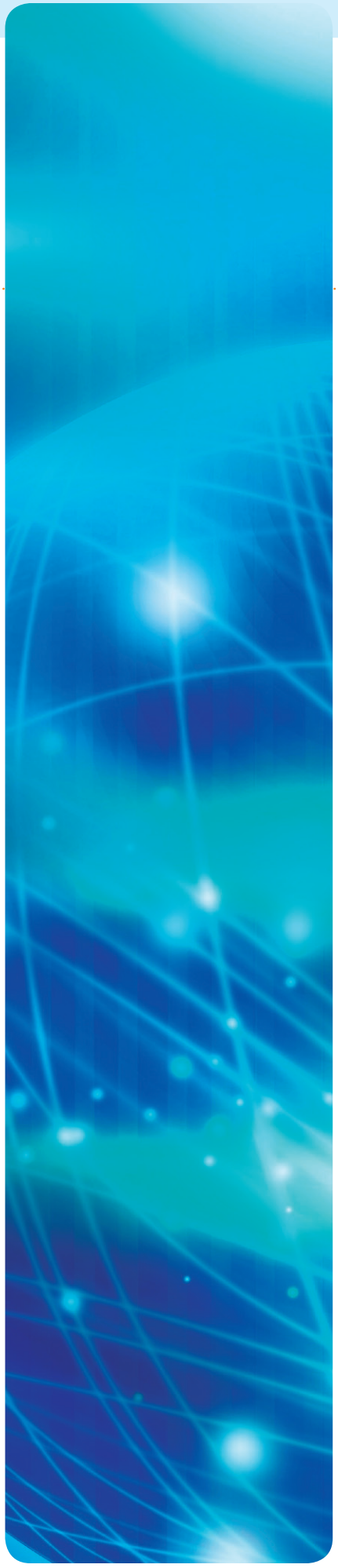


A Logility Demand Optimization White Paper

Seven Methods That Improve Forecast Accuracy

Forecasting Best Practices for Varying Supply Chain Scenarios

LOGILITY

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Introduction

Typically, a variety of forecasting methods are applicable to any particular type of supply chain scenario. Smart supply chain planners use multiple methods tuned to perform well at different phases of the product life cycle, chosen to best exploit the available historical data and degree of market knowledge. The key is to pick the most effective and flexible models, blend their best features, and shift between them as needed to keep forecast accuracy at its peak.

In this paper we will take a brief look at seven methods that have produced superior results for Logility's many clients in a variety of industries and market conditions around the world.

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Three Categories of Forecasting Models

Forecasting models classically fall into three categories: qualitative, quantitative and hybrid. The primary differences between them include the type of input data and the mathematical and statistical methods employed to generate forecasts.

Qualitative models are experience-driven, relying on subjective inputs from knowledgeable personnel, such as salespeople, account managers, and the like.

Quantitative models are statistically driven, drawing heavily on historical performance data as the basic data input. The calculating logic is defined and operations are purely mathematical.

Hybrid models typically draw on historical demand information as a starting point, then use empirical data to further refine the forecast.

Forecasting models classically fall into three categories: qualitative, quantitative and hybrid.

Three Categories: Forecasting Models

Category	Sub	Description
Qualitative Experience driven	Subjective	Relies on subjective inputs from knowledgeable personnel, such as salespeople, account managers, and the like. This approach typically sets up formal procedures for data review, and requires a consensus to determine the value of various forms of information. Consensus among forecasters may be obtained by aggregating individual estimates or through structured polling methods.
Quantitative Statistically driven	Time Series	Employs a time-ordered sequence of observations of a particular variable, and uses only the history of that variable to determine future values. For example, if monthly sales volumes of lawnmowers sold in the Southeast display a linear pattern, a linear trend model would provide the best basis for the forecast.
	Derived	Creates a new forecast based on an existing forecast. When a new item's forecast is thought to be fundamentally the same as an existing item's, characteristics can be used in creating the new forecast, which may be factored up or down by a percentage. This preserves the overall trend and seasonal characteristics of the item, providing a good starting point for the new item.
Hybrid Historical demand plus empirical data	Attribute-based	Employs user-defined attributes to model new product introductions, seasonal or fashion driven products, and product end-of-life retirement based on a demand profile.
	Causal	Uses a causal relationship between a particular time series variable and other time series factors to calculate the forecast. Causal techniques are useful in forecasting 'lift' during promotional campaigns, where demand caused by promotional factors has an established relationship to base demand. Additional factors can be used, such as end-cap displays, seasonality of the product, etc. Factors are not additive but are used together to calculate the expected lift for your product.

