COORDINATING DEMAND FORECASTING AND OPERATIONAL DECISION-MAKING: RESULTS FROM A MONTE CARLO STUDY AND A CALL CENTER

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ABSTRACT

Decision-makers cannot always adopt forecasts of demand as given because they must balance the asymmetric effects that forecasting errors have on their expected opportunity loss. An appropriate adjustment is required which explicitly considers the relative costs of over-forecasting and under-forecasting. This article presents a simple, practical approach for coordinating demand forecasts and operational decision-making by adding an easily calculated adjustment value to the original forecasts.

After illustrating the approach with two common time series patterns, a Monte Carlo simulation study is presented that tests the adjustment procedure under more general circumstances. The simulation confirms that, for a wide range of cost ratios, the adjustment approach can significantly reduce opportunity loss over both historical and post-sample periods. For example, when the ratio of overage to underage costs exceeds either 3:1 or 1:3, adjustment lowers the mean opportunity loss by at least 15% for a variety of forecasting methods. Finally, we examine the case of a technical support call center that makes its staffing decisions based on forecasted call volumes. Applying the adjustment procedure to actual data from six phone queues yields benefits consistent with those reported by the Monte Carlo simulation study.

INTRODUCTION

Forecasters and decision-makers often have different objectives. While forecasters strive to make accurate predictions, decision-makers try to control risk and are concerned with profit and loss. Forecasters tend to use models that minimize forecasting error but decision-makers want to minimize expected opportunity loss. Forecasters routinely use symmetric performance measures even though decision-makers may face asymmetric loss functions. We will examine these differences and address the resulting coordination problem.
The problem is well known. Gilchrist (1976, p. 274) points out that “it is incorrect to regard forecasting as an exercise that can be done on its own, without reference to the use to which we put the forecasts.” Granger (1980) stresses the need for a clear understanding between forecasters and decision-makers about what is being forecast, what information is being used, and what assumptions are being made. Marshall and Oliver (1995, p. 25) state that “many measures of forecast performance based on mean squared error and point predictors evaluate inappropriate aspects of the forecasting problem and are quite often irrelevant to decision-making.” Thus, forecasting and decision-making need to be integrated, as Remus and Simpkin (1987) advocate.

While known, the problem is overlooked in many leading POM texts, e.g., Chase, Aquilano and Jacobs (1998), Heizer and Render (2001), Hillier and Lieberman (1995). None makes a strong link between forecasted demand and the decision based on the forecast. When addressing the single period inventory problem, for example, they assume that demand is stationary, and ignore the possibility of a pattern in the time series data, such as trend or seasonality. This article describes an easy-to-use approach that solves the coordination problem not only for the single-period inventory setting, but also for multi-period situations in which a manager must make decisions based on a set of forecasts of a possibly non-stationary time series. It is illustrated with both real and simulated data.

**PROBLEM FORMULATION**

To begin, assume that a set of \( n \) recent observations \( \{x_1, x_2, \ldots, x_n\} \) of a time series is available. The objective of the forecaster who makes forecasts \( \{f_1, f_2, \ldots, f_n\} \) of this series is to minimize some measure of forecast error, such as the mean squared error, mean absolute error, or mean absolute percentage error, all of which put equal weight on positive and negative errors. However, as Gardner (1990, p. 498) states, “such measures are of little interest to managers, who are concerned instead with whether forecasting will improve decision-making.”

