How to Mathematically Forecast Veterinary Inventory Demand

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1. Introduction
A key component of lean processes in inventory management entails an accurate forecast of the demand for future inventory. Lean inventory management systems have been previously described and concentrate in the reduction of total annual inventory costs by reducing ordering costs and holding costs, both of which rely on demand quantity for their calculation. Whereas all practitioners have to utilize experience and knowledge of external factors to help forecast demand, qualitative techniques do not, by themselves, provide a significant level of accuracy. The established practitioner, however, can improve the forecasting accuracy by utilizing known data on previous demand. The use of a quantitative forecasting technique, together with qualitative techniques, will improve the accuracy of demand forecasting and help the practitioner improve the practice’s lean inventory management system.

2. Using the Data
Holt-Winters Seasonal Method (Triple Exponential Smoothing)
For the most part, the veterinary practitioner is faced with a demand that has both a trend and a seasonality component. Holt (1957) and Winters (1960) extended on Holt’s original linear trend method of demand forecasting to capture seasonality by creating a forecasting equation that includes three smoothing equations: level, trend, and seasonality; each being affected by the smoothing parameter $\alpha$, $\beta$ and $\gamma$, respectively. Utilizing historical data, the Holts-Winters seasonal forecasting method produces a demand forecast that takes into consideration the expected trend and seasonality of future demand. This paper utilizes a multiplicative Holt-Winters seasonal method due to the expectation that seasonal variations will change in proportion to the level of the data series.

A triple exponential smoothing forecasting calculator has been created and the Excel spreadsheet can be downloaded at https://db.tt/xzw2oxvT. Be sure to enable macros in your program.

Historical Data
For each inventory item to be analyzed, the practitioner should have on hand the historical sales data for the previous 4 years in order for the spreadsheet to define the trend and seasonality of demand. There are four columns and the quarterly data must be entered with the oldest year to the left and the newest year to the right. As newer yearly data becomes available, all previous years’ data gets shifted one column to the left and the previously oldest data gets removed from the chart. Some of the calculations cannot handle a zero value for any...
sales data and therefore a number 1 should be entered for any quarter in which the sales data was zero. The spreadsheet will calculate the seasonal index for each quarter of data and will generate the corresponding level, trend and seasonal components based on the Holt-Winters Seasonal formula. Each smoothing equation will utilize a pre-populated arbitrary number for its respective smoothing parameter α, β, and γ, which will be corrected during a process of optimization to follow. The resulting forecast for each of the 16 quarters of data will be compared with the actual sales data to determine the mean squared error of the difference between the forecast and the actual sale.

Optimizing the Formulas
The mean squared error (MSE) is a statistics formula that measures the average of the squares of the errors in the data and, in this case, presents the difference between the forecast and the actual sales data. The smaller the MSE, the more accurate the calculated forecast for the actual historical demand. Microsoft Excel has a data analysis tool called Solver that can minimize the value of an objective cell by changing the values of variable cells, which are subject to a constraint. The objective cell for our model is the calculated value of the MSE provided by the analysis. The variable cells are the values of α, β, and γ that the smoothing equations use in the calculations. The value of these smoothing parameters are constrained to individual values between 0 and 1. Optimization of the smoothing parameters will provide the smallest possible MSE and therefore help improve the accuracy of the forecast.

The process of optimization has been enabled in a macro embedded within the spreadsheet (after entering the sales data click the Optimize button) but the process is as follows: in your Excel program, install the Solver analysis tool under File-Options-Add ins and make Solver Add-in an active application. Find Solver under Data menu. Set Objective as the cell containing the mean squared error value. Set TO to minimize (you want to reduce the value of the objective cell). Set the variable cells, separated by a comma, as the cells containing the values for α, β, and γ. Add two constraints to each variable cell, one as “cell” ≥ 0, and another as “cell” ≤ 1 (sets each smoothing parameter to be constrained at (0 ≤ value ≤ 1). Select the Solving Method as “GRG Nonlinear.” Click on Options and then on the GRG Nonlinear Tab and check the Use Multistart box, click OK. Once returned to the Solver Parameters window click Solve. Once the optimization is calculated, select Keep Solver Solution in the Solver Results window, and click OK.

