REVISITING TOP-DOWN VERSUS BOTTOM-UP FORECASTING

By Kenneth B. Kahn

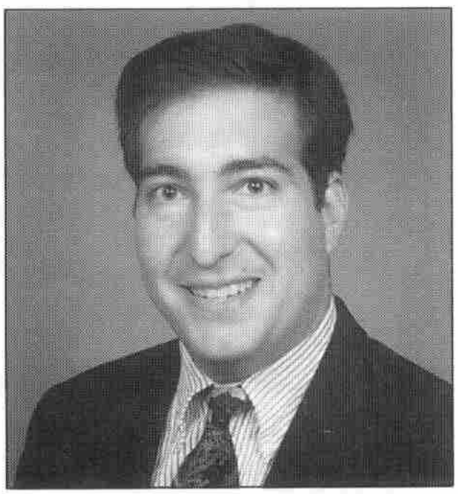
Top-down approach achieves a better forecast at the aggregate level and bottom-up approach, at the lowest level ... a top-down approach assumes that one seasnonal pattern fits all, that is, the seasonal pattern both at the aggregate and disaggregate levels are the same, which is often not the case ... a hybrid approach which combines both may be the solution.

What is the best approach to sales forecasting? Is it a top-down approach, where national brand forecasts are proportioned down to individual product items per location forecasts? Or is it a bottom-up approach, where item per location forecasts are aggregated up to create a national brand forecast?

Various opinions support either approach. Proponents of top-down forecasting favor smoothing lower level data by aggregating it so that one can develop a better fitting model (the top-level model will reflect a better R^2 value than lower level models). It is also felt that top-down models often reflect better accuracy for top-level forecasting. The problem is top-down models typically do a poor job of forecasting at lower forecast levels (e.g.,' at the item per location level). The reason: aggregated data at the top-level is an artificial representation of the true nature of the business because such data does not typically reflect sales low level "peaks and valleys," which are canceled by aggregation.

Proponents of bottom-up forecasting point to the fact that one can achieve a better mean absolute percent error (MAPE) value at the lower level (see Gordon, Morris, and Dangerfield 1997). This is due in part to the fact that the lower level models reflect the actual nature of the business. A bias also has been documented in regression coefficients when aggregated data is used (see Blattberg and Neslin 1990). While this supports a bottom-up approach, bottom-up forecasting often has very poor accuracy at higher forecast levels. This may be a result of forecast error at intermediate (middle) levels accumulating as data moves up to higher levels.

Naturally, choosing whether to use a top-down or bottom-up forecasting approach should depend on the objective driving why one forecasts. If the company uses forecasts to develop strategic plans and budgets, then top-down forecasting would be preferable. Conversely, if production and distribution schedules (tactical side of the business) are driven by forecasts, then bottom-up forecasting would probably be a preferred choice. There are, of course, many companies that generate one forecast by reconciling top-down and bottom-up forecasts. Which approach should be used?



KENNETH B. KAHN

Dr. Kahn is an Assistant Professor in the DuPree School of Management at the Georgia Institute of Technology. He has published in a variety of journals and conference proceedings, including the Journal of Business Research.

Based on research conducted with a major consumer products company, a hybrid approach may be preferable. That is, a top-down model can be created and forecasts proportioned down to lower forecast levels by lower level models (lower level analyses). The purpose of this paper is to overview such an approach.

UNDERLYING ISSUES

The basic problem with top level and low level data stems from the issue of variability. As shown in Figure 1, aggregated data at the highest level is smoother than lower level data and corresponds to lower percent differences about the means of individual time series at respective forecast levels. Thus, aggregation reduces variability. Interestingly, research indicates that top-level data reflects more randomness than lower level data. That is, top-level data, while smoothed, exhibits small random fluctuations. One should therefore realize that aggregation of sales data reduces data swings (reduces variability), but introduces random fluctuations (increases random-ness) (see Kahn 1998).