The decision-maker's goal is usually different from the forecaster's goal because positive and negative errors usually have different impacts, i.e., the cost of overestimating demand differs from the cost of under-estimating it. Consequently, the decision-maker often adjusts the given forecast(s) to minimize the expected opportunity loss rather than the expected measurement of forecasting error. Here we assume that the decision-maker knows or can estimate a unit underage cost \( c_u \) and a unit overage cost \( c_o \) that reflect his opportunity losses. The value of his decision variable \( d_i \) will be \( d_i = f_i + a \), where \( a \) is an adjustment whose value will be shown to depend on \( c_o \), \( c_u \) and the set of forecast errors. A reasonable and flexible goal for the decision-maker is to determine the values of the decision variables \( \{d_i\} \) that minimize the mean opportunity loss (MOL) over the last \( n \) periods:

\[
\text{Minimize MOL} = \left[ \frac{\sum x_i d_i - \sum c_u (x_i - d_i)}{n} \right] / n
\]

This criterion is reasonable because it is equivalent to maximizing expected profit; it is flexible because different values of \( c_o \) and \( c_u \) may be chosen to reflect a variety of risk situations, resulting in different levels of adjustment to the forecasts. For example, if \( c_u \) is much greater than \( c_o \), the decision-maker should adjust the forecasts in a way that tends to overestimate rather than underestimate demand. The next section shows exactly how to do so.

Many asymmetric cost situations arise in practice, e.g., in MRP-based manufacturing systems, Lee and Adam (1986) find that over-forecasting by 10–30% can actually reduce total system costs. Sanders and Ritzman (1995) describe how a warehouse manager uses demand
forecasts to develop daily worker schedules. While under-forecasting results in too few workers being scheduled (requiring the use of expensive overtime labor), and over-forecasting leads to excess labor and idle workers, these costs are likely to differ. Other asymmetric cost situations involve goods that become obsolete or perish quickly. For example, when an airline overbooks a particular flight, the cost of under-forecasting the number of no-shows is the lost profit from unfilled seats, while the cost of over-forecasting is tied to the cost of compensating bumped passengers with vouchers that can be redeemed on other flights (Smith, et al., 1992). The approach described next can benefit decision-makers who must act on a given set of forecasts and can specify either the absolute or relative costs of negative and positive forecasting errors.

COORDINATING FORECASTING AND DECISION-MAKING

While good forecasts lower opportunity losses arising from uncertainty about future conditions, they are seldom perfect, i.e., residual randomness remains after the forecasts are made. The following adjustment procedure shows how the forecasts can be easily modified to solve the decision-maker's problem stated in (1). It assumes only that a set of \( n \) forecasts \( \{f_t\} \) of the time series \( \{x_t\} \) is available, but makes no assumptions about the distribution of demand.

Adjustment Procedure

**Step 1:** Determine the forecasting errors \( e_t = x_t - f_t \), for \( t = 1, 2, \ldots, n \).

**Step 2:** Rank the forecasting errors in increasing order so that \( e_t \leq e_{t+1} \), for \( t = 1, 2, \ldots, n-1 \).

**Step 3:** Compute the critical ratio \( S = c_u/(c_u + c_o) \).

**Step 4:** If \( S = 0 \), then set the adjustment \( a^* = e_1 \) and go to Step 7.

**Step 5:** If \( S = 1 \), then set the adjustment \( a^* = e_n \) and go to Step 7.

**Step 6:** If \( nS \) is not an integer,

- then set \( a^* = e_k \), where \( k \) is the integer that satisfies \( nS < k < nS + 1 \);
- else set \( a^* = (e_k + e_{k+1})/2 \), where \( k = nS \).

**Step 7:** Set the values of the decision variables \( d_{n+h}^* = f_{n+h} + a^* \), for \( h = 1, 2, \ldots \).

Simply put, \( a^* \) is the \( S^{th} \) fractile of the distribution of forecasting errors. Setting \( d_t^* = f_t + a^* \), for \( t = 1, 2, \ldots, n \) minimizes the MOL over the \( n \) historical periods. (This can be proven via either marginal analysis or linear programming.) Similarly, \( d_{n+h}^* \) is the value of the decision variable that minimizes the *expected* opportunity loss for period \( n+h \), assuming that the error distribution remains stable in the near future.

