



Forecasting method selection in a global supply chain

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ABSTRACT

In supply chains, forecasting is an important determinant of operational performance, although there have been few studies that have selected forecasting methods on that basis. This paper is a case study of forecasting method selection for a global manufacturer of lubricants and fuel additives, products usually classified as specialty chemicals. We model the supply chain using actual demand data and both optimization and simulation techniques. The optimization, a mixed integer program, depends on demand forecasts to develop production, inventory, and transportation plans that will minimize the total supply chain cost. Tradeoff curves between total costs and customer service are used to compare exponential smoothing methods. The damped trend method produces the best tradeoffs. © 2011 International Institute of Forecasters. Published by Elsevier B.V. All rights reserved.

1. Introduction

A comprehensive review of research in forecasting for supply chains is given by Fildes and Kingsman (2010), who conclude that there are few findings of any managerial importance. We agree. To ensure mathematical tractability, most researchers have assumed greatly simplified operating systems and cost structures. Furthermore, most have also failed to match the generation process for demand with the choice of a forecasting method. Thus, forecast errors have been compounded with misspecification errors, making it difficult to understand the effects of forecasting on efficiency, costs, inventory investment, or customer service levels. In a careful MRP simulation, Fildes and Kingsman set out to correct many of the fallacies in previous research. They found that the benefits of improved forecasting are considerably greater than the effects of choosing inventory decision rules, and that a misspecification of the forecasting method leads to increases in costs.

Fildes and Kingsman call for more empirical modelling of the supply chain that is grounded in observed practice, and that is the theme of this paper. We model the relationship between forecasting and operational performance

in the supply chain of a global manufacturer of lubricants and fuel additives, products which are usually classified as specialty chemicals. The model includes four manufacturing plants and daily time series of actual demand collected over a four-year period. Both optimization and simulation techniques are used to develop production schedules, inventory targets, and transportation plans for shipments between plants and to customers. Optimization depends on demand forecasts, supplied by exponential smoothing, and is done with a mixed integer program in order to minimize total variable supply chain costs.

Management asked for forecasting methods that were simple and easily automated, making some form of exponential smoothing the only reasonable choice. We considered three methods: simple exponential smoothing (SES), Holt's additive trend (Holt, 2004), and the damped additive trend (Gardner & McKenzie, 1985). SES and the damped trend are obvious choices, given their long record of success in empirical studies (Gardner, 2006); the data suggested that the Holt method would not perform well, but it was retained as a benchmark for the other methods. To select the best method, tradeoff curves were computed between total supply chain cost and several measures of customer service. The damped trend gave the best operational performance for any level of cost, followed by

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SES and Holt. It is interesting to contrast these results with traditional method selection based on average forecast accuracy measures; surprisingly, SES gave the best overall average accuracy.

2. The supply chain model

The company produces lubricants and fuel additives for automobiles, farm equipment, marine vessels, trains, construction equipment, and power tool motors. There are four manufacturing plants, located in North and South America, Europe, and Asia. The scheduling of production orders is best described as a combination of push and pull processes. Ten component chemicals are produced in a push mode based on forecasts from one to six months ahead, while end products are produced in a pull mode by blending the components according to individual product recipes as customer orders are received. Forecasting is done at the component level by aggregating component requirements across the end products at each plant. Considerations of technology, production and shipping costs, and plant capacity are such that not all components are produced in all plants. Thus, we have only 25 time series of component demands rather than 40 (4 plants \times 10 components).

The supply chain model, depicted in Fig. 1, integrates optimization and simulation and performs tactical planning at two levels. At the first level, the model produces a monthly master production schedule and a stock transfer plan over a six-month planning horizon. These plans are generated by a mixed integer programming (MIP) model that incorporates demand forecasts as described below, pending orders, beginning inventory levels, machine and storage capacities, alternative modes of transportation, and shipments in transit. The model also incorporates company business rules for minimum run lengths and transportation carrier selection. The objective is to minimize the total variable supply chain cost, including costs of production, transportation, inventory carrying, and import tariffs. Tactical planning at the second level uses another MIP model to break down the first level results into a detailed weekly production schedule for each machine at each plant over a 12-week planning horizon. For a complete mathematical formulation and solution methodology for the MIP models, see Acar, Kadipasaoglu, and Day (2009); Acar, Kadipasaoglu, and Schipperijn (2010). The models of Acar et al. were developed using simple assumptions about demand, whereas in this paper we study the behavior of the models when they are driven by a forecasting system using real data.

The simulation model at the second level executes the manufacturing plans on a daily basis, using the actual daily demand history that occurred over a four-year period. The model reads the first-level production schedule and manufactures components accordingly, placing them in inventory. Production is measured in tons, and total demand for the last year of operations was about 250,000 tons. As customer orders arrive, the demand is met by blending end products from the component inventory. There are a total of 15 machines in the four plants, and production lead-times range from two to seven days,

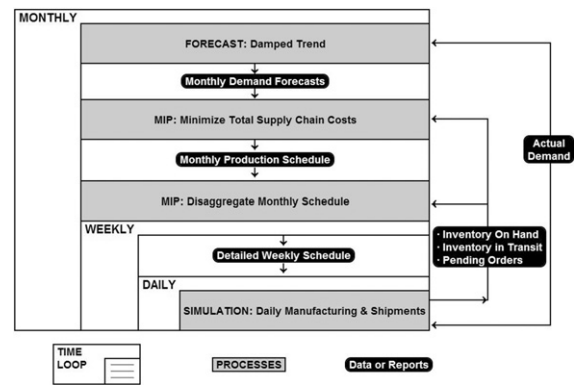


Fig. 1. The supply chain model.

depending on product and order size. If the available inventory is not sufficient to meet demand, backorders are generated. The second-level model also transfers stock between plants as required, debiting inventory from the sending plant on the departure date and crediting inventory at the receiving plant on the arrival date. There are numerous transshipments between plants, and the average transportation lead-time is 47 days. All shipment quantities are set as close as possible to those determined in the first-level model (based on inventory availability). If a shipment quantity is significantly less than that suggested in the first-level model, no further shipments can be scheduled until that model is run again.

There are three sources of uncertainty in the simulation. First, actual demand is of course uncertain. Second, transportation lead-times are generated from a set of truncated normal distributions, one for each source-destination pair. Means and standard deviations are based on actual experience, and the distributions are truncated such that the minimum lead-time is 85% of the mean. The reason for the truncation is that most of the transportation is by marine vessel, and it is impossible to achieve lead-times any shorter.

Finally, there is some supply uncertainty due to machine breakdowns. We did not have empirical data available to enable us to develop distributions of machine breakdowns, so we chose the following simulation procedure in consultation with maintenance and supply chain managers. The occurrence of breakdowns for each machine was generated from a uniform distribution; for each breakdown, the duration was generated from a normal distribution with a mean of five days and a standard deviation of two days. It might seem that the probability of a breakdown should increase with time, but the company disagreed because rigorous maintenance schedules were enforced. Managers reviewed the simulated breakdowns and found them to be reasonable.

At the end of each week, the second-level model records inventory levels, pending orders, quantities shipped to other plants, and costs incurred. The model also records two measures of customer service: number of orders late and weighted lateness. The latter measure, considered by management to be the most important, is defined as the number of days an item is backordered times the backorder quantity.

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