This explains why top-down and

TABLE 1
DATA PATTERN CHARACTERISTICS

Level	Brand	Item	Location	Volume %	Description
Top	A			100%	Evidence for 12 month seasonality, no trend
Intermediate	A	1		14%	Evidence for 6 month seasonality, no trend
Intermediate	A	2		86%	Evidence for 12 month seasonality, no trend
Total Brand	**A**			**100%**	
Lowest	A	1	T	16%	No seasonality, no trend, some randomness
Lowest	A	1	U	7%	No seasonality, no trend, some randomness
Lowest	A	1	V	42%	Evidence for 12 month seasonality, no trend
Lowest	A	1	W	35%	No seasonality, no trend, some randomness
Total Item		**1**		**100%**	
Lowest	A	2	X	30%	Evidence for 12 month seasonality, no trend
Lowest	A	2	Y	47%	Evidence for 12 month seasonality, no trend
Lowest	A	2	Z	23%	Evidence for 12 month seasonality, no trend
Total Item		**2**		**100%**	

bottom-up approaches have difficulty forecasting at the opposite end of the spectrum. Top-down forecasts have difficulty with lower level forecasting because the model is based on an artificial, more random data set. But forecasts based on top-level data achieve a better model fit at higher levels because there is less relative variability in the data.

Bottom-up forecasts often have difficulty with top-level forecasting because the wide variability reflected at the lowest level introduces greater variability into the forecast, thereby widely under-forecasting or over-forecasting at the top-level. Bottom-up forecasts achieve a better MAPE at the lowest level because they reflect the actual demand pattern. In fact, individual item locations can have unique seasonality patterns — a top-down approach assumes that one seasonal pattern fits all. It is recommended that the forecaster investigate to see if individual items locations do indeed have similar seasonal patterns.

A CASE STUDY

An empirical case study shows that there are cases where a bottom up approach performs better than a top down approach and vice-versa. Because both top-down and bottom-up forecasting offer benefits in their own right, a merging of these two approaches or a hybrid approach is suggested.

The case study is based on a small sample data set comprising a real data that represents three forecast levels: 7 locations, 2 items, and 1 brand. Four of the locations correspond to one item, and the remaining three locations correspond to the other item. Both items correspond to the same brand.

The data is first analyzed to reflect the pattern characteristics for each forecast. Simple time series regression was used to determine trend, and autocorrelation analysis was employed to assess seasonality (refer to Makridakis, Wheelwright, and McGee 1983). As shown in Table 1, four of the locations reflect a 12 month seasonality and no trend (locations V, X, Y, and Z), while three locations reflect no seasonality and no trend (locations T, U, and W). Analysis further indicates that these three latter locations reflect some degree of randomness (a battery of seven tests for randomness were used). At the intermediate level (item level), item 1 reflects a 6 month seasonality with no trend, and item 2 reflects a 12 month seasonality. The overall brand reflects a

TABLE 2
COMPARISONS OF MAPE ACROSS FORECAST LEVELS

Brand: **Item:** **Location:**	A	A 1	A 2	A 1 T	A 1 U	A 1 V	A 1 W	A 2 X	A 2 Y	A 2 Z
Individual ES Model w/o Seasonal Indices ($\alpha = .2$)	20	22	28	97	83	57	68	26	25	42
Individual ES Model with Seasonal Indices ($\alpha = .2$)	10	11	18	na	na	48	na	19	16	23
Bottom-Up Model (Sum of Individual ES Models with Seasonal Indices)	10	23	11	na	na	na	na	na	na	na
Top-Down Model (Proportion Breakup of Top-Level Model w/o Seasonal Indices)	na	22	25	84	77	54	62	25	24	40
Top-Down Model (Proportion Breakup of Top-Level Model w/ Seasonal Indices)	na	11	21	74	71	46	60	18	16	25
Top-Down Model (Proportion Breakup of Top-Level Model w/o Seasonal Indices Modified by Low Level Seasonal Indices)	na	11	18	na	na	42	na	17	15	21
Top-Down Model (Proportion Breakup of Top-Level Model w/ Seasonal Indices Adjusted by Low Level Seasonal Indices Ratio)	na	30	24	na	na	43	na	20	17	25

Note: 1. MAPE = Mean absolute percent error 2. ES = Exponential smoothing

seasonality of 12 months and no trend.

This analysis confirms that individual locations can reflect their own seasonalities. Only one location corresponding to item 1 has a seasonal pattern, and interestingly, this pattern differs from the overriding item's seasonality (12 month versus 6 month seasonality). Conversely, all locations corresponding to item 2 except one reflect item 2's twelve month seasonality. This short analysis illustrates that an individual analysis of specific locations can lead to a better understanding of the business and customers. The forecaster might consider further analyses to find out why such differences may exist, which in turn, may be useful for improving forecast accuracy at the location level.