To illustrate this approach in the stationary data case, consider the stationary time series plotted in Figure 1. Visual inspection reveals neither seasonal variation nor obvious serial correlation. Thus, a forecaster is likely to assume that the series is generated by a process of the form \( x_t = \alpha_t + \varepsilon_t \), where \( \alpha_t \) is a stationary level to be estimated and the \( \varepsilon_t \)'s are independent and identically distributed random variables with mean zero and standard deviation \( \sigma \). Since the corresponding forecasts are \( f_{t+h} = \alpha_t \) for all \( h \geq 1 \), the forecaster's job simply boils down to finding an acceptable estimate of the level \( \alpha_t \).

In this example, suppose that the decision-maker views an underage as three times as costly as an overage, e.g., a department store manager who wishes to provide a high level of service. For concreteness, take \( c_o = $25 \) and \( c_u = $75 \), so that \( S = 0.75 \). Now consider five common methods to estimate \( \alpha_t \) and generate the corresponding forecasts listed in the 2nd column.
of Table 1: the mean and median of the data; the two-period moving average MA(2); exponential smoothing with parameter set (arbitrarily) to 0.6; and the naïve approach. Applying each method to the data yields a set of forecasting errors, which in turn leads to the optimal adjustment factor $a^*$ shown in the third column of Table 1. Adding $a^*$ to the forecast $f_{21}$ gives the optimal decision value $d_{21}^*$ (or “adjusted forecast”) shown in the fourth column. Columns 5 and 6 show the historical MOL with and without adjustments.

Table 1: Optimal decision and MOL for various forecasting methods applied to stationary data when $S = 0.75$ ($c_o = $25 and $c_u = $75).

<table>
<thead>
<tr>
<th>Forecasting Method</th>
<th>Forecast $f_{21}$</th>
<th>Optimal Adjustment $a^*$</th>
<th>Optimal Decision $d_{21}^*$</th>
<th>MOL ($) Without Adjustment</th>
<th>MOL ($) With Adjustment</th>
<th>Decrease in MOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>72.1</td>
<td>12.9</td>
<td>85.0</td>
<td>1037</td>
<td>973</td>
<td>6.2%</td>
</tr>
<tr>
<td>Median</td>
<td>69.0</td>
<td>16.0</td>
<td>85.0</td>
<td>1093</td>
<td>973</td>
<td>11.0%</td>
</tr>
<tr>
<td>MA(2)</td>
<td>78.0</td>
<td>23.5</td>
<td>101.5</td>
<td>1381</td>
<td>1154</td>
<td>16.4%</td>
</tr>
<tr>
<td>Expo(0.6)</td>
<td>73.5</td>
<td>30.7</td>
<td>104.2</td>
<td>1512</td>
<td>1173</td>
<td>22.4%</td>
</tr>
<tr>
<td>Naïve</td>
<td>72.0</td>
<td>39.0</td>
<td>111.0</td>
<td>1832</td>
<td>1301</td>
<td>29.0%</td>
</tr>
</tbody>
</table>

In all cases, adjusting the historical forecasts by $a^*$ substantially lowers MOL, ranging from 6% for the best method (Mean) to 29% for the worst method (Naïve). Note that the first two methods, which both calculate a single value over the historical periods, are brought to the same decision value (85.0) and historical MOL ($973) after adjustment. For both methods, the adjustment automatically removes the bias inherent in their estimation of $\alpha_t$. Thus, the forecaster needs to focus only on verifying that the time series is indeed stationary.

One important consequence of the algorithm is that when $c_o = c_u$ ($S = 0.5$) the decision value that minimizes the MOL is the median of the data. In particular, setting $c_o = c_u = 1$ shows that the median minimizes the MAD over the $n$ historical periods under consideration (often the forecaster's goal). Assuming that the time series will remain stable in the near future, setting the short-term forecasts equal to the median will minimize the expected absolute error for all future periods $n + h$, where $h \geq 1$. When $c_u > c_o$, the adjustment causes the optimal decision value to be above the median; when $c_u < c_o$, the decision value is below the median.

