. Fully disaggregated (by rate category with length of stay)

3. **Unconstraining method**
   A. None
   B. Denials data
   C. Mathematical models
      1. Pickup
      2. Booking curve
      3. Projection

4. **Number of periods to include in forecast**
   A. All
   B. Selected number

5. **Which data to use**
   A. Only complete stay-nights
   B. All data (complete and incomplete stay-nights)

6. **Outliers**
   A. Included
   B. Not included

7. **Level of forecast accuracy (i.e., aggregation and error reporting)**
   A. Aggregated forecasts, errors reported as average across all reading days
   B. Aggregated forecasts, errors reported for each individual reading day
   C. Disaggregated forecasts, errors reported as average across all reading days
   D. Disaggregated forecasts, errors reported for each individual reading day

dicting national, regional, and local sales,[11] while in economics researchers try to predict economic-activity levels for national, regional, and local markets.[12]

It is often difficult to determine whether aggregation or disaggregation will render a more accurate forecast, because of possible differences in model specifications, possible offsetting errors as data are aggregated, and by aggregation and pooling bias. In addition, if the demand for different rate categories and lengths of stay are highly correlated, the interpretation of the results may be difficult.[13]

Top-down versus Bottom-up Forecasts

Top-down forecasts consist of one aggregate forecast that is then broken down to individual days by means of probability distributions, as discussed in the box on the next page. With bottom-up forecasts, individual forecasts are made for particular products or services, and the aggregate forecast is calculated by summing the individual forecasts. For example, a top-down forecast might consist of a daily-arrivals forecast to which probability distributions by rate category and length of stay were applied. Conversely, a bottom-up forecast would forecast arrivals by rate category and length of stay and the total forecast would be determined by adding the detailed forecasts together.

Proponents of top-down forecasting argue that the approach is superior because of its lower cost and greater accuracy during times of reasonably stable demand. If demand is stable, the probabil-

[11]See: D.M. Dunn and W.A. Spivey, "Analysis and Prediction of Telephone Demand in Local Geographic Areas," *Bell Journal of Economics and Management Science,* Vol. 2 (1971), pp. 561–576; and E.W. Foekens, P.S.H. Leeflang, and D.R. Wittink, "A Comparison and an Exploration of the Forecasting Accuracy of a Log-linear Model at Different Levels of Aggregation," *International Journal of Forecasting,* Vol. 10 (1994), pp. 245–261.

[12]See: Y. Grunfeld and Z. Giliches, "Is Aggregation Necessarily Bad?," *Review of Economics and Statistics,* Vol. 42 (1960), pp. 1–13; J.B. Edwards and G.H. Orcutt, "Should Estimation Prior to Aggregation be the Rule?," *Review of Economics and Statistics,* Vol. 51 (1969), pp. 409–420; and D.J. Aigner and S.M. Goldfeld, "Estimation and Prediction from Aggregate Data When Aggregates Are Measured More Accurately Than Their Components," *Econometrica,* Vol. 42, No. 1 (1974), pp. 113–134.

[13]Foekens *et al., op. cit.*

ity distribution needs only to be updated annually, which leads to fairly low-cost forecasts. If demand is unstable, on the other hand, these percentages must be constantly updated, and the amount of time required for top-down forecasting will approximate that needed for the bottom-up approach.[14]

Statistically, top-down forecasts should be more accurate than bottom-up forecasts because the average of a number of items is less variable than that of individual items.[15] A top-down forecast smoothes the loss in accuracy from variance when the demand for one set of items is much higher than it is for another set. While top-down forecasting reduces the effect of random error in item forecasts, it also introduces complex interactions between bias and outlier effects.

In general, although it may be appealing to minimize the number of forecasts, that approach is not always justified. For example, it may be easier for hotels to develop only one forecast for each day, but the demand for certain rate categories and lengths of stay may vary. If that occurs, the hotel may end up applying inappropriate capacity and rate restrictions. Individual forecasts are essential when it is important to detect distinctions between demand patterns for individual items.

