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Focus forecasting reconsidered

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Abstract

Focus Forecasting is a popular heuristic methodology for production and inventory control although there has never been a rigorous test of accuracy using real time series. We compare Focus Forecasting to damped-trend, seasonal exponential smoothing using five time series of cookware demand in a production planning application. We also make comparisons using 91 time series from the M-Competition study of forecast accuracy. Exponential smoothing was more accurate in both cases.

Keywords: Exponential smoothing; Forecasting; Focus forecasting; Inventory control systems

1. Introduction

Focus Forecasting is an heuristic methodology, developed by Smith (1978), that has received a great deal of attention by both academics and practitioners. In production and operations management textbooks, Focus Forecasting has consistently received favorable reviews. For discussions of Focus Forecasting, see Chase and Aquilano (1995); Gaither (1994); Krajewski and Ritzman (1996) and Vollman et al. (1992). For example, Chase and Aquilano state that: 'Focus forecasting appears to offer a reasonable approach to short-term forecasting, say, monthly or quarterly, but certainly less than a year. If there is one thing focus forecasting offers, it is close monitoring and rapid response.'

Focus Forecasting is also available in commercial software packages for forecasting, inventory control, and production planning. For a detailed review, see Tashman and Tashman (1993). One of the programs in their review, Demand Solutions, is in use at 850 sites, in 47 countries, and by more than 650 corporations.

Despite the popularity of Focus Forecasting, there appears to be only one published research study on the accuracy of the methodology, by Flores and Whybark (1986). This study compared Focus Forecasting to simple exponential smoothing using 500 simulated time series and 96 actual series. In the simulated time series, Focus Forecasting was more accurate, but simple exponential smoothing was more accurate in the actual series. Because of these differences in performance, the authors state that '... the results do not provide a consistently superior choice of forecasting technique...'.

We agree with Flores and Whybark that the results are ambiguous. We also believe that the results are

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biased. The reason Focus Forecasting was best in the simulated series was that the series contained trends and seasonal patterns. Simple smoothing is hopeless in such series and the authors did not test alternative smoothing methods such as Holt et al. (1960) or general exponential smoothing (Brown, 1963).

This paper is an empirical evaluation of Focus Forecasting. The study originated in a production planning project at a Houston-area manufacturer of cookware. Because production plans depend on forecasts, we were asked to evaluate the company's Focus Forecasting system, which predicts monthly demand for five major products. Focus Forecasting was compared to a damped-trend, seasonal exponential smoothing system in these time series. Comparisons were also made using 68 monthly and 23 quarterly time series taken from the 'M-competition' study of forecast accuracy [Makridakis et al. (1982)].

2. The cookware application

The cookware manufacturer purchases major components, called pot and pan 'bodies', under long-term contracts with suppliers. The company requires 1-month-ahead forecasts because delivery calls against most contracts must be placed early in the month, usually on the first working day. Just-in-time delivery in small batches of bodies to support daily production starts 1 month later. The manufacturing process has a short cycle, often 2 or 3 days, and includes application of protective coatings, decorative enameling, attachment of handles and knobs, and packaging. Finished products are packaged in five different sets, composed of six to twelve pots and pans each. The production environment is one of 'make-to-stock' rather than 'make-to-order'. The product line is standard, inventory is built in advance of peak periods, and company policy is to ship from one of several warehousing facilities rather than direct from the factory. At the time of the study, the product line had been essentially unchanged for the last five years, which provided a set of relatively long time series for forecasting tests.

We should point out that there is some make-to-order production from time to time. However, the work is done on overtime so as not to disrupt make-to-stock operations. Volumes are small and delivery promises are quite conservative to allow ample leadtime to obtain material. Therefore, management did not consider forecasting necessary for make-to-order production. We concurred with this opinion.

Monthly demand for the five cookware sets is highly seasonal, as shown by the time plots in Fig. 1. Note that the series start in different months and end in May, 1994. The peak month is in late spring or early summer, for the wedding season, while another peak occurs near the end of the year for holiday purchases. According to company managers, differences in ordering patterns from major distributors cause peak and trough months to vary slightly by series.