In the case of stationary data, the adjustment procedure agrees with the well-known solution of the classical newsboy problem as presented in most POM texts. However, such texts
tend to simply assume that the data are stationary. By contrast, our adjustment procedure does not make this assumption, nor does it require any particular shape for the demand distribution. Thus, the adjustment approach has much wider applicability than the newsboy problem because it allows the forecaster to first uncover whatever underlying structure exists in the observed time series, such as seasonality or trend.

A second time series, plotted in Figure 2, illustrates how the adjustment approach works when the data exhibit an observable pattern such as trend. Several standard forecasting methods were again applied to the data: exponential smoothing with parameter set (arbitrarily) to 0.6; naive or last value forecasting; and ordinary least squares (OLS) regression.

Figure 2: Plot of trend data along with OLS forecasts.

Table 2 shows that when $S = 0.75$ relatively large positive values of the adjustment $a^*$ are required for both the naive and exponential smoothing methods, bringing their optimal decision values close to that for OLS. Adjustment corrects the first two methods for their tendency to under-forecast upward-trending data. It is worth noting that all three adjusted forecasts for period 25 differ greatly from the classical newsboy decision. The newsboy solution would be to order the 75th percentile of the demand distribution, or only about 121 units, which seems an unlikely outcome given the overall trend in the data. Moreover, the disparity between the adjustment approach and the newsboy solution would grow as $S$ decreases.

In terms of MOL, both exponential smoothing and the naive method realize large reductions (47.4% and 30.6%, respectively) due to adjustment. Furthermore, for OLS regression, the method best suited to the pattern in the time series, adjustment still substantially lowers the MOL by nearly 16%.

Table 2: Optimal decision and MOL for various forecasting methods applied to trend data when $S = 0.75$ ($c_o = $25 and $c_u = $75).

<table>
<thead>
<tr>
<th>Forecasting Method</th>
<th>Forecast $f_{25}$</th>
<th>Optimal Adjustment $a^*$</th>
<th>Optimal Decision $d_{25}^*$</th>
<th>MOL ($) Without Adjustment</th>
<th>MOL ($) With Adjustment</th>
<th>Decrease in MOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expo(0.6)</td>
<td>128.4</td>
<td>17.3</td>
<td>145.7</td>
<td>778</td>
<td>409</td>
<td>47.4%</td>
</tr>
<tr>
<td>Naive</td>
<td>126.0</td>
<td>16.9</td>
<td>142.9</td>
<td>712</td>
<td>494</td>
<td>30.6%</td>
</tr>
<tr>
<td>OLS Regression</td>
<td>141.1</td>
<td>5.7</td>
<td>146.8</td>
<td>340</td>
<td>286</td>
<td>15.9%</td>
</tr>
</tbody>
</table>
A Monte Carlo simulation was conducted to test the impact of the adjustment approach on a wider range of time series and for a variety of critical ratios, as well as to assess its performance on post-sample data. The simulation experiments were run on a personal computer with Microsoft Excel and Visual Basic for Applications (Harris, 1996). Time series were randomly generated to exhibit either a level plus seasonal pattern, or an upward trend.

Seasonal data sets were constructed in several steps. First, each period was assigned a constant demand of 60. Second, a random variate from a Normal(0, 5) distribution was generated for each period and added to its initial demand of 60. Third, an index \( p \) between 1 and 5 was randomly selected to determine the peak of the 5-period cycles. Finally, a constant demand of between 30 and 60 (Uniformly distributed) was added to the \( p^{th} \) period of each cycle, e.g., if \( p = 5 \), the same constant was added to demand in periods \( t = 5, 10, 15, 20 \) and 25. Trend time series had the form \( x_t = a + bt + \varepsilon_t \), where the intercept \( a \) was arbitrarily fixed at 20, the trend \( b \) was randomly generated for each replication from a Uniform(3, 10) distribution, and the random errors \( \varepsilon_t \) were sampled from a Normal(0, 10) distribution.

