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TEACHING BRIEF

Classroom Integration of Statistics and Management Science Via Forecasting

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Subject Areas: **Q1**

INTRODUCTION

An integration of management science with statistics is naturally occurring in MBA programs, whether management scientists appreciate this integration or not. Through successful integration, students can see the value of both perspectives and can more easily make the leap from theory to practical application.

Traditionally, the business school management science class has focused upon the mathematics of this science, rather than being focused upon the management and application of this science. MBA students generally seek practical skills that will allow them to quickly advance in their careers; they are typically less interested in focusing upon algorithms and complex models. The good news is that OR/MS courses *can* meet our student requirements and these highly useful techniques *can* sustain relevance in an ever-changing world.

One area where management science techniques facilitate enhanced decision making is in the area of forecasting, which directly impacts many functional areas of business. Albritton, McMullen, and Gardiner (2003), in their assessment of OR/MS in AACSB-accredited U.S. business programs, report that only 53% of MBA-level professors include forecasting as a topic area in their courses. Given that the typical number of OR/MS course offerings at most business schools is very limited, Faculty must be selective about which topics to include. Perhaps forecasting, in particular, is omitted because of complexity when demonstrating in the classroom.

This teaching brief presents an approach that has been proven successful for forecasting in the classroom, using a spreadsheet. The use of spreadsheets for modeling and simulation is a valid approach for MBA students, as it facilitates

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positive learning and improved decision making, without the need to burden these students with deep mathematical details of the technique (Grossman, 2003). While this technique was originally designed to be user-friendly for the classroom, its unique contribution does not come from the fact that it is easy to demonstrate. This approach is highly innovative for several reasons: (1) it successfully integrates statistics and management science; (2) it performs better than more traditional approaches in handling nonlinear trends and forecast seasonality; and (3) it has received positive feedback from students from a pedagogical standpoint.

FORECAST MODELING USING SPREADSHEETS

Ordinary Least Squares Optimization and Estimation

Consider the standard Ordinary Least Squares (OLS) regression model. Ragsdale (2004) shows that nonlinear programming via Microsoft Excel's Solver can be used to find estimates for the simple OLS model that minimize the sum of squared errors (SSE). This aspect of the OLS model does not typically receive consideration in the literature; this is especially the case for complex, real-world problems. Nonlinear programming, on the other hand, can be used in the classroom to provide a reasonable solution to a more complex forecasting problem.

Seasonal Forecasting

Consider, the time series shown in Figure 1, representing historical quarterly sales data for a fictional toy manufacturer. An OLS regression approach could be used for parameter estimation; however, such an approach would perform poorly for three reasons. First, and most important, these data have a seasonal component (of order four [four periods for each repeating cycle]), which means that OLS would consistently miss the "peaks and valleys" of the actual observations. Second, the

Figure 1: Time series used for example problem.

