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Original Research Article

An Analysis of Lost Sales

Jarrett

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Jeffrey E. Jarrett*
Management Science and Finance, University of Rhode Island,
Kingston, RI 02881, USA.

***Correspondence:** jejarrett133@gmail.com

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Abstract

The purpose of this manuscript is to shed light on problems associated with lost sales and the incurring of cost associated with lost sales. An investigation is made to determine if seasonality in sales and lost sales have effects on the efficient operations of supply chains. Optimization is always a goal of management supply chains, but cost increases due to insufficient inventory, low-quality product and the like lead to customers not returning. These are lost sales that occur for many reasons. We study a data set to determine if the ignoring of time series component also has an effect on the variation in lost sales. If so, can we measure the magnitude of the effects of seasonal variation in lost sales, and what are their consequences?

Keywords: Lost sales; Supply chain; Time series; Components of time series; Seasonal component; Decomposition.

1. INTRODUCTION

Lost sales are those selling opportunities that a firm has lost because an item was out of stock, or a firm did not carry a particular brand, line of merchandise, and any other possibility that causes the seller to lose the opportunity to sell. These lost sales have costs that are considered to determine optimal inventory models in the supply chain. Brandenburg *et al*. (2014) did a remarkable study of the development of quantitative models for supply chain management to ensure that models are sustainable. These models would be sustainable because they achieve results that are at minimum costs to both profits and the environment. Lost sales and out-of-stock costs rely on inventory theory including an assumption that excess demand is backordered. In many environments, this is not so or the quality of the merchandise to be sold lessons resulting in returns, lost sales, and cost additions. Bijvank and Vis (2011) review the available models to minimize the cost of inventory in the supply chain. Further, Bijvank and Johansen (2012) and Baek and Moon (2015) consider models that minimize costs of inventory and lost sales aiming and producing optimality in the integrations of supply chain integration. Integration in the supply chain has become a very important goal in maximizing the benefits from optimal uses of the supply chain (Silvestro and Lustrato, 2014). Furthermore, Jarrett (2013) emphasized the use of multivariate quality processes to control quality and continually improve product output in the supply chain. For another series of arguments using standard statistical quality control and total quality management (TQM) methods, see Casadesus and de Castro (2005) and Romano and Vinelli (2001).

All of the above approaches have the goal of reducing the cost of lost sales as defined above, but they do not examine those costs of sales that can be prevented by considering sources of the increase in costs of lost sales occurring due to changes in time. A method by which one may examine sources of changes in the cost of lost sales is **Time series analysis and Decomposition**. This analysis comprises methods for analyzing **time series data** to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. The decomposition entails separating the time series into its components to determine the sources of variation. One such source, **seasonality**, accounts for the variation in data associated with changes in the calendar and their effects on lost sales. These calendar effects are due to culture, the environment, and everything else in the society that changes the motivations for achieving optimal inventory and sales programs of firms operating in the supply chain. For a full discussion of **supply chain management** and all its research directions, see Geunes *et al*. (2002)

By applying time series analysis and decomposition (Jarrett, 1991, chapter 3), one can determine home much of the source of variation accounted for by seasonality and possible improve forecasting and planning functions within supply chain management. Hence, the following sections of this study will be to (a) to find by standard time series analysis and decomposition how large the seasonal variation affects forecasting; and (b) to suggests improvement in the forecasting process to accomplish the goals of optimizing supply chain logistical and inventory control practices.

2. TIME SERIES

The data for this study consists of sixty observation of lost sales measured by a firm over a five-year history starting from July of year one until and including August of year six. The response variable is lost sales with (dummy or categorical) variables starting with

January = 1 or 0 if not January
February = 1 or 0 if not February
March = 1 or 0 if not March
...
...
December = 1 or 0 if not December

Designing the time series model in this manner will permit the identifying of seasonal variation in the data and allows us to interpret the degree of lost sales affected by seasonality. The model implemented in our analysis is called a multiplicative model. The assumption of a multiplicative model is that the data model in which the effects of individual factors are differentiated and multiplied together to model and predict the data. A multiplicative model is optional for decomposition procedures and differs from the requirement of the additive Winters' method for predicting seasonal data. We employ a multiplicative model when the magnitude of the data affects its seasonal pattern. Additive models are better for two-way analysis of variance where one desires this option to omit the interaction term from a model.

To begin, Figure 1 contains the original time series plot of the sales data with the index (month) as the horizontal variable. Note the fourth, sixteenth, twenty-eighth, fortieth, and fifty-second period of each year (twelve-month sequence) starting from July 1 of the first year are the months having

Figure 1. Original Lost Sales Time Series Data.

