How Intermittent

Demand Forecasting

Reduced Target Inventories

NSK Corp., Ann Arbor, Mich., is the U.S.-based operation of the world's second-largest provider of anti-friction bearings and precision products to the automotive and other industries. This quarter, the company is using the dedicated intermittent demand forecasting module from Smart Software's SmartForecasts software to estimate lead-time demand on a subset of NSK's after-market business unit's (ABU's) stockkeeping units (SKUs). Robert Schuster, senior supply chain analyst, describes the demand patterns of these SKUs as "very sporadic."

NSK, a General Motors Supplier of the Year, has made its reputation on product quality and availability. Suppliers in the $2 billion aftermarket industry win or lose business based on their in-stock position. Short lead times and quick response times are assumed. High service level inventories, estimated as accurately as possible, are often necessary. But estimating lead-time demand and target inventories for specific service levels in this environment is not easy.

Inventory tends to have a long life in the aftermarket. Product life cycles can average two years or more. Different SKUs have different inventory replenishment lead times, with imported products averaging several months. And in the case of two-thirds of the ABU's 7,000 SKUs, demand is highly intermittent, with half of the sales history data containing zero values. About 1,000 SKUs make up 90 percent of the unit's business, with the other items stocked to ensure NSK's reliability as a full-line distributor. "We might sell a $250,000 item once a year," notes Schuster, "or sell one or two every other month—and not always to the same customer. But our customers can always expect that we'll have the item they want in stock and that we'll respond quickly when they call."

The company began championing a program of inventory reduction and demand planning system automation in 1998, when Schuster first proposed a 40 percent target reduction in inventory, while maintaining on-time delivery performance. NSK's previous demand forecasting system computed average monthly product usage based on 12 months of sales history. The software then multiplied that number by the length of the average replenishment lead time to calculate lead-time demand and required inventory levels. But Schuster saw that 12 months of history did not provide enough information to forecast demand for products with 18-, 24- or 36-month cycles of sales. For such intermittently demanded items, these forecasts often yielded "zero" values.

In 1999, after using Smart Software's SmartForecasts forecasting software to forecast standard aftermarket products, NSK hit its target, reducing inventory by $1 million (representing a 30-day reduction in inventory), shortening lead times, and increasing on-time delivery above the 98 percent service level the company had already achieved. Now NSK intends to lower inventory targets further, even as the company expands its product lines. Schuster estimates that the software's intermittent demand forecasting technology will help produce annual savings of about $3 million for the ABU alone. He also anticipates that Smart's direct connectivity to NSK's Oracle and SQL Server databases will help facilitate the company's goal of an automated, enterprise-wide system of collaborative demand planning and inventory replenishment.

"[This software] will help us complete the process," says Schuster. "It was the missing piece."

—T.W. & C.S.

GOT INTERMITTENT DEMAND?

You can learn more about Smart Software's new U.S. patent-pending Intermittent Demand Forecasting technology by visiting www.smartcorp.com.

unreliable advice on setting reorder points and order quantities.

This bootstrapping approach provides fast and realistic forecasts of intermittent product demand over a lead time. In turn, these forecasts can be entered into inventory control models to strike the proper balance between keeping enough inventory on hand to satisfy customer demand and keeping as little inventory as possible to hold down costs.

Thomas Willemain, Ph.D., is professor of Decision Sciences and Engineering Systems at Rensselaer Polytechnic Institute, Troy, N.Y., and V.P. of Smart Software, Inc., Belmont, MA. Charles Smart is president of Smart Software, Inc. Both can be reached at 800/762-7899 or via info@smartcorp.com.

APICS
THE PERFORMANCE ADVANTAGE

GET REAL

A New Way to Forecast Intermittent Demand

Intermittent product demand creates headaches. Bootstrapping methods may be the cure.

By Charles Smart and Thomas Willemain, Ph.D.

Do your products exhibit intermittent demand patterns? It's an even bet that anyone who is a capital goods manufacturer or service (spare) parts inventory manager in the automotive, aerospace, utilities, or high-tech industries has wrestled with this common and costly inventory management problem.