Table 2 shows the results of applying an exponential smoothing approach to each of the data patterns at each level. The same simple exponential smoothing model with $\alpha = .2$ was applied to each time series because it generated the lowest overall MAPE; the use of the same forecasting model also served to control for the possible influence of added variation by a particular technique. In total, seven forecasting models were developed: (1) individual exponential smoothing model without seasonal indices; (2) individual exponential smoothing model with seasonal indices; (3) bottom-up model using the seasonal exponential smoothing model; (4) top-down model based on decomposing the nonseasonal exponential smoothing model at the brand level down to the location levels; (5) top-down model based on decomposing the seasonal exponential smoothing model at the brand level down to the location levels; (6) top-down model based on decomposing the nonseasonal exponential smoothing model and using lower level (location level) seasonality indices; and (7) top-down model based on decomposing the seasonal exponential smoothing model and adjusting the forecast by the ratio of lower level (location level) seasonal indices to top level seasonal index.

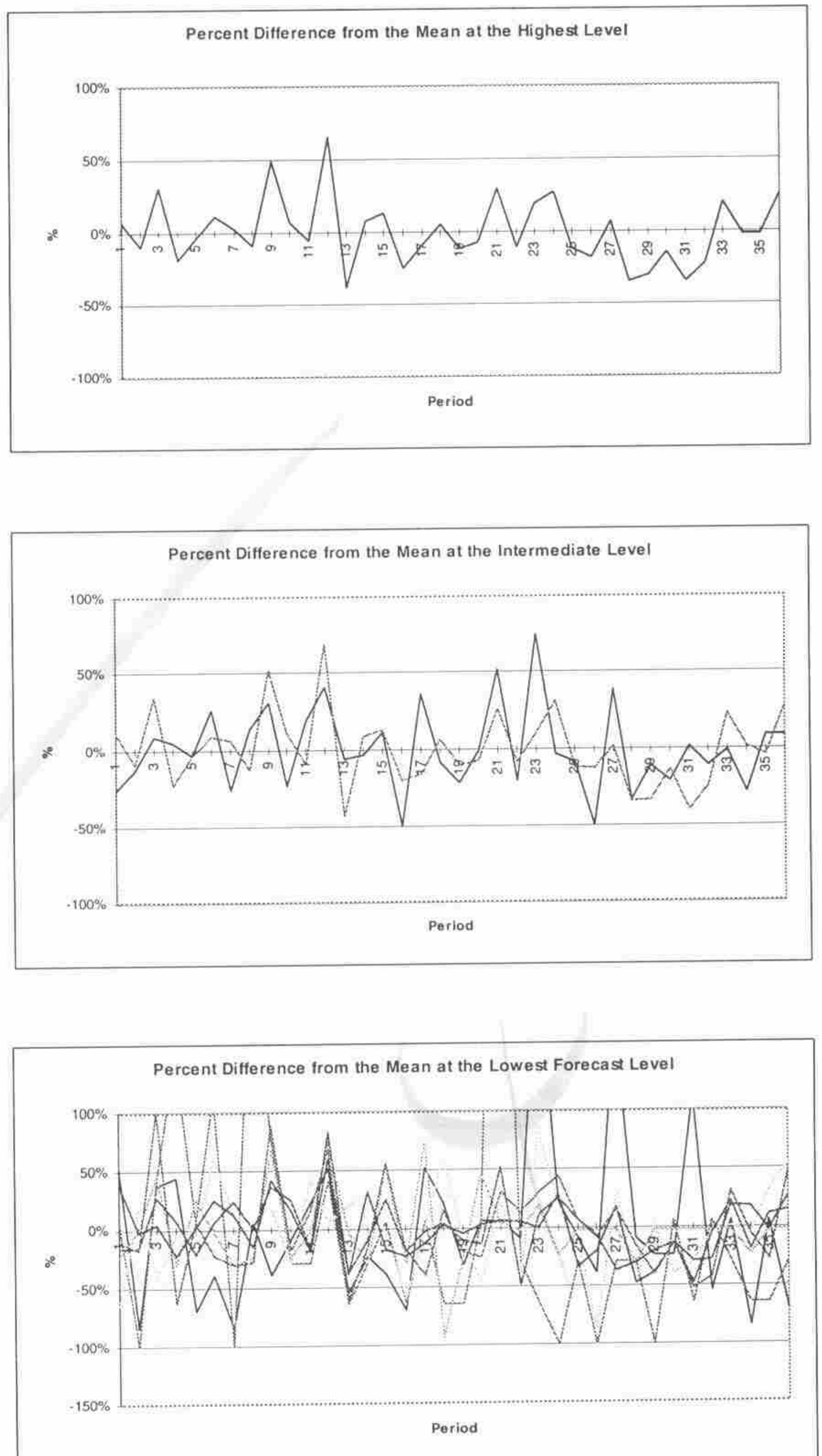
As expected, Table 2 shows that forecast error diminishes as one moves up to a higher forecast level. This is due to the smoothing of data swings as previously discussed, thereby allowing a better fit of the data by the respective model.