The last series in Fig. 1, demand for 12-piece cookware sets, accounts for about 55% of dollar

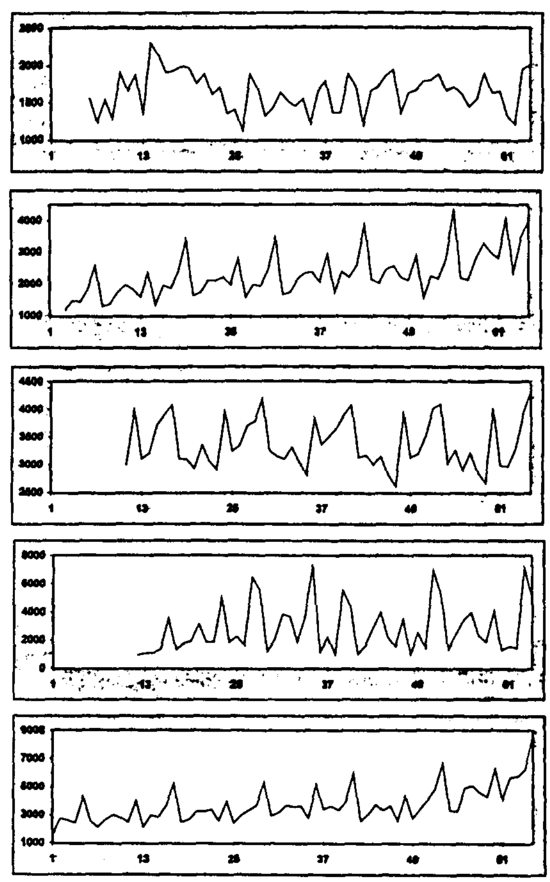

Fig. 1. Cookware series, January, 1989–May, 1994.

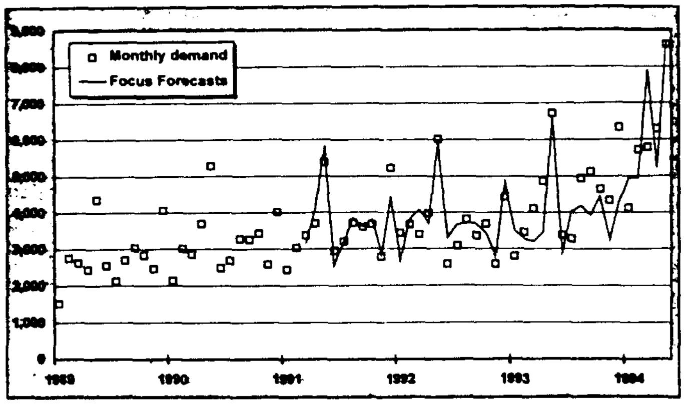

Fig. 2. Monthly demand and focus forecasts for 12-piece cookware sets, January, 1989–May, 1994.

sales. This series is plotted in Fig. 2 together with 1-month-ahead Focus Forecasts. The forecasts were produced by selecting from a set of eight decision rules:

1. The forecast for next month is the actual demand for the same month last year.
2. The forecast for next month is 110% of the actual demand for the same month last year.
3. The forecast for next month is the 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 the total actual demand for the last 6 months (a two-quarter moving average).
5. The forecast for next month is one-third of the actual demand for the previous 3-month period (a one-quarter moving average).
6. The forecast for next month is one-third of the 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 the demand for the 6 months preceding that, the forecast for next month is one-third of 110% of the demand for the same 3-month period last year.
8. If the demand in the last 6 months is more than 2.5 times the demand for the 6 months preceding that, the forecast for next month is one-third of the demand for the same 3-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. Note that the absolute value is taken after the average is computed. The method with the lowest error measure is selected to make the forecast for the next month. This procedure is the same as that of Flores and Whybark and company managers felt that it was reasonable at the time Focus Forecasting was implemented. Managers were not concerned with bias and believed that shortages of product (from under-estimation) were just as undesirable as excess stocks (from over-estimation).