Error Measurement

Forecast error can be measured in a number of ways, including the mean absolute deviation (MAD), the mean absolute percentage error (MAPE), and root mean squared error (RMSE). Armstrong and Collopy, in their extensive study of error measurements, evaluated the various approaches according to their reliability, construct validity, outlier protection, sensitivity, and applicability to decision-making.[16] They presented

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[14]See: A.B. Schwarzkoph, R.J. Tersine, and J.S. Morris, "Top-down versus Bottom-up Forecasting Strategies," *International Journal of Production Research,* Vol. 26, No. 11 (1988), pp. 1833–1843; K.B. Kahn, "Revisiting Top-down versus Bottom-up Forecasting," *Journal of Business Forecasting,* Summer 1998, pp. 14–19; and L. Lapide, "New Developments in Business Forecasting," *Journal of Business Forecasting,* Summer 1998, pp. 28–29.

[15]Schwarzkoph *et al., op. cit.*

[16]J.S. Armstrong and F. Collopy, "Error Measures for Generalizing about Forecasting Methods: Empirical Comparisons," *International Journal of Forecasting,* Vol. 8 (1992), pp. 69–80.

Figuring Probabilities

Consider a hotel which has forecasted 100 arrivals for next Tuesday. It does not have detailed information on the length of stay and rate categories for each of the arrivals, but does know that historically on Tuesdays, 80 percent of guests stay for one night and 20 percent for two nights. It uses these percentages (or probabilities) to forecast that 80 of the Tuesday arrivals will stay for one night and 20 for two nights.

Similarly, if the hotel has been keeping track of Tuesday arrivals over time, its managers know that 40 percent of Tuesday arrivals pay a $150 rate and 60 percent pay a $100 rate. They can then forecast that of the 100 Tuesday arrivals, 40 will pay $150 and 60 will pay $100.

If the hotel wants to develop detailed forecasts by LOS and RC, it can simply multiply the above probabilities together. For example, to determine the number of guests staying for one night who pay $150, the managers can multiply 100 arrivals times 80 percent (for one night) times 40 percent (for those paying $150) = 32 guests.

At the highest level of aggregation, the hotel would just forecast the number of Tuesday arrivals. To create detailed forecasts by rate class (RC) and length of stay (LOS), managers would multiply the different probabilities together. If the hotel managers chose to forecast by LOS, they would forecast the number of one-night and two-night arrivals for next Tuesday and then apply the RC probabilities (i.e., 40 percent pay $150 and 60 percent pay $100). Conversely, if they chose to forecast by RC, they would forecast the number of $100 and $150 arrivals for next Tuesday and then apply the LOS probabilities (i.e., 80 percent stay for one night and 20 percent stay for two nights).

Finally, if they chose to forecast at the completely disaggregated level, they would develop four detailed forecasts for Tuesday arrivals: $150 and one-night stay; $150 and 2-night stay; $100 and one-night stay; and $100 and two-night stay.

The example given is simplified and only assumes two rate classes and two lengths of stay. Consider the number of forecasts (as in the case of the accompanying study) that are required for a hotel that forecasts, say, seven lengths of stay and eight rate classes!—*S.E.K.*
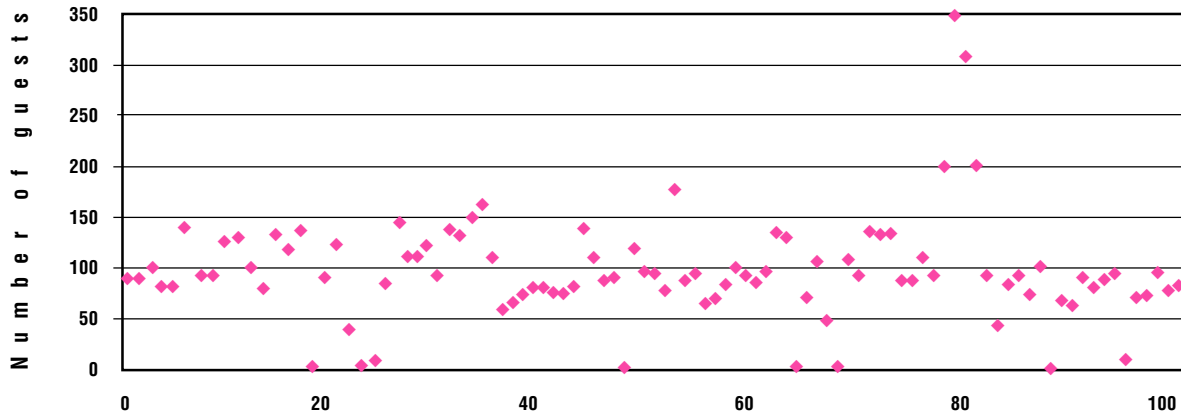
EXHIBIT 4

