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Forecasting the forecastability quotient for inventory management

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ABSTRACT

This research develops and empirically tests a model for estimating the economic advantage of using a time phased order point system (TPOP) with time series forecasting rather than a simple reorder point system in an independent demand inventory management context. We define the forecastability quotient (Q) to support this economic analysis. We implement TPOP in our empirical analysis via double exponential smoothing with a damped trend, and implement ROP through a simple moving average.

Our empirical study of a large dataset of time series from a Fortune 100 firm found that Q in the holdout sample can be predicted using just three variables from the estimation sample. Surprisingly, many highly touted time series metrics (e.g., the coefficient of variation and approximate entropy) and forecast accuracy metrics (e.g., the mean absolute percentage error) were not good predictors of Q. We then validated this model on four additional datasets. This research contributes both to the research literature and to managers who need to decide whether an independent demand item should be managed with a TPOP or reorder point system.

1. Introduction

A demand forecasting system that can reduce the inventory carrying cost and/or improve service levels can give manufacturing, distribution, and retail firms a significant competitive advantage (Chopra & Meindl, 2010; Gilliland, 2010; Syntetos, Boylan, & Disney, 2009). It is our observation, however, that many firms fail to achieve the anticipated financial benefits of a forecasting system, in part because their managers naïvely assume that the mere existence of a forecasting system is *prima facie* evidence that it is better than a simple reorder point system. Inventory managers therefore need an economic model that can be used to estimate the future economic advantage of a time series forecasting system over a reorder point system.

To the best of our knowledge, no research has addressed this important need. Most forecasting research has focused on developing and refining mathematical forecasting models (Corberán-Vallet, Bermúdez, & Vercher, 2011; McKenzie & Gardner, 2010; Taylor, 2010), or empirically testing forecasting models (Armstrong, 2006; Fildes, Goodwin, Lawrence, & Nikolopoulos, 2007; Taylor, 2003, 2007). The research on time series stability metrics (Kahn, 2006; Pincus, 1991) and forecast accuracy metrics (Armstrong & Collopy, 1992; De Gooijer & Hyndman, 2006; Hyndman, 2006; Hyndman & Koehler, 2006; Mahmoud, 1984; Mathews & Diamantopoulos, 1994; Valentin, 2007) implies that these metrics can be used to measure the economic benefit of a forecasting system and to help determine whether a time series is "forecastable". However, we argue that these met-

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rics are not adequate in an inventory management context because they are not based on an economic model.

We found two Fortune 500 firms (disguised as firms G and H) that use simple heuristics to help managers evaluate the benefits of a time series forecasting system in an inventory management context. Firm G estimates the standard deviation of the forecast error for calculating safety stocks using $\hat{s}_{Et} = 1.25\, MAPE\, a_t$, where *MAPE* is the mean absolute percentage error and a_t is the smoothed average demand at the end of period t. They believe that a forecasting model that reduces *MAPE* by X% will reduce the safety stock carrying cost by the same amount. Firm H "triages" items based on the coefficient of variation (cv) of demand. If $cv < 1$, they manage the item using a forecasting/time phased order point (TPOP) system; however, if $cv \geq 1$, they classify the item as not "forecastable" and manage it with a simple "pull" system based on the moving average demand, which is essentially a reorder point system. (Note that all Materials Requirements Planning systems use TPOP to manage independent demand items such as end items and service parts, where the gross requirement for these items is the forecasted demand; see Silver, Pyke, & Peterson, 1998.) This research challenges both of these heuristics.