Except for Rule 3, all rules were taken directly from Flores and Whybark (1986). Rule 3 was added by the company during the initial implementation of Focus Forecasting. 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. Rules 7 and 8 may be ill-conceived because, as discussed below, the rule selection algorithm never used these rules to make any forecast in the cookware series.

For the time series in Fig. 2, Focus Forecasting was implemented in March, 1991, and gave excellent performance for the rest of that year. The only large error, an underestimate of demand, occurred in December, 1991. Good results were also obtained during 1992 and most of 1993. However, accuracy deteriorated from mid-1993 until the end of the series. In particular, the system greatly underestimated demand during the last half of 1993, which led to shortages of product and late shipments. This pattern of underestimation was followed by a large overestimate of demand in March, 1994.

Why did Focus Forecasting accuracy deteriorate? Many of the Focus Forecasting rules involve data comparisons to the same month or quarter a year ago. The result is that the forecasts can lag behind significant changes in both level and trend. In Fig. 2, demand jumped to a new level in August, 1993, and the rate of growth from that month forward was significantly greater than it had been in the past. For example, demand in November, 1993, was 68% greater than demand in November, 1992.

What happened to Focus Forecasting accuracy in the rest of the cookware time series? Similar problems occurred in the second series (see Fig. 1), while accuracy appeared to be reasonable in the others. However, the company was most concerned about the product illustrated in Fig. 2 because it contributed such a large share of sales revenues.

3. The exponential smoothing alternative

From the company's perspective, the major appeal of Focus Forecasting was that it could be used as an automatic forecasting system. Therefore, as an alternative to Focus Forecasting, we chose an exponential smoothing system which can be operated in a completely automatic fashion. The smoothing system is based on the class of autoregressive-damping forecasting systems, also known as damped-trend systems, developed by Gardner and McKenzie (1985). The multiplicative seasonal version of the damped-trend system (Gardner and McKenzie, 1989) was used in this research:

$$S_t = S_{t-1} + \phi T_{t-1} + h_1\left(\frac{e_t}{I_{t-p}}\right), \tag{1}$$

$$T_t = \phi T_{t-1} + h_2\left(\frac{e_t}{I_{t-p}}\right), \tag{2}$$

$$I_t = I_{t-p} + h_3\left(\frac{e_t}{S_t}\right), \tag{3}$$

$$\hat{X}_t(m) = \left(S_t + \sum_{i=1}^{m} \phi^i T_t\right) I_{t-p+m}. \tag{4}$$

S_t and T_t are the level and trend components of the series. The seasonal indices are denoted by I_k, $k = 1, 2, \ldots, p$, where p is the number of periods in 1 year. There are three smoothing parameters, h_1, h_2, and h_3 for the level component, trend component, and seasonal indices, respectively. The damping parameter ϕ controls the rate of growth in the forecasts. The one-step-ahead forecast error is defined as $e_t = X_t - \hat{X}_{t-1}(1)$.

4. Experimental design

The five cookware time series ranged in length from 53 to 65 observations. We divided each series into two samples. 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-step-ahead forecasting done for the remainder of each series. This procedure ensured that both Focus Forecasting and the smoothing models would have at least two complete years of history to detect and estimate the seasonal pattern.

To make the smoothing model fully automatic, we programmed a standard autocorrelation test for seasonality, using the first $n/2$ observations in each series. The result was used to choose the nonseasonal or seasonal version of the damped-trend model. In all series, the correct model (seasonal) was chosen automatically. Initial seasonal indices (I_k) were computed using the ratio-to-moving average method. Initial level (S_0) and trend (T_0) 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, model-fitting was done using a grid search procedure to minimize the mean-squared-error (MSE). The search was conducted over the range 0–1 for all smoothing parameters as well as the damping parameter. After the first $n/2$ observations, no changes were made to model parameters and Eqs. (1)–(4) were used to record errors, smooth components (level, trend, and seasonal index), and compute new forecasts.