Managers may know this type of demand pattern by another name—"irregular," "slow-moving," or "sporadic." Unlike most product sales and demand data, intermittent demand contains a large percentage of zero values, often 30 percent or more, with non-zero values mixed in at random. If there is great variability among the non-zero values, this demand pattern also is called "lumpy." Whatever it's called, the costs of inaccurately estimating lead-time demand and target service-level inventories in this environment are potentially huge.

What makes forecasting intermittent demand data so difficult? Largely, it's the

At-a-Glance

- Intermittent product demand patterns challenge inventory planners across the capital goods and service parts inventory spectrum, where millions of dollars in inventory costs and lost business can result from inaccurate planning.
- Traditional statistical forecasting methods have failed with this data because they assume a "normal" distribution of product demand over a lead time.
- A new bootstrapping methodology that accurately forecasts intermittent demand data promises to strike the right balance between minimum levels of required inventory and maximum levels of customer service.

predominance of zero data values. Familiar techniques useful in forecasting conventional or "smooth" demand, such as exponential smoothing and moving averages, ignore the special role of zero values and other key features of intermittent demand.

In the case of service parts, there is an additional twist to the forecasting problem. Here, forecasts are usually used as inputs to inventory control models. Inventory control theory requires forecasts of the entire distribution of possible demand values—not just a single number thought to be the most likely demand—and requires forecasts over a total lead time, not just a single time period. If these forecasts are accurate, then the inventory models can recommend correct procedures for inventory management, such as the size and timing of replenishment orders (order quantities and reorder points).

Traditional statistical forecasting methods fail because they assume that the probability distribution of demand over a lead time (lead-time demand) will resemble a "normal" bell-shaped curve. This certainly is not the case for most service parts. Instead, lead-time demand can have odd shapes, and classical forecasting methods can provide grossly misleading inputs to inventory control models. Most computerized forecasting tools identify recognizable patterns in the data, such as trend and seasonality. But there are no easily recognizable patterns in intermittent demand data.

Over the years, many experts in inventory management and statistics, including statistician J.D. Croston, have grappled with the challenge of statistically forecasting intermittent data. Now, recent business innovation research supported by the National Science Foundation has produced a new and more accurate method of forecasting intermittent demand. The study, performed by Smart Software, Inc., examined 28,000 commercial data series (inventory items from nine companies in the U.S. and Europe, representing the aircraft, high-tech, electronics components, marine equipment, and other capital-equipment industries).

An Aerospace Industry Perspective

By Robert Lamarre, B.B.A., M.A. Sc., cmc, Adm.A.

Forecasting the demand for products with intermittent demand patterns is a particular problem for those who manage spare parts. A good example is an aerospace industry client that our company is assisting with its forecasting and planning.

The client has more than 80,000 spare part items in stock. Our analysis indicates that for more than 80 percent of the parts, demand is less than 5 units per year, with many periods registering zero demand. Accurate planning is critical for the manufacturer as well as its customers, the aircraft operators. The price of not having the right part available at the right time in the right place is steep: an aircraft operator can incur costs of more than $50,000 for each hour a plane is on the ground. Of course, the manufacturer has an obligation to deliver the parts required by an operator within hours of the request. But if the part is not readily available from stock, the manufacturer could be forced to take a good part from an aircraft on the assembly line–a costly alternative. Even the cost of expediting shipment of a part from one corner of the globe to another can be significant.

Hence, the need for an accurate forecasting tool. But traditional forecasting tools generate forecast results with such large error margins that some managers find them useless. When applying the results produced by these tools for spare parts with intermittent demand, the organization continually encounters major difficulties in achieving the desired service level. In reaction to the pressures created by too many stock-outs, the tendency is to overstock. Given the costs of spare parts in this industry, such a strategy is unacceptably expensive.

The new intermittent-demand bootstrapping approach offers a practical solution to this forecasting problem. The approach is designed to provide a desired service level, but with minimal inventory requirements. Even given the difficulty of the problem, the solution can be implemented easily on a PC. The payback period of implementing such an approach in the aerospace industry proves to be extremely short. It would be interesting to see more research on how to apply a similar approach when historical information is unavailable and when we can use only the mean time between failure (MTBF) to forecast the future, such as is the case when a new aircraft type is launched.