Sample data set for Thursday arrivals

This graph plots the actual number of guests staying on 100 Thursday nights.
These data can be used to develop a probability analysis for future Thursday-night arrivals.

the concept of a relative absolute error in which the absolute error resulting from a particular forecasting method is compared against the absolute error resulting from a random-walk approach. They found that with a small number of data series the median relative absolute error (MdRAE) and the geometric mean of the relative absolute error (GMRAE) worked best to calculate errors. With a moderate to large number of data series, they recommended that the median absolute percentage error (MdAPE) and the GMRAE provided the most robust results. The root mean squared error, a common method for comparing forecast accuracy, was found to be highly inaccurate.

Schnaars compared the results of five popular forecasting methods with those of a random walk for 1,500 time series.[17] He found that random-walk forecasts outperformed the popular approaches, particularly when the data were highly variable. He also found that smoothing models were more accurate than other methods because of the flexible weights that mimic the results obtained from the random walk.

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[17]S.P. Schnaars, "Situational Factors Affecting Forecast Accuracy," *Journal of Marketing Research,* Vol. 21 (1984), pp. 290–297.

Description of the Study

We obtained data from Marriott for two large business hotels that recorded less than 10-percent group business. The data comprised two years of daily unconstrained transient arrivals by length of stay and rate category. The detailed arrivals data included information on the number of reservations on hand at 16 different reading days (to wit, 84 days before arrival, 70, 56, 42, 35, 28, 21, 14, 7, 6, 5, 4, 3, 2, 1, and 0), for arrivals by length of stay (7 different categories), and rate category (8 different categories).

The data showed the volatility typical in the hotel industry (see Exhibit 4). Demand for Thursday-night arrivals for rate category 1 and two-night length of stay averaged 95 customers with a standard deviation of 51. The number varied between 0 and 347 over the two-year period. This volatility makes it extremely difficult to achieve accurate forecasts, and may cause the random-walk forecast to outperform other forecasting methods.[18]

In this research, we examined each of the following approaches in developing forecasts for each reading day and each day of arrival: the

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[18]*Ibid.*

EXHIBIT 5

Mean absolute deviations for property 1 for different aggregation schemes

	A	B	C	D
		Aggregated	Aggregated	
Rate	Fully	by rate	by length	Fully
category	aggregated	category	of stay	disaggregated
1	52.14	50.51	44.32	40.97
2	0.92	0.83	0.94	0.73
3	2.97	2.49	2.98	1.81
4	12.24	10.93	12.00	9.46
5	7.47	6.65	7.48	5.85
6	3.65	2.77	3.61	2.73
7	0.16	0.07	0.16	0.07
8	8.77	7.67	8.95	6.91

EXHIBIT 6

Mean absolute deviations for property 2 for different aggregation schemes

	A	B	C	D
		Aggregated	Aggregated	
Rate	Fully	by rate	by length	Fully
category	aggregated	category	of stay	disaggregated
1	101.84	94.24	100.81	92.93
2	2.40	2.10	2.42	1.95
3	24.31	20.24	23.89	18.43
4	8.38	7.12	8.36	6.14
5	12.14	10.32	12.01	9.46
6	11.34	8.23	11.29	7.25
7	6.20	5.14	6.17	4.25
8	13.12	10.66	12.96	9.53

classical-pickup method,[19] moving averages, linear regression, simple exponential smoothing, and random walk.[20] Previous research showed that the classical-pickup and exponential-smoothing models produced a lower error than did other methods tested.[21] The random-walk forecasts were used to check whether we gained additional accuracy by using exponential smoothing and the classical-pickup method.