The traditional design for testing forecasting methods on time series data (Makridakis, et al., 1982) was followed. Time series of total length \( T = n+h \) were randomly generated as described above. Data from the first \( n \) periods were used to estimate the parameters of each forecasting method while data from the last \( h \) periods served as a basis of comparison for the set of post-sample forecasts made by each method. For seasonal time series, we set \( n = 20 \) and \( h = 5 \) (\( T = 25 \)); for series with trend, \( n = 24 \) and \( h = 6 \) (\( T = 30 \)).

Successively applying each forecasting method to each time series yielded a set of \( n \) historical forecasts and a set of \( h \) post-sample forecasts. The MOL across the \( n \) historical periods and across the \( h \) post-sample periods were calculated separately. After repeating this process for 1000 (independent) time series of each type, averages were taken over the 1000 replications and are reported below. The entire procedure was repeated for 21 different values of the critical ratio \( S \) in which \( c_u \) was varied from $0 to $100, in increments of $5, while \( c_o \) was set to \( 100 - c_u \).

With seasonal data, adjustment brings increasing benefit in the MOL as \( c_o \) and \( c_u \) diverge, i.e., as \( S \) moves away from 0.50. For example, at \( S = 0.60 \) (\( c_u:c_o = 3:2 \)), the reduction in the historical MOL due to adjustment is about 5% (from $162 to $154), while at \( S = 0.75 \) (\( c_u:c_o = 3:1 \)), the reduction is almost 23% (from $162 to $125). Similar reductions occur as \( S \) decreases from 0.50. Over the post-sample periods, the benefit of adjusting shows a pattern similar to that found over the historical periods, but is somewhat weaker in magnitude (see Figure 3-left). Specifically, at \( S = 0.60 \), the reduction in the post-sample MOL due to adjustment is less than 1% (from $219 to $218), while at \( S = 0.75 \), the reduction jumps to about 15% (from $212 to $181).

**Figure 3.** Post-sample MOL vs. \( S \) for data with seasonality (left) and with trend (right).
With trend data, adjusting the forecasts generated by ordinary least squares (OLS) regression always reduces the historical MOL. For example, at $S = 0.60$, adjustment lowers the historical MOL by 4.4% (from $384 to $367), while at $S = 0.75$, the reduction due to adjustment grows to almost 22% (from $384 to $301). Once again, over the post-sample periods, adjustment generates benefits similar in pattern but slightly weaker in magnitude to those achieved over the historical periods (see Figure 3-right). Specifically, at $S = 0.60$, the reduction in MOL is only about 2% (from $453 to $445), but grows to 20% (from $453 to $362) at $S = 0.75$. It appears that when $S$ is between 0.45 and 0.55 adjustment provides no benefit for an unbiased forecasting method such as OLS. This is because when the average error is close to 0, the optimal adjustment $a^*$ for this range of $S$ values will also be close to 0. However, as $S$ moves away from 0.5 toward either 0 or 1, adjustment is again increasingly beneficial.

APPLICATION TO A CALL CENTER

Having reported on simulated time series in the previous section, this section examines how the adjustment procedure performs on real data from a call center. The third author consults extensively with the managers of a call center that provides technical support for users of the firm's software products. Each week managers receive call volume forecasts for each day of the next week and translate them into appropriate numbers of technical support agents. As in other settings, however, the costs associated with over-forecasting and under-forecasting differ.

The process of determining the relative costs of under-forecasting and over-forecasting is a challenge for all call centers, but it is something that managers understand they must grapple with. Over-forecasting the number of calls leads to overstaffing, and thus, excessive labor costs. Since direct labor constitutes 60–80% of the cost of operating the center, over-forecasting leads directly to a great deal of wasted money. Similarly, under-forecasting call volumes also has a number of negative implications: long customer waiting times, call abandonment, and multiple calls by frustrated callers who cannot get through quickly. Customer dissatisfaction may not only tarnish the company's reputation, it may eventually lead to a loss of customers and their associated lifetime value, as discussed in Anton (1996).