A best practices approach also must include the ability to incorporate personal expertise and weight the various factors in generating forecasts.

Seven Forecasting Methods that Improve Supply Chain Performance

For many supply chain scenarios, it's typically best to employ a variety of methods to obtain optimal forecasts. Ideally, managers should take advantage of several different methods and build them into the foundation of the forecast.

The best practice is to use automated method switching to accommodate selection and deployment of the most appropriate forecast method for optimal results.

In order to ensure optimal demand forecasting, managers must employ the forecasting methods that best serve the unique dynamics of their business at a specific moment in time.

Advanced demand planning and forecasting systems automate many of the functions required to select, model and generate multi-echelon forecasts, lifting the burden of manually intensive approaches and accelerating sensitivity to model changes as market conditions evolve. A best practices approach also must include the ability to incorporate personal expertise and weight the various factors in generating forecasts.

In Logility's experience working with over 1,000 organizations ranging across dozens of industries, seven specific forecasting methods stand out. Their unique strengths combine to deliver powerful, flexible, and accurate results.

Seven Methods for More Accurate Forecasting

Type	The 7 Methods	Description
Best-Fit statistical	Modified Holt / Holt-Winters	Use Holt when demand is trended, but does not vary by the time of the year. Use Holt-Winters when demand is often higher or lower during particular times of the year.
	Moving Average	Use for products with demand histories that have random variations, including no seasonality or trend, or a fairly flat demand.
Derived	Inhibited	Use to produce a zero forecast.
	Modified Parent-Child	Use to forecast products as a percent of the forecast for another product (dependent demand).
Intermittent Demand	Modified Croston	Use for products with low demand or for some zero demand periods, such as slow-moving parts.
Attribute-based	Demand Profile	Employs user-defined attributes to model new product introductions, seasonal or fashion driven products, and product end-of-life retirement.
Causal	Promotions	Use to calculate "lift" from promotions in addition to the normal forecast.

Best-fit Statistical Modeling

For most levels of management within an organization, aggregated demand history for product family, brand category, country and/or selling region are good predictors of future performance. Such demand history also serves as a baseline for effectively forecasting Stock Keeping Units (SKUs.) When there are more than four-to-six periods of sales history, SKUs can be effectively forecast with moving average and basic trend methods. SKUs with at least one year of sales history offer sufficient information to incorporate a seasonal profile into the projected trend.

A modified **Holt-Winters decomposition model** with best-fit analysis can generate forecasts based on demand history that incorporate trends and seasonal information. The method "senses" the amount of history available for each time series or segment to create a basic model that best fits the history. Then it uses the best combination of smoothing factors to enable the model to react to changing conditions going forward without over¬reacting to anomalies in demand (such as unplanned seasonal events, transportation disruptions, and so on).

For factors relating to seasonality, planners need the ability to 'weight' the historical demand. Under the assumption that the previous year is the best indicator of what will happen next year, most forecast systems apply a higher weighting factor to the previous year's demand, less to the year before and even less to the years before that. But if the previous year was unusual in any significant way, the planner must have the capability to change the historical weighting factors (so that the history two years ago has more impact on the current forecast than last year, for instance) so as not to under- or over-forecast the business.

Seasonal methods can be effective with less than 24 months of history; the minimum required is 12 months. An effective approach for expected seasonal items with less than 12 months of history is to assign a seasonal curve that has been captured from a similar item or item group.

A powerful best-fit statistical method should include flexible features such as trend, seasonal-with-trend, moving average and low-level pattern fitting, as well as trend models for products with sporadic, low-volume demand.

The method should provide limiting and damping, as well as seasonal smoothing, demand filtering, reasonability tests, tracking signals and tests for erratic nature that evaluate the validity of each element, determining which are anomalous and should be filtered. These parameters give the planner the flexibility to tune the process to best fit conditions at any element of the organization.

"Best fit" refers to the ability to change forecast methods as a product evolves. The process may start out as a demand profile method, evolve to a modified Holt-Winters method as the product becomes stable, and ultimately transition to a demand profile method again as the product life cycle comes to an end.

Capabilities that will automatically change the forecast method are important features of a comprehensive forecasting solution.

Forecast models change as a product evolves—perhaps starting out with a demand profile model, then evolving to another as the product becomes stable and transitioning back to a demand profile model again at the end of the life cycle.