We developed forecasts for four different levels of aggregation:

A. Completely aggregated with RC and LOS probability distributions;

B. Disaggregated by RC with LOS probability distributions;

C. Disaggregated by LOS with RC probability distributions; and

D. Disaggregated by RC and LOS.

We calculated the probability distributions by taking the historical averages (updated for each forecast made) for each rate-category and length-of-stay combination. In terms of the forecasting typology presented in Exhibit 3, the approach we took for this project could be described as 1A-2ABCD-3B-4A-5A-6A-7C. That is, different levels of aggregation were tested (2ABCD) on arrivals-based data (1A) that had been unconstrained using denials data (3B).[22] Forecasts were developed using all periods (4A) and then only for completed stay-nights (5A). Outliers were not removed (6A), and forecast errors were averaged and reported over all reading days (7C).

We determined the MAD, MAPE, and MdRAE for each method for each reading day. The relative absolute error was calculated as the ratio of the absolute error obtained with one of the four forecasting methods (i.e., exponential smoothing, moving average, classical pickup, and linear regression) divided by the absolute error obtained from the random-walk forecast. The random-walk forecasts and the MdRAE measure were used as a comparison to check whether additional accuracy was obtained by using a formal forecasting method such as exponential smooth-

[19]See: L'Heureux, *op. cit.*; and R.R. Wickham, "Evaluation of Forecasting Techniques for Short-term Demand of Air Transportation," Massachusetts Institute of Technology Flight Transportation Lab Ph.D. Thesis, 1995.

[20]Schnaars, *op. cit.*; Armstrong and Collopy, *op. cit.*

[21]Kimes and Weatherford, *loc. cit.*

[22]At the time of this study, Marriott tracked not only reservations that were booked, but also those that were denied because of capacity limitations. For a full discussion of denials, please see Orkin, *op. cit.*

EXHIBIT 7

Mean-absolute-deviation (MAD) ratios for Property 1

ing, the moving average, the classical-pickup method, or linear regression.