Consultants wrestle with managers to make sense of the tradeoffs between over-forecasting and under-forecasting call volumes. In this case, managers had been systematically overstaffing due to their bias toward providing outstanding levels of customer satisfaction “at any cost.” However, several economic factors conspired to force them to examine this bias more critically, including rising labor costs for skilled technical workers (due to low unemployment rates at the time), and an increased focus on controlling hard costs. Consequently, in analyzing their forecasts, the managers agreed on the following values: $c_o = $25 and $c_u = $10.

The time series data here represent daily (Monday-Friday) call volumes for six phone queues, referred to as AP, AR, GL, JC, PM and PR. Thirteen weeks (65 days) of both actual and forecasted data (April 3 - June 30, 2000) were used altogether for each queue. Figure 4 shows all six times series, along with the original forecasts. These forecasts assume that a daily seasonality component is present, e.g., the forecast for Tuesday of a given week is based on call volumes from the preceding five Tuesdays.

Six weeks of data were analyzed at a time, with the first five weeks representing the relevant historical data and the sixth week being used to judge post-sample performance. An adjustment factor was calculated from the 25 errors (from the historical forecasts) and then used to create a set of adjusted forecasts for each day of the sixth week. The MOL incurred by both the original and adjusted forecasts in the sixth week was then recorded. Repeating this process for weeks 1-6, 2-7, 3-8, etc., resulted in a separate MOL for weeks 6-13 (see Table 3).
Adjusting the original forecasts reduces the post-sample MOL in 29 of the 48 weeks. More importantly, the last column of Table 3 shows that the MOL averaged across the eight weeks decreases after adjustment for all six queues, ranging from 8.7% (for AP) to 41.1% (for PR). The last rows of the table sum the weekly MOL across the queues and indicate that, overall, adjustment reduces the MOL by an average of 25.5% or $338 per day. Assuming similar savings would be realized over a 250-day year leads to an annual reduction in MOL of $84,500.
Finally, we note that the benefits of the applying the adjustment procedure to the call center data, when $S = 0.286$, are consistent with those found in the simulation study for seasonal data when $S = 0.25$ and $S = 0.30$ (see Figure 3-left). In particular, at $S = 0.25$, adjusting the additive seasonal forecasts reduced the MOL by 26.2% (from $234$ to $173$), while at $S = 0.30$ the MOL was reduced by 19.8% (from $232$ to $186$).

## CONCLUSION

In some cases demand forecasting and operational decisions can be easily and sensibly coordinated. Our approach encourages forecasters to do their best to accurately predict demand using whatever method they deem best. It requires the decision-maker only to specify the relative weights of under-forecasting and over-forecasting, and the number of historical periods that are relevant to the decision. Once specified, the decision-maker can easily calculate an adjustment $a^*$ to add to any forecasts of future demand.

The adjusted forecasts (decision quantities) reduce the historical MOL of any forecasting method, and appear to provide similar MOL benefits on post-sample data. Simulation results demonstrated that the reduction in MOL due to adjustment can be quite significant over a wide range of $c_u/c_o$ ratios, with benefits increasing rapidly as $c_u$ and $c_o$ diverge. Certainly for $c_u/c_o$