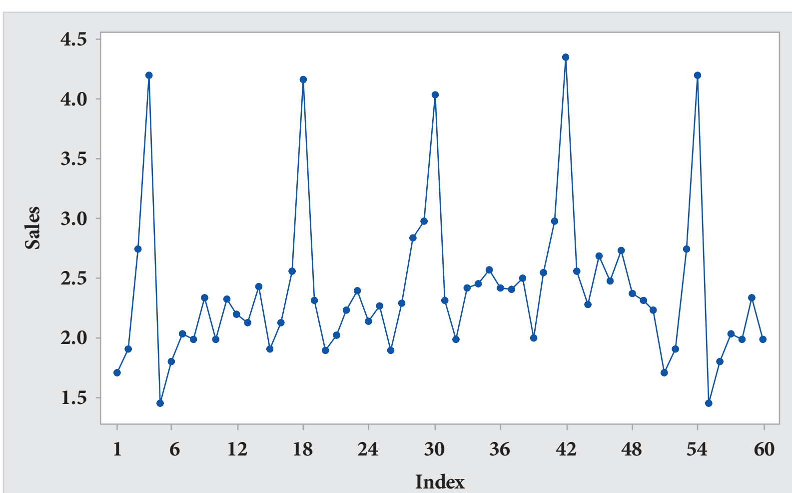

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Figure 2. Component Analysis for Lost Sales.

the largest value for lost sales. This would be the month of October for each year. By this time series plot, we observe that October has the largest amount of lost sales in every year for this firm studied in the six-year sequence. In addition, we observe large declines in lost sales in the fifth and sixth periods of each year (November and December). The seasonal pattern is evident and observable, which permits us to employ time series decomposition to find the extent of the seasonal variation in lost sales.

The component analysis stage of the decomposition, permits analysts to observe the original lost sales data after the trend component is removed, after only the seasonality is removed and both the seasonality and trend were removed. We note for the detrended data that there is little change in the time series movement from the original data. Hence, we conclude that the trend in the data is minimal at best and other sources of variation are present and substantially affect the movement of the data across time. The bottom left graph shows the result of seasonally adjusting the data. Only the lost sales of period 4 of year one contains a relatively large value very distant from the surrounding data. Periods 16, 18, 40, and 52 no longer have peaks. This, we observe as the seasonal adjustment removes the extreme variation from those data points. Furthermore, the figure in the bottom right indicates that adjusting both seasonality and trend leaves a graph that is very similar to the bottom left where only a seasonal adjustment was accomplished.

From Figure 2, we conclude that for the most part, trend variation was not important in analyzing time series. Large values appeared in October of each of the six years studied. The graph for the first twelve-month sequence and for all the other twelve-month sequences indicated that a seasonal adjustment is necessary to improve the forecasting of twelve-month periods. The first four months do appear as an anomaly from the seasonally adjusted and detrended data. However, before one observes that the first twelve patterns are an anomaly in comparison with the other twelve-month sequences, we should note that the decomposition method uses on a few observations in predicting the first year. Hence, the first is a statistical anomaly resulting from the method used, and we should not interpret anything of value from the data as adjusted in the first year. There are many analogies to this phenomenon, and we can ignore the first year.

Another important result is indicated by examination of the following table of monthly seasonal index (SI) compiled by the analysis. Consider the following table.

Table 1. Seasonal Index (SI) for Each Month.

Month	Seasonal Index (%)
January	91.97
February	93.32
March	77.61
April	92.44
May	114.03
June	168.23
July	92.73
August	82.65
September	92.73
October	82.65
November	103.08
December	93.20