An interesting finding was that the brand forecast from top-level forecasting was equivalent to the brand forecast derived from bottom-up forecasting (both reflected a MAPE equal to 10). One possible explanation is that the data is heavily influenced by locations X, Y, and Z, which comprise 86% of the brand volume. These three locations reflected a twelve-month seasonality akin to the brand and corresponding item. Furthermore, aggregating X, Y, and Z makes a very good forecast of the size 2's volume (MAPE = 11), and thus, because these locations comprise a significant portion of the brand, would more correctly forecast the brand.

However, the best values of MAPE for the location level forecasts were generated by a top-down approach. Specifically, the top-down model without seasonal indices modified by location (low) level seasonal indices reflected the lowest MAPE values for locations V, X, Y, and Z. The top-down model with seasonal indices proportioned down to lower levels was best in the cases where no location level seasonality existed, i.e., locations T, U, and W.

Overall, these results indicate that both top-down and bottom-up approaches are

FIGURE 1
TOP-LEVEL DATA VERSUS BOTTOM-LEVEL DATA



useful. Moreover, the results point to several tentative guidelines about employing top-down and bottom-up approaches:

- Top-down forecasting appears to be most successful at low level forecasting when a nonseasonal top-level model is proportioned down and low level seasonal indices are used.

- When data are not seasonal at the lowest level, a top-level model with seasonal indices proportioned down to lower levels appears to be more successful.

- Bottom-up forecasting appears to be most successful when the low-level data streams are homogeneous, i.e., low level data reflect the same patterns of seasonality and trend (which conceivably means that the same data patterns will be reflected at higher levels).

- Bottom-up forecasting appears not to work well when low level data are heterogeneous, i.e., low level data are comprised of different pattern fluctuations.

- Developing individual sales forecasting models at each forecast level can be undertaken and achieve some degree of accuracy, but these models are not significantly more accurate than forecasting using those models associated with a top-down or bottom-up approach.

SUMMARY

While further analysis into the debate into top-down and bottom-up forecasting is needed, both approaches appear to have their usefulness. What is suggested is a compromise between the two approaches leading to a hybrid approach. Sales forecasters might consider developing forecast models at both higher and lower levels, using aggregated data to model the overall business and then lower level models to allocate down the forecast on a proportional basis. It appears that this may be the best solution in some, if not, most cases.

An advantage for undertaking this hybrid approach is that lower level information can be particularly useful in specifying forecasting technique requirements. One can determine which techniques would be most appropriate for which products versus a one technique fits all solution, which often is unsuccessful. A key disadvantage is the amount of time needed to conduct such an analysis. The forecaster could consider segmenting low level analyses/model-building by first analyzing critical items (A items), and then continuing with analyses of less critical items when time allows. For those companies employing regression for high level/strategic forecasts, it is possible to proportion forecasts by developing lower level models/analyses as discussed above.

Overall, one should realize that the ultimate decision to use top-down or bottom-up forecasting stems from which is more valuable to the company: forecasting with understanding at lower levels or general knowledge of the business at the upper level. It is speculated that most companies would prefer to control variation and accept lower level inaccurate forecasting as a reality of business. But better companies see value in performing analyses at both ends and are able to more accurately predict their business. Indeed, a careful analysis at all levels can lead to greater understanding of the business, which should be the objective of sales forecasting in the first place.■

REFERENCES

Blattberg, Robert C. and Scott A. Neslin. **Sales Promotion: Concept, Methods, and Strategies.** Englewood Cliffs, New Jersey: Prentice Hall, 1990.

Gordon, Teresa P., John S. Morris, and Byron J. Dangerfield. "Top-Down or Bottom-Up: Which Is the Best Approach to Forecasting." **Journal of Business Forecasting.** Volume 16 (3), Fall 1997, pp. 13-16.

Kahn, Kenneth B. "Sales Data Randomness: A Definition And Examination." Georgia Institute of Technology Working Paper, Atlanta, Georgia, 1997.

Makridakis, Spyros, Steven C. Wheelwright, and Victor E. McGee. **Forecasting: Methods and Applications** (Second Edition). New York, New York: John Wiley and Sons.