In addition, the MAD from each aggregation level was compared to the MAD of the fully disaggregated forecast. A MAD ratio greater than 1.0 indicates that the disaggregated forecast produces better results, while a MAD ratio of less than 1.0 shows that the aggregated approach produces better results. The MAD ratio gives a clearer means of comparing the error resulting from the various aggregation approaches.
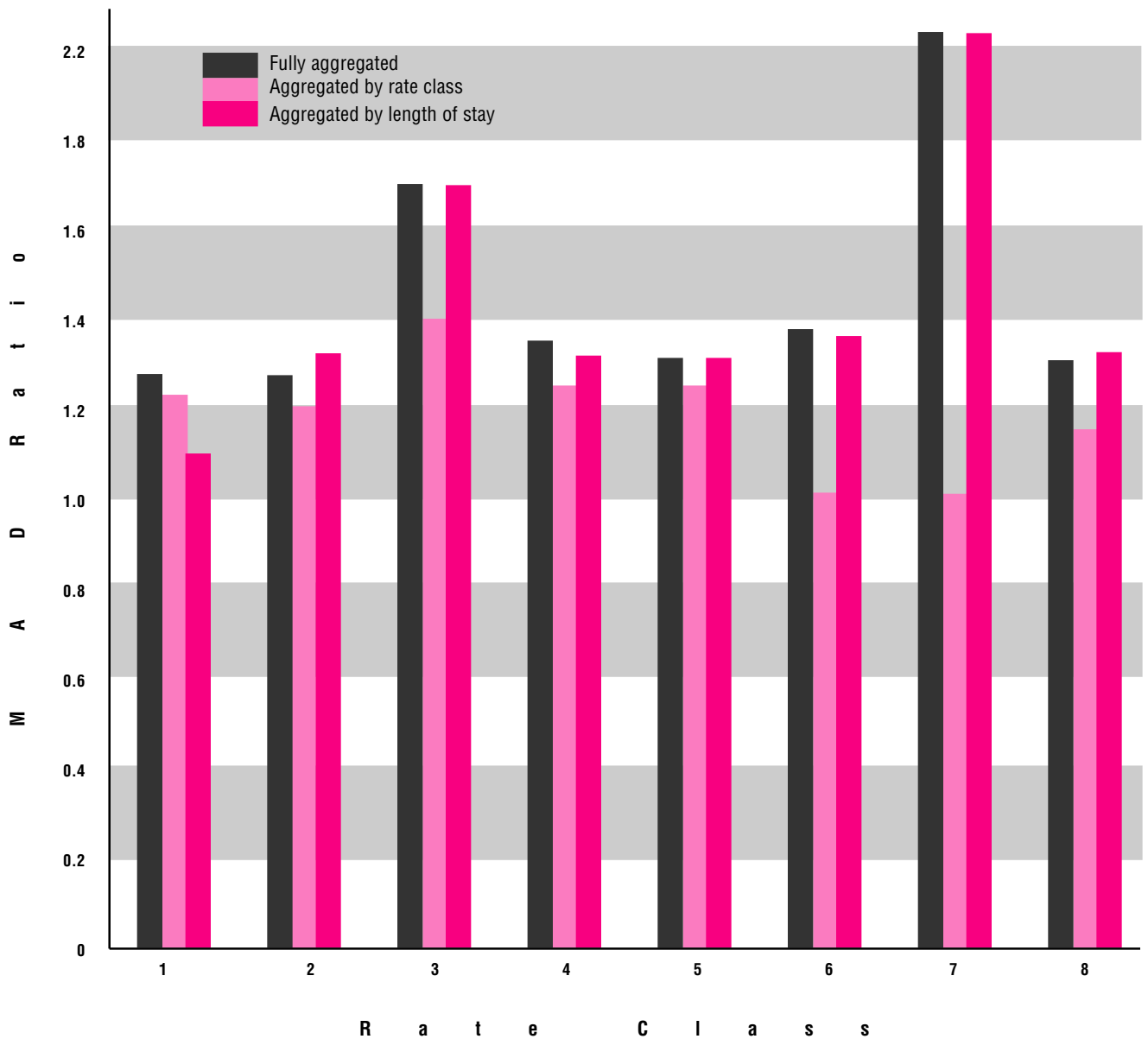
Results

We present the results for the four different aggregation schemes:

   A. Completely aggregated with RC and LOS probability distributions;

   B. Disaggregated by RC with LOS probability distributions;

   C. Disaggregated by LOS with RC probability distributions; and

   D. Disaggregated by RC and LOS.

## Mean-absolute-deviation (MAD) ratios for Property 2

We compared aggregation approaches A through C to the fully disaggregated scheme, D. Because of the large number of data sets for which forecasts were generated, we report the results as a summary, even though we made a disaggregated forecast and measured the error at each property, rate category, and length-of-stay. Thus, for instance, we grouped the values for property 1, rate category 1, and all 7 lengths of stay into one summary measure that showed the average MAD over all reading days for the best forecasting methods for the set. We report the MAD for the two properties (Exhibits 5 and 6), MAD ratios (Exhibits 7 and 8), and median RAE (Exhibits 9 and 10) for each aggregation scheme. To get an idea of how the MAD varied