3. Results
The values for α, β, and γ tell each smoothing equation how much weight to place on the different components of each equation for the process of exponential smoothing. Given that the forecast is based on the level, trend, and seasonality, optimization of the smoothing parameters leads to a more accurate forecast as Solver finds the values for α, β, and γ that lead to minimization of the calculated MSE. The end result being a projected forecast for the next four quarters that has been optimized for accuracy through exponential smoothing that took into account the level, trend and seasonality of the previously observed data.

Although MSE provides the statistics analysis to help us improve accuracy in the forecast, the statistics of mean absolute percent error (MAPE) can be used as a more easily understandable measure of how well we are doing over time in our forecasting. A statistics measurement that compares the forecast to a perfect forecast, MAPE expresses accuracy in terms of percentage so that we can see, on average, how far off the forecast has been. By entering into the spreadsheet the actual sales data for each quarter related to the forecasted period, the calculator will compute the MAPE over time to give an indication of the level of accuracy achieved. This will allow the practitioner to evaluate the forecast in light of the qualitative aspects of the forecasting that statistics cannot foresee and therefore cannot compute.
4. Translating the Calculated Demand Forecast Into Cost Savings

Table 1 presents a real scenario encountered by the author during the 2015 breeding season. Historical data over the last four years showed that, on average, 42 cases of an inventory item were used over the first 6 months of the year. Normal routine would have been to place a single order during the American Association of Equine Practitioners convention for the expected 2015 breeding season average-based demand. Holt-Winters Seasonal Method analysis of the same 4-year historical data, however, suggested that the demand for the period would be 36 cases. In addition, economic order quantity analysis based on this calculated demand suggested that eight cases per order would minimize the actual inventory cost for this size of the demand. Actual sales during the 2015 breeding season were 34 cases. With a state sales tax of 6%, per order cost of $10, and using a holding rate of 35%, the calculated demand forecast translated into a 22.55% savings over what would have normally been incurred had the calculations not been performed.

5. Conclusion

Lean inventory management relies on cost reduction through the reduction of purchase cost and order cost. Both cost formulas rely on the forecasted demand. The third inventory cost component, holding cost, depends on the order quantity which, in turn, also relies on the forecasted demand. As such, improvement in the accuracy of inventory demand forecasting will serve as a major component of enacting and improving lean processes. The example presented clearly shows an opportunity to improve cash flows, to reduce invested capital, and to improve operational efficiency; all of which translate into improved margins, improved profits, and increased practice value.

The demand forecasting spreadsheet calculator should serve as a guidance tool to help accomplish the quantitative analysis of historical data. The goal is to help reduce the MSE of the calculations and therefore improve the accuracy of future forecasts. The data that a quantitative statistics analysis might provide, however, will be of minimal value if the qualitative components of demand forecasting are not taken into account. More accurate numbers will help improve forecasting accuracy only if the numbers are looked at through the eyes of experience that take into account all of the practice’s external factors.

Acknowledgments

Declaration of Ethics

The Author declares that he has adhered to the Principles of Veterinary Medical Ethics of the AVMA.

Conflict of Interest

The Author declares no conflicts of interest.

References


Appendix: Formulas

<table>
<thead>
<tr>
<th>Description</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Seasonal index (where m denotes the period of</td>
<td>$s_{t,m} = [(\text{Sum of all data for specific quarter})/(\text{Sum of all data})] \times 4$</td>
</tr>
<tr>
<td>the seasonality)</td>
<td>Have all years]] \times 4]</td>
</tr>
<tr>
<td>Holt-Winters seasonal forecast (multiplicative;</td>
<td>$F_{t,m} = (l_t + hb_t) \times s_{t-m+1:m-1}$ utilizes $b_0 = \text{sum}(Y_t,Y_m))/m$</td>
</tr>
<tr>
<td>where $Y_t = \text{period's actual data}$</td>
<td>and $b_0 = \text{sum}(Y_{m+1}-Y_{m+1}^m)Y_{m+1}Y_m)/m$</td>
</tr>
<tr>
<td>Level component</td>
<td>$l_t = [\alpha \times (Y_t/s_{t-m})] + [(1 - \alpha) \times (l_{t-1} + b_{t-1})]$</td>
</tr>
<tr>
<td>Trend component</td>
<td>$b_t = [\beta \times (l_t - l_{t-1})] + [(1 - \beta) \times b_{t-1}]$</td>
</tr>
<tr>
<td>Seasonal component</td>
<td>$s_t = [\gamma \times (Y_t/l_{t-1} + b_{t-1})] + [(1 - \gamma) \times s_{t-m}]$</td>
</tr>
</tbody>
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