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Further results on focus forecasting vs. exponential smoothing

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Abstract

In an earlier paper, we found that damped-trend, seasonal exponential smoothing was more accurate than a simple version of Focus Forecasting, based on Flores and Whybark [*Production and Inventory Management Journal*, (1986), *14*, 339–366]. This note tests Demand Solutions, a more sophisticated version of Focus Forecasting. As in the earlier paper, we used five time series of cookware demand from a production planning application and 91 time series from the M-Competition study of forecast accuracy. Results are much the same as in our earlier paper. Exponential smoothing is substantially more accurate than Demand Solutions. This is perhaps not surprising in that Demand Solutions' forecasting rules are arbitrary, with no statistical rationale. Users of Focus Forecasting have much to gain by adopting statistical forecasting methods.

Keywords: Exponential smoothing; Focus forecasting; Comparative forecasting methods – time series; Production and operations planning

1. Introduction

The term ''Focus Forecasting'' was coined by Smith (1978) to describe an heuristic methodology that appears to be widely used in practice. The basic idea is to specify a set of alternative decision rules for forecasting one step ahead. All rules are tested each time period. The rule that yields the smallest error in the current period is selected to make the forecast for next period.

In Gardner and Anderson (1997), we compared the accuracy of damped-trend, seasonal exponential smoothing to a Focus Forecasting system drawn from Flores and Whybark (1986). The data included five monthly time series of cookware demand from a real production planning application in which Focus Forecasting had been in use for some years. We also made comparisons for 68 monthly and 23 quarterly time series from the Makridakis et al. (1982) collection of 111 series. Exponential smoothing was more accurate than Focus Forecasting, regardless of error measure or data set.

Would these comparisons to exponential smoothing change with a more sophisticated version of Focus Forecasting? The aim of this note is to answer this question. Most forecasting tests in our earlier paper were repeated using a demonstration version of Demand Solutions

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(DS), a Focus Forecasting program distributed by Demand Management, Inc. (1997). According to Tashman and Tashman (1993), DS is in use at more than 850 customer sites, in 47 countries, and by more than 650 corporations.

2. The Flores–Whybark version of focus forecasting

A brief review of the Focus Forecasting system used by the cookware manufacturer is provided here for comparison to the DS methodology. The forecasting rules below are identical to Flores and Whybark (1986) except for Rule 3, which was developed by the company:

1. The forecast for next month is actual demand for the same month last year.
2. The forecast for next month is 110% of actual demand for the same month last year.
3. The forecast for next month is actual demand for the same month last year multiplied by a growth ratio: last month's demand divided by the same month a year ago.
4. The forecast for next month is one-sixth of total actual demand for the last 6 months (a two-quarter moving average).
5. The forecast for next month is one-third of actual demand for the previous three-month period (a one-quarter moving average).
6. The forecast for next month is one-third of actual demand for the same 3-month period last year, multiplied by the growth or decline since last year. The growth or decline is measured by the ratio of demand for the last 3 months to demand for the same 3 months last year.
7. If the demand in the last 6 months is less than 40% of demand for the 6 months preceding that, the forecast for next month is one-third of 110% of demand for the same three-month period last year.
8. If demand in the last 6 months is more than 2.5 times demand for the 6 months preceding that, the forecast for next month is one-third of demand for the same three-month period last year.

For each rule, a monthly error measure is computed: the absolute value of the average forecast error for the last 3 months. The method with the lowest error measure is selected to make the forecast for next month. Rules 7 and 8 are complex attempts to forecast the extreme months (trough and peak) of the annual seasonal cycle. No rationale for these rules is given in Flores and Whybark and we find them difficult to justify.