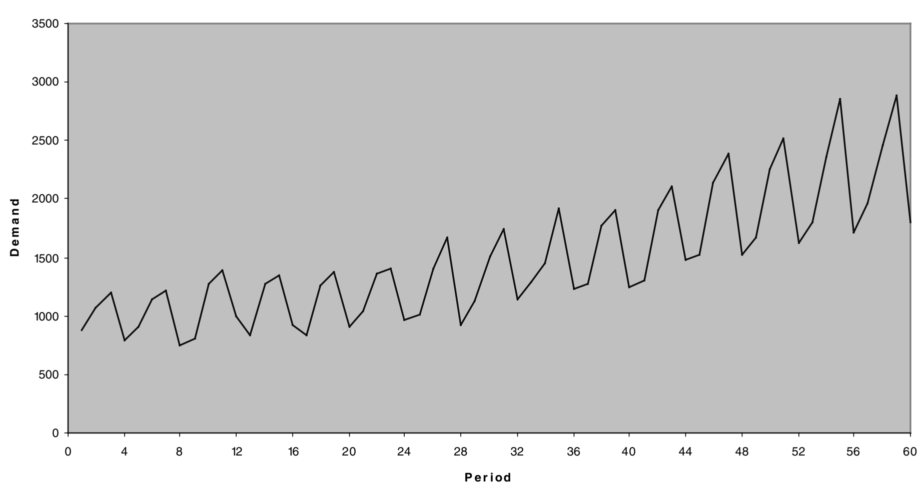
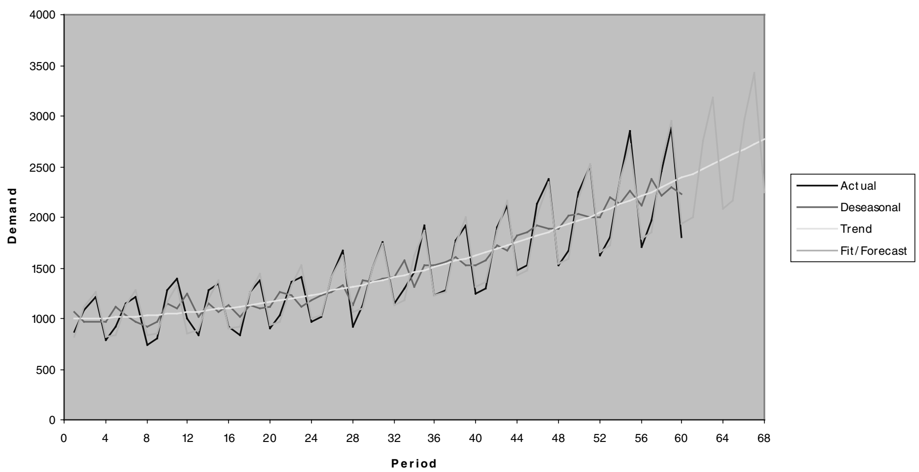


Figure 2: Results from seasonalized time series regression forecasting approach.



trend appears to be slightly nonlinear in the upward direction, causing a linear trend estimate to provide suboptimal fit. Third, the seasonal pattern seems to "fan out," or exhibit heteroskedasticity in latter periods; this cannot be adequately addressed via OLS.

From a statistical forecasting standpoint, this problem can be fitted/forecasted adequately, via a seasonalized time series regression technique (STSRF; Gaither & Frazier, 2002), also referred as multiplicative forecasting techniques. The steps to this approach are straightforward.

Figure 2 displays the components used to forecast this series eight periods into the future. The spreadsheet detail of these calculations is found at http://www.joydivisionman.com/DSJIE/. The approach first determines the order of seasonality; "deseasonalizes" the data and exposes the trend. The trend is then estimated, and the seasonality is factored back into the model for the forecasts. For the 60 periods of historical data, the actual demand is compared with the "fitted" demand, and the objective function value of SSE is calculated, which is 306,469.

Improved Seasonal Forecasting

The STSRF approach above is a very traditional one, and is featured in many Quantitative Methods textbooks in one form or another. The authors, however, consider this approach to be one that can be improved upon, while at the same time, providing an opportunity for an innovative and creative teaching experience; particularly with respect to a "fusion" between management science and statistical analysis.

The STSRF approach states that for some period i, the seasonal "fit," or estimate ($\hat{Y}_i$) is computed by multiplying the seasonal component (seasonal index, SI_i) by the trend component. Mathematically, this is as follows:

$$\hat{Y}_i = \mathrm{SI}_i \times \mathrm{Trend}_i. \quad (1)$$

Using the quadratic form of the trend component, the above equation becomes:

$$\hat{Y}_i = \mathrm{SI}_i(a + bi + ci^2). \tag{2}$$

In the general case, assume that there are *m* seasons per repeating cycle. For our specific example, there are four periods per cycle ($m = 4$). These $m\mathrm{SI}_i$ values repeat themselves each cycle. Mathematically, this is as follows:

$$\mathrm{SI}_{i+m} = \mathrm{SI}_i. \tag{3}$$

For our example, then, because $m = 4$, $\mathrm{SI}_5 = \mathrm{SI}_1$, $\mathrm{SI}_6 = \mathrm{SI}_2$, etc. Combining equation (2) above with the logic to derive error for period *i*, we can arrive at an SSE value, which is as follows:

$$\mathrm{SSE} = \sum_{i=1}^{n} \left(Y_i - \left(\mathrm{SI}_i(a + bi + ci^2)\right)\right)^2. \tag{4}$$

In the language of mathematical programming, the SSE value of equation (4) is treated as the objective function value, while the *m* values of SI_i, and the *a*, *b,* and *c* values are treated as decision variables It is important to note that these decision variable values are "solved for" simultaneously, as opposed to how they are solved for via the STSRF approach detailed above. Equation (4) is of a quadratic and convex nature, which enables most "solvers" to find an optimal solution. The relevant decision variable and objective function values are displayed in Table 1.

