How Intermittent Demand Forecasting
Reduced Target Inventories

NSK Corp., Ann Arbor, Mich., is the US-based operation of the world’s second-largest producer of anti-friction bearings and precision products for the automotive and other industries. This quarter, the company is using the dedicated intermittent demand forecasting module from Smart Software’s SmartForesight software to estimate lead-time demand on a subset of NSK’s after-market business unit’s (ABUs) 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 after-market industry win or lose business based on their quick response time. Short lead times and quick response times are assumed. High service levels, inventories estimated 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 after-market. Product life cycles can average two years or more. Different SKUs have different inventory replenishment lead times, with imported products averaging several months. And the case of two-thirds of the ABU’s 7,000 SKUs, demand is highly intermittent, with half of the sales history containing zero values. About 5,000 SKUs make up 90 percent of the unit’s business, with the other items assumed 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 on average between 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 projected 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 SmartForesight forecasting software to forecast standard after-market 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. New 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 database 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.”)

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

By Charles Smart and Thomas Willmumin, PhD.

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 is called “jumpy.” 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

interunadvice 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.

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A New Way to Forecast Intermittent Demand

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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.
An Aerospace Industry Perspective

By Robert Lamarr, B.B.A., M.A. Sc. c.c., AIA

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 50,000 spare parts in stock. Our analysis indicates that for more than 80 percent of the parts, the 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 $100,000 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 errors 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.

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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.

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.

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, 6, and 20 again, giving a lead time demand of 0 + 35 + 35 = 70 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 non-zero 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