3. The demand solutions forecasting system

DS includes twenty alternative forecasting rules. Three are based on simple exponential smoothing with different parameters: 0.10, 0.20, and a fitted parameter from the range 0.05 to 0.95. Seventeen additional rules are functions of previous quarterly data:

1. Next quarter will equal last quarter.
2. Next quarter will equal last quarter plus a growth factor.
3. Next quarter will equal the same quarter a year ago.
4. Next quarter will equal the same quarter a year ago plus a growth factor.
5. Next quarter will equal the average of the last two quarters.
6. Next quarter will equal the average of the last two quarters plus a growth factor.
7. Next quarter will equal the average of the last two quarters, with the last quarter double-weighted.
8. Next quarter will equal the last quarter plus the difference of the corresponding quarters last year.
9. Next quarter will equal the average of the

last three quarters, with the last quarter double-weighted, and with seasonal adjustment.

10. Next quarter will equal the average of the same quarter in the last two years plus a growth factor.
11. Next quarter will equal the average of the last quarter of the current year plus the difference of the corresponding quarters from last year plus the difference of the corresponding quarters from two years ago.
12. Next quarter will equal the average quarter of the last year.
13. Next quarter will equal the average quarter of the last year plus a growth factor.
14. Next quarter will equal the average quarter of the last two years.
15. Next quarter will equal the average quarter of the last two years with seasonal adjustment.
16. Next quarter will equal the average quarter last year plus the change from the average quarter two years ago.
17. Next quarter will equal the average quarter last year, plus the change from the average quarter two years ago, with seasonal adjustment.

It is important to understand that quarters are defined by DS not as calendar quarters, but as successive three-month periods. DS forecasts the last 3 months of historical data with each of its twenty formulas, calculates a variance for the three-month period, and stores the variance in memory. This process is defined as an iteration. DS repeats this procedure for consecutive three-month periods. For example, if the fit sample contains 42 periods of data, DS will forecast and calculate the variance for periods 40 through 42, 39 through 41, 38 through 40, etc., up to a maximum of 12 iterations. An error measure is computed by dividing the sum of the stored variances by the sum of the periods in the iteration process. The formula which yields the lowest error measure is selected to produce the next forecast.

This three-period evaluation procedure is confusing. Furthermore, it seems difficult to justify aggregation of monthly data to quarterly in order to make decisions regarding which model to choose, and then disaggregate to produce monthly forecasts. One of the referees for this paper pointed out that aggregation of the data could produce worse forecasts than if the decision rules were based on monthly data in the first place.

It is not clear that DS forecasting rules should perform well in any particular type of time series although Fildes et al. (1998) show that it is important to match forecasting methods with the structure of time series. No consideration is given to robustness in DS although Fildes et al. demonstrate that robust estimates improve forecast accuracy. In DS, outliers can easily result in ill-advised changes in forecasting rules.

The DS methodology has also been criticized by Carbone (1999), who compared the DS seasonal adjustment procedure to standard decomposition, using data from the DS manual. Classical decomposition outperformed DS dramatically and in some cases the seasonal indices generated by the two methods were of opposite sign. Carbone also fitted a linear trend and Holt's version of exponential smoothing to data from the DS manual and produced more accurate forecasts.

4. Forecast accuracy comparisons

The methodology in Gardner and Anderson (1997) was replicated as much as possible to compare damped-trend, seasonal exponential smoothing to the DS system. The same five time series from the cookware manufacturer were used. The first $n/2$ observations (rounded to the next higher integer in the case of a fractional result) were used for model fitting, with one-and six-step-ahead forecasts calculated for the remainder of each series. An adjustment to the model-fitting procedure was made for DS, which limits the number of periods used in model fitting to 42. In the cookware series this made no difference since the longest series contained 65 observations. In the Makridakis data, when the model-fitting portion of the time series was longer than 42 observations, we truncated the beginning of the series.