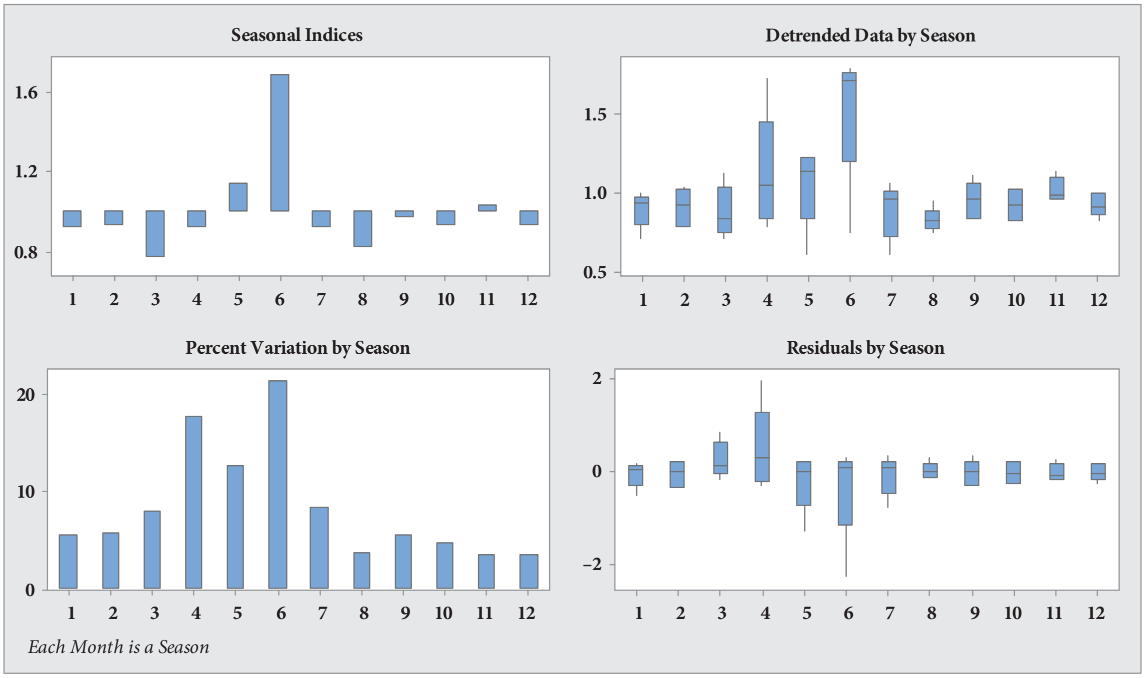
From Table 1, we observe the SIs (in percentage) for each month computed by the Time Series Decomposition Analysis (MINITAB^{R}) for the lost sales data. The SI for June has the largest index of 168.23%. On average, the data for June would be 68.23% larger than the average month having no seasonal variation. Only three months—May, June, and November—have an SI that is larger than 100 indicating that these months would have a smaller value for lost sales if there was not any seasonal component. The other nine months have values less than 100 with the smallest SI being for March. These SIs indicate by month the influence of the seasonal component. We observe that the seasonal component is different from month-to-month comparison indicating that inventory and marketing programs for firms must recognize that the seasonal component in the supply chain will not be occupying an important role. Furthermore, we need to observe the effects of seasonality on the indexes and the possible ability to plan well for the future.

3. ADDITIONAL ANALYSIS OF SEASONAL COMPONENT

By additional analysis, we observe month by month analysis of the data on the seasonal component of the time series depicted in a series of four plots from the multiplicative model in Figure 3. The top left is a bar chart of the variation in the seasonal indices by month over the six-year period. The important observant is for month six containing the largest bar from top to bottom indicating the largest disparity in the data for that month over the six-year period of the study. This affirms a previous observation that month six (June) has the largest seasonal component. From the note in the bottom left of Figure 3, we observe that period six contains the percent variation by season (month in this case). Month (season four [April]) has the second largest percent variation followed by month five. There is a consistency in a pattern observed in this graphical analysis.

The top right graph, the detrended data by season (each month is again a season), observe that boxplots are drawn for the data month by month. The boxplots again reveal the greatest variability exists in month six with months four and five following in order. As noted earlier, the detrending of the data had little effect since there was only a minimal trend in the time series. A similar pattern will be observed in the bottom right graph, which yields boxplot for the residuals by month (season in

Figure 3. Seasonal (Monthly) Analysis for Sales.



plot). Hence, we must conclude that seasonality exists in the time series data, and the extent of the seasonality varies from month to month.

4. CONCLUSION AND FUTURE RESEARCH

In this study, we observed that supply chain management includes planning and forecasting which give rise to lost sales when factors exist and when disturbances to the supply chain intervene. The common disturbances found by other often refer to suboptimization in inventory management where customers are discouraged from finding the products and quantities they desire. For many goods, low quality and no quality control and continuous improvement programs result in low quality goods and services. To borrow from TQM, we want the customers back and not the "goods."

Lost sales have costs, and not much is known about optimal replenishment programs when excess demand is lost. In this project, we aim at one source of lost sales and that is the seasonal component of the time series for lost sales. Lost sales have a seasonal variation that can be measured, analyzed, and treated and accounted for in optimal planning programs for the supply chain. The supply chain is a portion of optimal analysis in operations management programs. The use of time series analysis and decomposition should always be explored in the development of planning models. Future research will implement process management forecasting, inventory control, and logistical models using time series methods to finalize and produce the models necessary for best results.

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