Robert Lamarre is president of Robert Lamarre & Associates, Management Consultants, St. Lambert, Quebec, Canada, experts in supply chain management with special expertise in spare parts management. He can be reached at 450/671-5736 or via e-mail at gcrl@ibm.net.

Traditional statistical forecasting methods fail because they assume that the probability distribution of demand over a lead time (lead-time demand) will resemble a "normal" bell-shaped curve.

The research confirmed that both exponential smoothing and a variant of exponential smoothing, developed by Croston in 1972, are effective in forecasting mean (average) demand per period when demand is intermittent. But the study also confirmed that neither Croston's method nor exponential smoothing accurately forecasts the entire distribution of demand values. This is especially true with customer service level inventory requirements—for example, a 90 percent, 95 percent, or 99 percent likelihood of not running out of a product item—for satisfying total demand over a lead time.

Although there are additional elements that make this new forecasting method work well, the core idea is bootstrapping. Bootstrapping is a statistical method that accurately forecasts both average demand per period and customer service level inventory requirements. It does this by using samples of historical demand data to create a large number of realistic scenarios that show the evolution of cumulative demand over a lead time.

Better inventory control

CONSIDER THE 24 MONTHLY demand values show in Figure 1. Suppose forecasts are needed for the next three months because the parts supplier takes three months to fulfill an order to replenish inventory. A simple bootstrapping approach to this problem is to sample from the original 24 values, with replacement, three times, creating a bootstrap scenario of demand over the lead time.

Month	Demand
1	0
2	0
3	0
4	**6**
5	**4**
6	0
7	0
8	**35**
9	0
10	0
11	0
12	**9**
13	**7**
14	0
15	0
16	**3**
17	0
18	0
19	**6**
20	0
21	**8**
22	0
23	0
24	0

Figure 1: Frequent zero values make intermittent product demand difficult to forecast

For example, we might randomly select months 7, 12, and 5, which would give us demand values of 0, 9, and 4, respectively, for a total lead time demand in units of 0 + 9 + 4 = 13. Repeating the process, we might randomly select months 20, 8, and 20 (again), giving a lead time demand of 0 + 35 + 0 = 35 units. By continuing to generate bootstrap scenarios in this way, we can build a statistically robust picture of the lead-time demand distribution.

The histogram in Figure 2 shows the results of 10,000 bootstrap scenarios. (These bootstrap scenarios reflect all elements of the new methodology, including the real-world possibility that nonzero demand values that appear in the future may differ from those that appeared in the past.)

In this example, the most likely lead-time demand value is 0, but demand can extend up to 80 or more units. Obviously, the lead-time demand distribution in Figure 2 looks nothing like a bell-shaped curve—and any inventory models assuming it does will provide

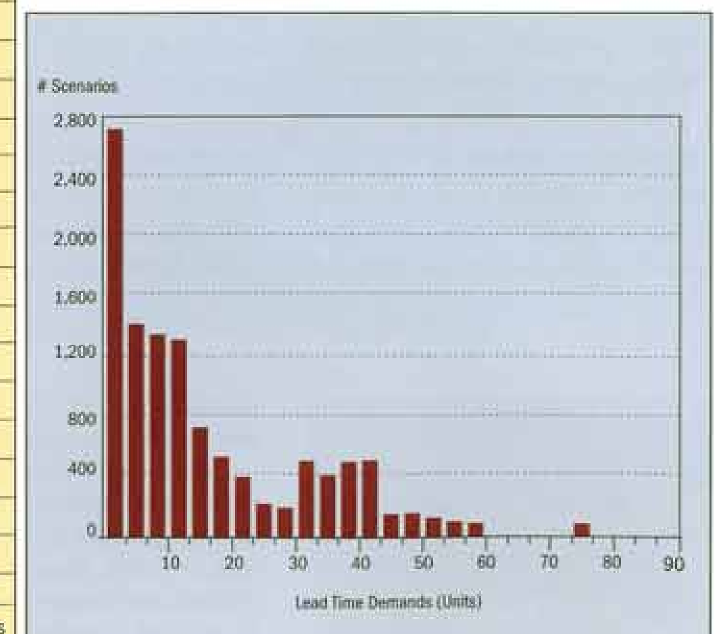

Figure 2: Bootstrapping produces an accurate picture of leadtime demand.