The three goals of this research are to (1) develop a simple forecastability metric that can be used to estimate the economic benefit of time series forecasts for an inventory item; (2) identify which time series metrics and forecast accuracy metrics are good predictors of forecastability; and (3) develop and validate a parsimonious model that can predict the forecastability of a time series. The remainder of this paper is organized to support these three goals as follows. Section 2 draws on inventory theory to develop the forecastability quotient that can be used to estimate the economic benefit of a forecasting system, based on a reduction in the safety stock. Section 3 relies on the forecasting literature to identify time series metrics and forecast accuracy metrics that are plausible predictor variables for the forecastability quotient. Section 4 reports an empirical analysis on a large dataset from a Fortune 100 firm for developing a parsimonious Forecasting the Forecastability Quotient (FFQ) model. Section 5 validates the FFQ model on four additional datasets from different industries. Section 6 concludes with a discussion of the contributions and limitations of the research and three final observations for managers.

2. The forecastability quotient

Boylan (2009, p. 39) proposes the following as "a more precise definition of forecastability" of a time series:

> Forecastability is the range of forecast errors that are achievable on average, in the long run. The lower value of the range represents the lowest forecast error achievable. The upper value of the range represents an upper bound based on a benchmark forecasting method.

He argues that it is easy to determine an upper bound on the forecast accuracy using a naïve method such as a random walk, but that it is difficult to get a lower bound on the forecast accuracy. He suggests that the lower bound be estimated either by using the automatic selection method available in commercial forecasting software or by using a number of methods and taking the best *ex post* forecast for each period. He notes that this definition does not require the specification of a forecast accuracy metric. However, this definition has several problems, in that it does not meet the requirements of a formal definition (Wacker, 2004), is difficult to implement, and is not based on the economics of a forecasting system.

Granger and Newbold (1976) define forecastability as σ_D^2/σ_E^2, where σ_D^2 is the variance of demand and σ_E^2 is the variance of the forecast error for a specific forecasting model. Their definition requires covariance stationarity, assumes optimal forecasts based on the population rather than a sample realization, and does not relate to the economics of forecasting. They discuss forecastability only briefly, and do not attempt to apply the concept.

We argue that any measure of forecastability should be based on an economic model. The relevant costs of operating a forecasting system in an inventory management context include: (1) the administrative cost of operating the system, (2) the stockout (shortage) cost, and (3) the inventory carrying cost. The administrative cost depends upon various systems issues that are unique to each forecasting software vendor and firm, and is therefore outside the scope of this research. Most firms and systems control the stockout cost by means of management-defined target service levels that balance carrying and stockout costs. These target service levels constrain the stockout cost to an acceptable level, which means that the stockout cost is also outside the scope of this research. The inventory carrying cost is the sum of the lotsize inventory carrying cost and the safety stock carrying cost. Given that the forecasting accuracy does not usually affect lotsizing decisions or the lotsize inventory carrying cost (Silver et al., 1998), the main economic benefit of a forecasting system in an inventory management context is a reduction in the safety stock carrying cost.

The above discussion assumes that the forecasts are unbiased. A negative forecast bias will cause a forecasting/TPOP system to have excess inventory and a positive forecast bias will cause the service level to be poorer than planned. If a consistent forecast bias is present, it can be detected easily with a tracking signal, and corrected. The remainder of this paper therefore assumes that the forecast bias does not need to be considered in the economic model.

The standard model for safety stock for an item managed with a forecasting/TPOP system is $S_{TPOP} = z\sqrt{L}\, s_E$, where S_{TPOP} is the safety stock in units, z is the safety factor, L is the planned leadtime, and s_E is the sample standard deviation of the forecast error per period (Silver et al., 1998). If a reorder point (ROP) system is used, s_E is replaced by the sample standard deviation of demand per period (s_D), i.e., $S_{ROP} = z\sqrt{L}\, s_D$. The above safety stock model, known as the "cycle service level model", is implemented in SAP (Hoppe, 2006) and recommended in many standard operations management textbooks (e.g., Schroeder, Goldstein, & Rungtusanatham, 2011). (SAP implements the cycle service level model with s_D based on the forecast error *MAD* rather than on the historical standard deviation of demand. SAP therefore requires a forecasting system to be in place.) More complicated safety stock models define z as a function of other variables such as the lotsize and the standard