The exponential smoothing system used in our earlier paper was the multiplicative seasonal version of the damped-trend model developed by Gardner and McKenzie (1989). The intent was to use an exponential smoothing system in a completely automatic fashion. Initial seasonal indices were computed using the ratio-to-moving average method. Initial level and trend were computed using a linear regression on time fitted to the deseasonalized data. The initial level was set equal to the intercept of the trend line, and the trend was set equal to the slope. Next, models were fitted using a grid search procedure to minimize the mean-squared-error (MSE). The search was conducted over the range 0 to 1 for all smoothing parameters as well as the damping parameter. See Gardner and Anderson (1997) for a complete description of experimental design.

Forecast accuracy comparisons of damped-trend seasonal exponential smoothing, the Flores–Whybark (FW) Focus Forecasting system, and DS for one- and six-step-ahead forecasts are given in Tables 1–6. The six-step-ahead results (Tables 2 and 4) compare only exponential smoothing and DS since the FW system is unable to forecast more than one step ahead. In Gardner and Anderson (1997),

Table 1
Cookware: One-step-ahead error measures

Series	RMSE			MAD			MAPE			Median APE		
	Exp.sm.	FW	DS	Exp.sm.	FW	DS	Exp.sm.	FW	DS	Exp.sm.	FW	DS
1	200.6	333.6	161.1	160.0	241.0	128.0	4.6	6.9	3.9	4.5	4.1	3.5
2	213.6	344.6	339.5	154.2	279.4	238.6	5.6	11.1	8.4	5.1	8.6	5.7
3	439.1	822.2	649.0	354.1	634.8	523.4	8.4	14.7	12.0	8.9	14.7	10.4
4	264.1	316.8	283.8	220.6	266.4	232.1	13.8	17.0	14.4	12.8	14.3	11.1
5	715.4	1,056.3	1,159.3	490.5	848.1	848.7	17.7	39.1	30.1	14.0	23.6	20.5
Mean	366.5	574.7	518.5	275.9	453.9	394.2	10.0	17.7	13.8	9.1	13.1	10.2

Table 2
Cookware: Six-step-ahead error measures[a]

Series	RMSE			MAD			MAPE			Median APE		
	Exp.sm.	FW	DS	Exp.sm.	FW	DS	Exp.sm.	FW	DS	Exp.sm.	FW	DS
1	264.6	NA	186.4	222.5	NA	163.1	6.7	NA	5.0	4.9	NA	4.6
2	425.8	NA	600.0	339.3	NA	460.9	11.9	NA	16.0	9.6	NA	14.1
3	775.8	NA	941.1	628.4	NA	803.5	13.5	NA	18.2	13.8	NA	20.4
4	235.9	NA	261.8	196.7	NA	225.1	12.4	NA	14.0	12.0	NA	12.2
5	708.0	NA	1,058.4	615.9	NA	854.3	25.0	NA	31.9	20.7	NA	26.3
Mean	482.0	NA	609.6	400.6	NA	501.4	13.9	NA	17.0	12.2	NA	15.5

[a] Note: The Focus system used in this paper is unable to forecast more than one step ahead.

Table 3
M-Competition: One-step-ahead error measures

Series	MAPE			Median APE		
	Exp.sm.	FW	DS	Exp.sm.	FW	DS
Quarterly	8.1	11.7	16.4	2.8	3.7	6.9
Monthly	10.4	12.0	12.0	6.2	7.3	6.8

Table 4
M-Competition: Six-step-ahead error measures[a]

Series	MAPE			Median APE		
	Exp.sm.	FW	DS	Exp.sm.	FW	DS
Quarterly	18.4	NA	23.1	6.0	NA	13.3
Monthly	15.5	NA	16.4	9.8	NA	11.5

[a] Note: The Focus system used in this paper is unable to forecast more than one step ahead.

Table 5
M-Competition: Percent of series in which exponential smoothing was better than DS (one-step-ahead)

Series	RMSE	MAD	MAPE	Median APE
Quarterly	95.7	91.3	87.0	91.3
Monthly	70.1	70.1	68.7	66.2

Table 6
M-Competition: Percent of series in which DS was better than FW (one-step-ahead)

Series	RMSE	MAD	MAPE	Median APE
Quarterly	21.7	17.4	13.0	21.7
Monthly	65.7	58.8	55.9	45.6

geometric MSE results were given. We did not compute the geometric MSE for DS errors because of limitations in our demonstration version of the DS software. The geometric MSE requires time series of ratios of squared errors from two competing forecasting methods. It was possible to compute error measures for DS results by themselves but we could not export files to construct time series of ratios.