To initialize the Focus Forecasting system, forecasting was started after the first year of data. The best rule was selected each period according to the procedure described above. For comparison to exponential smoothing, forecast errors were recorded starting at period $n/2+1$.

Within each time series, we computed five error measures using the one-step-ahead forecasts from $n/2+1$ until the end of the series: the relative Geometric Root Mean Squared Error by series, referred to simply as GRMSE hereafter, root-mean-squared-error (RMSE), mean absolute error (MAD), mean absolute percentage error (MAPE), and median absolute percentage error (median APE).

The GRMSE may be unfamiliar. Fildes (1992) presents formulas and a complete notation system for this measure. For this application, we can simplify Fildes' presentation to the following:

$$\mathrm{GRMSE} = [(e_{11}^2/e_{12}^2)\cdot(e_{21}^2/e_{22}^2)\cdot(e_{31}^2/e_{32}^2)\cdot\cdot\cdot\;\cdot(e_{T1}^2/e_{T2}^2)]^{1/T} \tag{5}$$

Inside the brackets, we take the product of the ratios of squared one-step-ahead errors for two alternative forecasting methods. The product is then raised to a power of one over T, the number of such errors. Note that each one-step-ahead error in (5) has two subscripts: the first denotes the time period in the hold-out sample, from 1 to T, and the second denotes the forecasting method, 1 or 2.

Because the GRMSE is based on ratios, the measure is both scale and unit-independent, an important consideration in choosing models for groups of time series. For a complete discussion of the advantages and disadvantages of the GRMSE, see Fildes (1992). Similar measures are also discussed in Armstrong and Collopy (1992).

5. Forecast accuracy comparisons

Forecast accuracy comparisons for the cookware series are summarized in Table 1 (Series 5 is the most important of the series, displayed in Fig. 2). Exponential smoothing was better in every comparison save the median APE for Series 1. In many cases the differences in favor of smoothing are quite large. Given these comparisons, the company discarded the Focus Forecasting system and implemented exponential smoothing.

To at least partially confirm the cookware series results, we simulated one-step-ahead forecasting using data from the Makridakis collection of 111 time series (Makridakis et al., 1982). This collection includes 68 monthly series and 23 quarterly series. The other series are annual data and thus too short to analyze with Focus Forecasting. The same experimental design was used as in the cookware series except that obvious modifications were made to the Focus Forecasting rules to accommodate quarterly series. Table 2 summarizes GRMSE, MAPE, and median APE over all quarterly and monthly series. RMSE and MAD were not included because these measures are scale-dependent. Table 3 reports the percentage of the series in which exponential smoothing was better. Again, the results favor exponential smoothing.

Did Focus Forecasting use a dominant rule to compute forecasts? For the cookware series, we compiled a distribution of the rules used, shown in Table 4. This was not done for the Makridakis data

Table 1
Cookware series: One-step-ahead error measures

Series	GRMSE	RMSE		MAD		MAPE		MEDIAN APE	
		Exp. sm.	Focus	Exp. sm.	Focus	Exp. sm.	Focus	Exp. sm.	Focus
1	0.94	200.6	333.6	160.0	241.0	4.6	6.9	4.5	4.1
2	0.77	213.6	344.6	154.2	279.4	5.6	11.1	5.1	8.6
3	0.83	439.1	822.2	354.1	634.8	8.4	14.7	8.9	14.7
4	0.94	264.0	316.8	220.6	266.4	13.8	17.0	12.8	14.3
5	0.85	715.4	1,056.3	490.5	848.1	17.7	39.1	14.0	23.6
Mean	0.86	366.5	574.7	275.9	453.9	10.0	17.7	9.1	13.1

Note: Exponential smoothing is the base in Eq. (5) for the GRMSE.