Logility Voyager Solutions™ products provide a variety of forecasting models to suit commonly encountered supply chain planning scenarios across many industries. Logility's automated model switching ensures that the most appropriate forecast model is applied, given the type of scenario under consideration.

Derived Modeling

One method of generating new product forecasts is to use demand variations or extensions from existing products, families or brands. Consequently, they draw on the historical data of existing products or families. When combined with causal effects or management-selected overrides to accommodate introductory promotions, derived modeling can provide a realistic and dynamic forecast for new products.

Using this approach, new products are assigned a percentage of the parent, family and/or brand, enabling them to proportionately inherit a forecast that contains the base, trend and seasonal elements of the associated category. As the forecast for the associated category is adjusted to reflect changing conditions over time, so too is the derived product's forecast. If the derived product's point-of-sales (POS) or demand levels deviate from the forecast and exceed a user-defined tolerance, the system can generate a performance management alert to notify forecast analysts to take corrective action.

Once the product has accumulated sufficient demand history of its own, the link to the derived model's source model is severed and the product is then forecasted on its own using multiple best-fit statistical methods.

Modeling for Intermittent Demand

Slow-moving parts typically exhibit irregular demand that may include periods of zero or excessively lumpy demand. A Modified Croston Method handles low and lumpy demand that exhibits either a patterned variation or no pattern.

The **patterned variation** looks at available history and classifies each demand element relative to those around it. It classifies the periods into peaks, valleys, plains, plateaus, up-slopes and down-slopes. It measures the duration of plateaus and plains, as well as the severity of peaks and valleys. It then conducts pattern-fitting analysis to find regularity over time, attempting to fit the pattern to the history and averaging for low and high points. The patterned forecast is put in context of future periods with the average trend, and the pattern is re-evaluated using demand history of subsequent periods.

If no pattern is present, the **unpatterned variation** method attempts to use averaged highs and lows to create a step-change forecast for future demand.

Both techniques permit zero demand to reside in the history, and will acknowledge such in the future demand forecast. In forecasting for spare parts, for example, the demand is frequently low-level and spotty, containing many periods of zero demand interspersed with low-level demand. This forecasting technique allows patterns of zero demand to be forecast into the future.

Attribute-Based Modeling

What if lack of data, short life cycle, or other mitigating factors make it difficult to forecast using time series or qualitative techniques? Forecast creation for new product introductions, short-life or seasonal products, and end-of-life products calls for **attribute-based modeling** techniques.

The attribute-based model provides a wide variety of demand profiles by which to characterize the product, and can adjust the product's plan dynamically in response to early demand signals. The method will analyze historical sell-in and/or sell-through data to develop a wide variety of demand and seasonal profiles. These profiles are assigned to individual planning records. Then, as actual demand information is captured, the current profile is validated or alternate profiles identified to dynamically adjust the product's plan.

Attribute-based modeling consists of four unique processes:

1. ***Creation of Demand Profiles***

   Creation of demand profiles is based on mathematical concepts known as Chi-squared analysis. The demand planner selects products to be included based on attribute similarities, and multiple attributes can be used at once.

2. ***Assigning Demand Profiles***

   New, seasonal, and end-of-life products can now be assigned to Demand Profiles. Advanced attribute-based models offer 'user-defined attribute' matching capabilities, allowing the planner to set criteria for how a new product's attributes must match the attributes of a demand profile.

3. ***Automatic Revision of the Forecast Based on Demand Signals***

   Forecast accuracy must be monitored continually. Accuracy can be monitored using Point-of-Sale (POS) data, which is the demand signal that most accurately reflects customer buying patterns, or other demand signals such as syndicated data. Correctness-of-fit modeling adjusts the forecast to reflect what is happening in the marketplace, quickly reacting to real-world changes.

4. ***Assess Accuracy of Demand Profile Based on Demand Signals***

   New products do not always sell just like previous products with similar attributes. The accuracy of the assigned profile can be checked against others. Through Relative-Error-Index (REI) calculations the planner can quickly see which demand profile now has the best fit based on current demand trends and swap it into place.

Proportional Profile Planning

Demand Planning, Sourcing, Supply and Production Planning all perform better when demand is disaggregated from a high-level forecast down to accurate, granular, sub-SKU forecasts as early as possible in the product life cycle. Sub-SKU forecasting based on attributes (translating high-level forecasts into specific quantities for each size, color, configuration, etc.) lets forecasters create more accurate forecasts across thousands or tens of thousands of SKUs.