EXHIBIT 9

Median relative absolute error (RAE) for Property 1
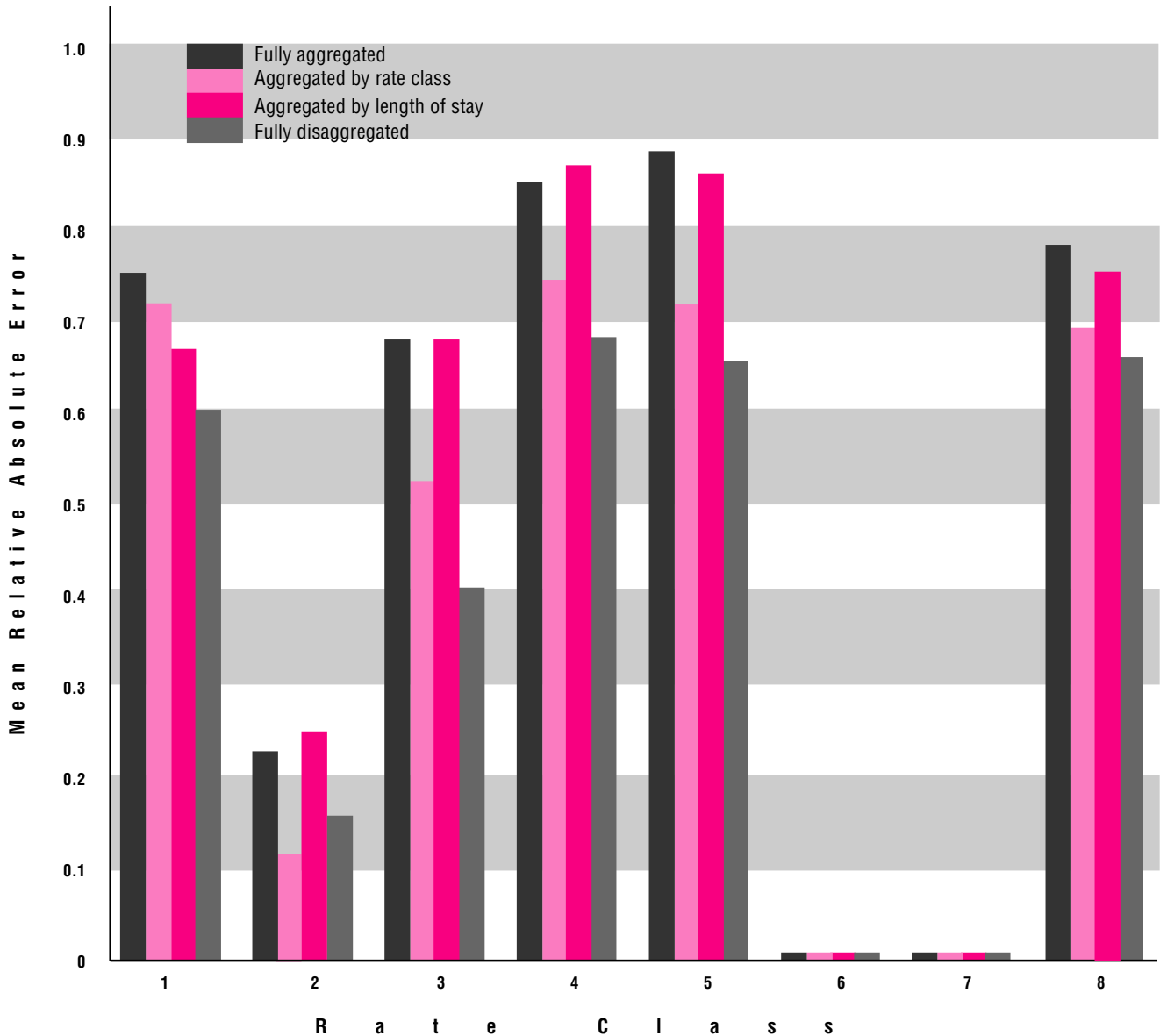
by the actual number of days left (as opposed to the average MAD across all reading days), we include one sample figure (Exhibit 11).
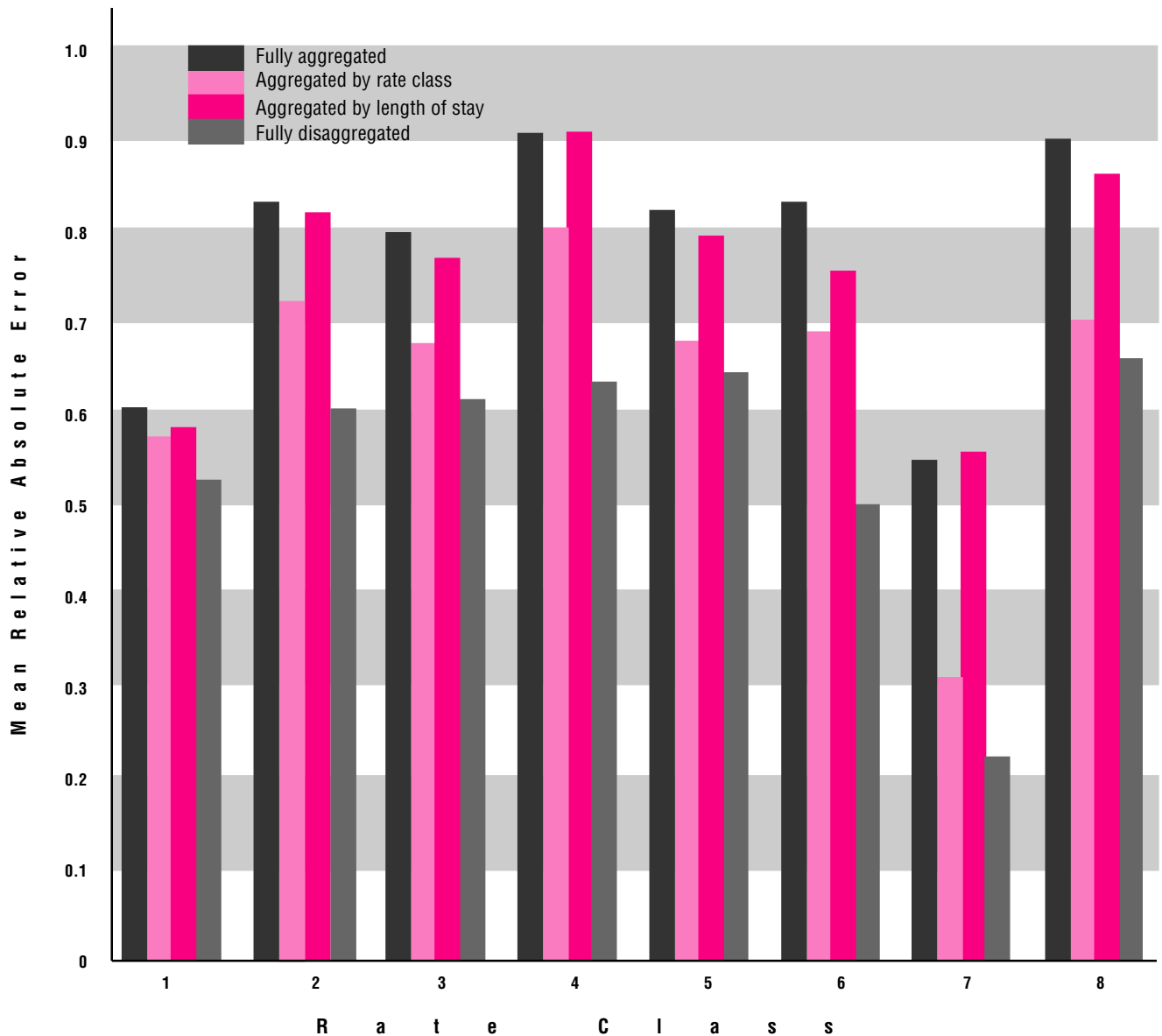
The conclusion that we draw from the calculations shown in the accompanying exhibits is this: The disaggregated forecast (D) outperformed the other aggregation approaches (A, B, and C; see Exhibits 5 and 6). Aggregation by rate category was superior to aggregation by length