Table 1 gives one-step-ahead results for the cookware series. DS was more accurate than exponential smoothing in Series 1. For the remaining cookware series, smoothing was consistently more accurate, with the exception of the Median APE for Series 4. Some of the differences in Series 2–5 are quite large. For example, in Series 5, smoothing produces an RMSE about 62% of that for DS. The mean RMSE and MAD (averaged over all five series) are scale-dependent, so they have little meaning. However, the MAPE and Median APE over all series are meaningful. The smoothing MAPE is 72% of that of DS (10.0% vs. 13.8%). Median APEs are closer but the smoothing value is smaller (9.1% vs. 10.2%).

Table 2 gives six-step-ahead results comparing exponential smoothing and DS. The results are much the same as the one-step-ahead, with exponential smoothing outperforming DS in all series except for the first. Next, we computed the MAPE and Median APE for the 91 M-Competition series, as shown in Tables 3 and 4 for one- and six-steps-ahead, respectively. Again, smoothing did much better than DS, particularly in the quarterly series. The same conclusion holds for the one-step-ahead percent better results shown in Table 5.

Note that the results in Tables 3 and 4 are not comparable to the original M-Competition results. In the M-Competition, all forecasts were made from one time origin. In Tables 3 and 4, model components are continuously updated and the time origin changes with each forecast.

It is interesting that DS generally improves on the FW one-step-ahead results in the cookware series but not in the Makridakis series. In cookware forecasting, DS gives a better RMSE and MAD than FW in four series, and a better MAPE and Median APE in all five. In the quarterly Makridakis series, FW is certainly the preferred Focus Forecasting method. Note the small percentage of quarterly series in Table 6 in which DS was better. In the monthly series, DS and FW give much the same results.

5. Conclusions

This study reaffirms two conclusions by Fildes et al. (1998) in their study of the empirical performance of extrapolative methods: (1) select methods that match the characteristics of the time series under analysis and (2) use robust estimates of trend in the data and any other structural parameters. Focus Forecasting rules are arbitrary and robustness is ignored. The result is that damped-trend, seasonal exponential smoothing proved to be substantially more accurate than either the simple Flores–Whybark version of Focus Forecasting or the more sophisticated DS version.

Carbone (1999) provides additional support for the forecast accuracy comparisons in this paper by showing that there are fundamental statistical shortcomings in the DS methodology. In particular, the methodology for computing seasonality is seriously flawed. Carbone also argues that DS is cumbersome to use and the rationale for the forecasting rules is difficult to understand.

Given these problems, how can DS be justified in practice? DS has some features not reviewed here that are useful in inventory control. However, one of the referees pointed out a problem that limits the value of DS in inventory applications. Inventory systems frequently require forecasting for a multi-level product hierarchy of time series with reconciliation across levels. In the process of reconciliation, there are opportunities for improved forecasting of noisy item-level data. For example, top-down reconciliation can estimate seasonality in a product-aggregate series and then apply that seasonality to item-level data, giving structure that could never be estimated directly from the item series. DS does not possess this capability, a serious omission that could be more important than the forecast accuracy problems discussed in this paper.

In conclusion, we reiterate that users of DS or other versions of Focus Forecasting should benchmark forecast accuracy against exponential smoothing or other statistical methods. Our results show that there is much to gain in forecast accuracy. In inventory control, multi-level forecasting capability should be considered in choosing a forecasting package.

A note on replication: the cookware time series are available from the authors upon request. The exponential smoothing calculations can be replicated using Peer Planner (Delphus, Inc., 2000).

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