<table>
<thead>
<tr>
<th>Queue</th>
<th>Week 6</th>
<th>Week 7</th>
<th>Week 8</th>
<th>Week 9</th>
<th>Week 10</th>
<th>Week 11</th>
<th>Week 12</th>
<th>Week 13</th>
</tr>
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<tbody>
<tr>
<td>AP</td>
<td>353</td>
<td>237</td>
<td>102</td>
<td>228</td>
<td>138</td>
<td>172</td>
<td>122</td>
<td>125</td>
</tr>
<tr>
<td>Adjusted FC</td>
<td>392</td>
<td>87</td>
<td>200</td>
<td>118</td>
<td>98</td>
<td>188</td>
<td>152</td>
<td>101</td>
</tr>
<tr>
<td>% Change</td>
<td>11.0</td>
<td>-63.3</td>
<td>96.1</td>
<td>-48.2</td>
<td>-29.0</td>
<td>9.3</td>
<td>24.6</td>
<td>-19.2</td>
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<tr>
<td>AR</td>
<td>615</td>
<td>159</td>
<td>110</td>
<td>62</td>
<td>262</td>
<td>235</td>
<td>111</td>
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<td>144</td>
<td>113</td>
<td>121</td>
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<td>147</td>
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<tr>
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<td>32.1</td>
<td>118.2</td>
<td>133.2</td>
<td>-56.9</td>
<td>-48.5</td>
<td>3.6</td>
<td>-19.7</td>
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<tr>
<td>GL</td>
<td>393</td>
<td>295</td>
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<td>147</td>
<td>35</td>
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<td>118</td>
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<tr>
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<td>266</td>
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<td>127</td>
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<tr>
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<td>335</td>
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<tr>
<td>Adjusted FC</td>
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<td>147</td>
<td>170</td>
<td>86</td>
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<td>222</td>
<td>185</td>
</tr>
<tr>
<td>% Change</td>
<td>-9.4</td>
<td>6.0</td>
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<td>8.9</td>
<td>-29.4</td>
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<tr>
<td>PM</td>
<td>220</td>
<td>89</td>
<td>56</td>
<td>71</td>
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<td>124</td>
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<tr>
<td>Adjusted FC</td>
<td>107</td>
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<td>118</td>
<td>74</td>
<td>104</td>
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<tr>
<td>% Change</td>
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<td>-21.3</td>
<td>110.7</td>
<td>4.2</td>
<td>-14.8</td>
<td>-46.6</td>
<td>-21.0</td>
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<tr>
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<td>765</td>
<td>625</td>
<td>575</td>
<td>170</td>
<td>144</td>
<td>181</td>
<td>330</td>
<td>330</td>
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<tr>
<td>Adjusted FC</td>
<td>362</td>
<td>210</td>
<td>161</td>
<td>288</td>
<td>340</td>
<td>220</td>
<td>63</td>
<td>424</td>
</tr>
<tr>
<td>% Change</td>
<td>-52.7</td>
<td>-66.4</td>
<td>-72.0</td>
<td>69.4</td>
<td>136.1</td>
<td>21.5</td>
<td>-80.9</td>
<td>28.5</td>
</tr>
<tr>
<td>Total</td>
<td>2687</td>
<td>1505</td>
<td>1252</td>
<td>896</td>
<td>780</td>
<td>1067</td>
<td>1097</td>
<td>1289</td>
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<tr>
<td>Adjusted FC</td>
<td>1740</td>
<td>765</td>
<td>976</td>
<td>921</td>
<td>875</td>
<td>877</td>
<td>762</td>
<td>1262</td>
</tr>
<tr>
<td>% Change</td>
<td>-35.2</td>
<td>-49.2</td>
<td>-22.0</td>
<td>2.8</td>
<td>12.2</td>
<td>-17.8</td>
<td>-30.5</td>
<td>-2.1</td>
</tr>
</tbody>
</table>

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ratios above 3:2 ($S > 0.60$) or below 2:3 ($S < 0.40$), it seems worthwhile to make the adjustment. Real data from a technical support call center support the conclusions of the simulation study.

This article represents a first step toward unifying two activities, demand forecasting and operational decision-making, that are often performed without coordination. Undoubtedly, there are other settings that deserve further investigation using a similar kind of adjustment approach.

REFERENCES