of stay or complete aggregation. The fully aggregated approach was clearly the worst performer.

We also calculated the MAD ratios for each of the aggregation methods (A, B, and C) with the fully disaggregated forecast (D). Once again, a MAD ratio greater than 1.0 indicated that the disaggregated forecast produced better results, while a MAD ratio of less than 1.0 showed that the aggregated approach produced better results

EXHIBIT 10

Median relative absolute error (RAE) for Property 2

Mean Relative Absolute Error

Legend:
- Fully aggregated
- Aggregated by rate class
- Aggregated by length of stay
- Fully disaggregated

Rate Class: 1, 2, 3, 4, 5, 6, 7, 8

(see Exhibits 7 and 8). Again, we found that the disaggregated approach was superior to the other aggregation schemes, followed by aggregating by rate category. Aggregation by length of stay and full aggregation produced poorer results as compared to the other two methods.

We calculated the median RAE for each aggregation scheme for each property to test whether the forecasts generated by the different aggregation schemes performed better than a random-walk forecast (see Exhibits 9 and 10). In all cases, the forecasts at the different levels of aggregation outperformed the random-walk forecast (as indicated by a MdRAE < 1.0), even though the data were volatile.

Full Disaggregation

Of the aggregation schemes (A, B, C, and D), the fully disaggregated forecast (scheme D) pro-

Sample MAD for Property 1, rate-category 1
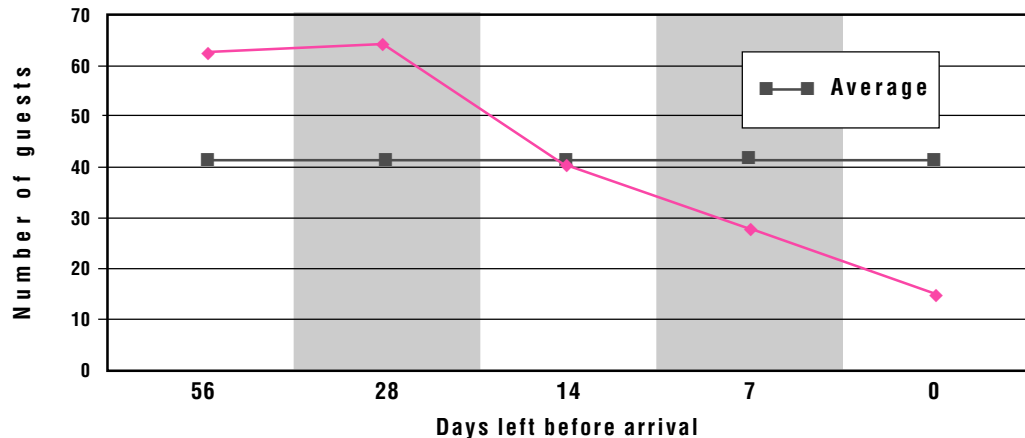
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duced the lowest error. Aggregating by rate category (scheme B) almost always resulted in a lower MAD, MAPE and MdRAE than either aggregating by length of stay (scheme C) or aggregating by both rate category and length of stay (scheme A).

The results of this study showed that a purely disaggregated forecast (even though it meant forecasting smaller numbers) strongly outperformed even the best aggregated forecast. So, even though forecasting larger numbers may be more accurate in itself, the process required to forecast at the combined level of rate category and length of stay resulted in lower accuracy than just forecasting at the more-detailed level in the first place.

As we found in our earlier research, the four forecasting methods tested (exponential smoothing, moving average, linear regression, and additive pickup) all performed about equally well.[23]

Given that an increase in forecasting accuracy has been shown to have a significant effect on revenue generated from a revenue-management system,[24] it behooves a hotel revenue manager to develop the data necessary to forecast at a disaggregated level. All aggregation approaches resulted in higher forecast error than a fully disaggregated method regardless of the error measurement used.

This finding implies that hotel revenue managers should track arrivals by rate category and length of stay for each day of the planning horizon. If it is impossible to track arrivals by both rate category and length of stay, the revenue manager should at least track arrivals by rate category. While the additional effort may seem considerable, the forecast is the most important driver of any revenue-management optimization approach. Our research shows that hotels should forecast at a detailed level if the true benefits available from revenue management are to be achieved. ■

[23]Kimes and Weatherford, *loc. cit.*

[24]Lee, *loc. cit.*