These parameters are different from those obtained via the STSRF approach. Also note that the objective function value associated with the nonlinear programming approach is lower than the STSRF approach by more than 13%—a substantial improvement. It should make intuitive sense that the nonlinear programming approach provides a more desirable SSE value, because the values of the decision variables are motivated to take on a combination of values that minimize SSE. No other combination of decision variable values can provide a superior value of SSE. A graphical depiction of the sample time series, along with the "fit" and forecast eight periods into the future via the nonlinear programming approach is shown as

Table 1: Decision variables and objective function values.

Decision Variable	Value
SI_1	0.9520
SI_2	1.2545
SI_3	1.4080
SI_4	0.8866
a	881.36
b	0.8556
c	0.3317
SSE	266,592

Figure 3: Result from nonlinear programming approach.

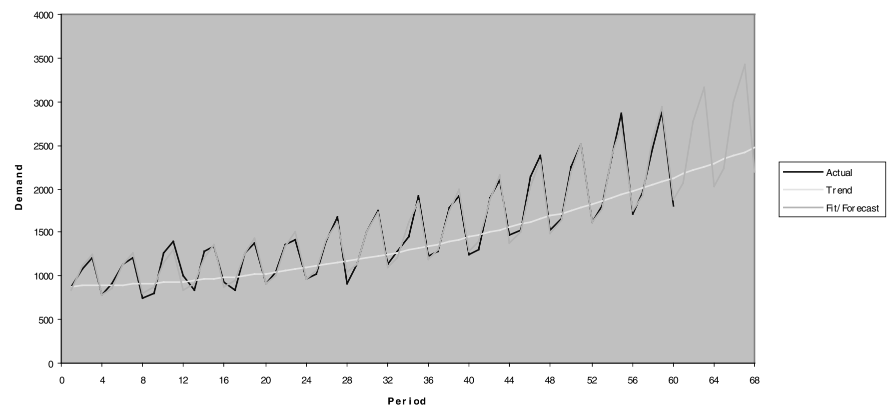


Figure 3. Please note that we have a generally tighter “fit” when compared to the result given in Figure 2. This would explain, in a graphical sense, the lower SSE associated with the nonlinear approach.

CONCLUSIONS

The example presented is designed to “close the gap” between statistical analyses and management science, by addressing an analytical problem from an optimization standpoint. The presented approach is innovative, because it offers significant improvements over accepted methodology. Ragsdale (2004), using Excel Solver for time series forecasting, found only the slope and intercept of a simple linear regression problem. Here, we use Excel Solver to find multiple parameters of a forecast problem that is both nonlinear and seasonal. Additionally, performance of the forecast is enhanced when using this technique, as demonstrated by a lower SSE (objective function value) when compared to more traditional approaches.

This problem, using a spreadsheet format for easy integration, has been presented to several student groups on multiple occasions at the end of an MBA quantitative methods course. The problem was given capstone treatment, intending to successfully integrate the statistics component with the optimization component of the course. Overall, positive reaction from these presentations has been noteworthy. Generally, student reactions are three-fold: (1) Students see the obvious relationship between classical statistics and optimization, via a relevant example; (2) They are given an opportunity to think on a more pragmatic scale, by taking a relevant business problem and finding an objective-based way to solve that problem; (3) They gain the benefits of traditional OR modeling without being expert modelers. They see the power of spreadsheets for modeling forecasting problems, as well as its potential for modeling other business problems.

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QUERIES

Q1 Author: Please provide “Abstract”; and “Subject Areas.”

Q2 Author: Please provide publisher location for reference “Ragsdale (2004).”

Q3 Author: Please check author biographies are not given.