Table 2
M-Competition series: summary one-step-ahead error measures

Series	GRMSE	APE		MEDIAN APE	
		Exp. sm.	Focus	Exp. sm.	Focus
Quarterly	0.91	8.1	11.7	2.8	3.7
Monthly	0.93	10.4	12.0	6.2	7.3

Notes: Exponential smoothing is the base in Eq. (5) for the GRMSE; GRMSE values are geometric means over all series; MAPE was averaged over all series; Median APE was computed over all series.

Table 3
M-Competition series: percent of series in which exponential smoothing was better

Series	GRMSE	RMSE	MAD	MAPE	MEDIAN APE
Quarterly	83	91	87	87	83
Monthly	66	84	81	76	68

Note: Exponential smoothing is the base in Eq. (5) for the GRMSE.

Table 4
Cookware series: Focus Forecasting rules used

Rule	Logic	Percent of forecasts
1	Demand for same month last year	15.9%
2	110% of demand for same month last year	11.7%
3	Same month last year times growth factor	33.1%
4	Two-quarter moving average	12.4%
5	One-quarter moving average	15.2%
6	1/3 of same quarter last year times growth factor	11.7%
7	Seasonal rule: trough month	0.0%
8	Seasonal rule: peak month	0.0%
		100.0%

because there is little if any similarity amongst time series. The dominant rule in the cookware series was Rule 3, developed by the company to supplement the Flores and Whybark system. Company managers added this rule after examining a marketing report showing tables of monthly growth ratios from one year to the next. The company rule was the only rule specifically tailored to the data, which is one explanation for its performance.

It is interesting that the seasonal Rules 7 and 8 were never used, a possible indication that we could expect Focus Forecasting to perform better in the nonseasonal series in the Makridakis collection. However, this was not the case. There was no significant difference in Focus Forecasting performance between seasonal and nonseasonal time series.

6. Conclusions

The aim of this paper was to evaluate the performance of a set of Focus Forecasting rules in practical use as production planning tools in a real manufacturing firm. Exponential smoothing proved to be more accurate than Focus Forecasting and was implemented by the company as the basis for monthly production planning and purchasing of component parts. In preparing the final revision to this paper, we discussed with our client the performance of exponential smoothing since our consulting engagement in 1994. The damped-trend, seasonal system has been used continuously. Performance has been satisfactory, with forecast errors no worse than those described in the exhibits to this paper.

One could invent an extraordinary number of additional Focus Forecasting rules so we cannot claim that exponential smoothing will always be more accurate than Focus Forecasting. However, we recommend that Focus Forecasting users benchmark accuracy in a true ex ante forecasting test against exponential smoothing or some other simple alternative. We recommend benchmarking for any forecasting system, but it seems especially indicated for Focus Forecasting given that our results favor exponential smoothing by a large margin.

Why did exponential smoothing perform better than the company's Focus Forecasting system? This is a difficult question to answer because Focus Forecasting is a purely ad hoc system with no theoretical basis to aid analysis or understanding. It is impossible to compute confidence intervals, regions of stability for the forecasts, or other standard analytical results. Since there has been no previous empirical research other than that of Flores and Whybark (1986), there is no way to predict how Focus Forecasting should perform compared to any other forecasting system.

We believe that the best answer to the relative performance question is that the Focus Forecasting system in use by the company was not specifically tailored to the cookware data. Except for Rule 3, developed by the company, all of the forecasting rules were chosen independently of the data.

One of the referees suggested that better Focus Forecasting rules might be developed using the rule-based forecasting methodology of Collopy and Armstrong (1992), a structured system for validating forecasting rules through prior research and empirical testing. We agree that the Collopy-Armstrong methodology offers promise in the development of Focus Forecasting rules. The methodology is as much a system of evaluation as a forecasting system and guarantees that only rules with a significant performance advantage will be adopted for practical use. The disadvantage of the Collopy-Armstrong methodology is its complexity, a problem acknowledged by the authors in their original paper.

The cookware time series are available from the authors upon request.

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