Creating sub-SKU forecasts based on attributes such as finish, style, color, size, gender, region, speed, power, material type, trim level, configuration, and more is called ***proportional profile planning.*** Many industries create unconstrained demand plans at the category or product level, but have insufficient resources to break these plans into accurate proportional profiles, because an aggregate demand plan can explode into orders-of-magnitude greater complexity at the SKU level.

Proportional profile planning allows demand planners to work at a level of aggregation that matches their business requirements, while allocating the forecast accurately across product attributes and options at lower levels of aggregation before submitting to the supply-side team. The profile library may contain hundreds or thousands of named, relevant demand histories built from items with similar attributes from previous seasons, other product families, etc. These histories become templates for new profiles of size, configuration, color, or any other attribute.

Causal Event Modeling

Causal modeling can specifically address the effects of promotional elements such as price discounts, coupons, advertising and product placements. It supports input from multiple marketing groups, and aids the identification and reconciliation of potential conflicts or overlaps in promotional planning proposals.

Causal modeling enables planners to quickly simulate marketing program options and refine forecasts. Using pre-trained neural network technology in causal-based modeling is a unique best practice that lets planners quickly start to model the cause-and-effect relationship of different promotional elements.

"Backcasting" is a technique in which past promotional events are entered into the neural network, which then learns the relationship of various elements. The pre-trained network takes on customized characteristics and behaviors quickly, rather than requiring 12—18 months to build from scratch. Using pre-trained neural network technology, planners can incorporate marketing activities into supply chain forecasts much more quickly.

Logility Voyager Demand Planning™ employs a Modified Holt Model, Modified Holt-Winters, Moving Average, as well as two types of Derived models. To handle low and lumpy demand, a Modified Croston Model offers versions for patterned and unpatterned variation.

Logility Voyager Life Cycle Planning™ uses a Demand Profile Model to forecast items where there is a lack of data or other mitigating factors. Logility Voyager Event Planning™ employs a Causal Model to calculate lift from promotions in addition to the normal forecast.

About Logility

With more than 1,250 customers worldwide, Logility is a leading provider of collaborative, best-of- breed supply chain solutions that help small, medium, large, and Fortune 1000 companies realize substantial bottom-line results in record time. Logility Voyager Solutions™ is a complete supply chain management solution that features a performance monitoring architecture and provides supply chain visibility; demand, inventory and replenishment planning; sales and operations planning (S&OP); supply and inventory optimization; manufacturing planning and scheduling; transportation planning and management; and warehouse management. Leading apparel companies such as VF Corp, Polo Ralph Lauren, Hanes Brands, New Balance, Brown Shoe, Williamson-Dickie and more rely on Logility Voyager Solutions to drive excellence across their supply chains.

Summary: Flexibility and Ease of Use are Vital to Good Forecasting

Optimal demand planning and forecasting requires comprehensive modeling capabilities plus the flexibility and ease-of-use to shift methods as life cycles progress and market conditions change. Advanced forecasting systems (such as the Logility Voyager Solution) use a combination of qualitative and quantitative techniques to generate reliable forecasts.

As we have seen, Attribute-based methods that use demand profiles are often suited to new product introduction and end of product life cycles, at times when reliable historical demand data is lacking or the available data is less relevant.

At the more mature stages of the product life cycle, five different time-series statistical models come into play, including modified Holt, Holt-Winters, moving average, and intermittent for low demand, whether patterned or unpatterned. These models are used to create retrospective forecasts that cover prior periods (typically three years) of documented demand. The forecasts are then matched to actual demand history to determine which one best fits the real-world data. The best-fit winner is used to create an objective base forecast. At this point, planners may include more qualitative calculations based on personal knowledge and experience with intangible market factors.

Causal methods are used throughout the life cycle to adjust forecasts in anticipation of promotional events. Causal methods allow planners to predict how discounting and other promotional factors will affect volume, and layer the impact of these events on top of the underlying base forecast.

Finally, Derived models can be used to create a Parent-Child relationship in which forecasts for closely related products are driven as a percentage of the forecast for a ‘leader’ product. This ensures that when the forecast is modified for the ‘parent’ all the ‘child’ forecasts would be updated accordingly.

To prevail in a business economy shaped by uncertain demand and rapid market changes, all of these forecasting methods must be harnessed within one practical, comprehensive solution suite. Advanced demand management software can automate much of the selection and switching of methods as a product moves through its life cycle. A best-in-class forecasting system is one that provides flexibility for users to weight elements and override key parameters in the forecast calculation based on their intuitive knowledge and market expertise.

Logility’s powerful software solutions help planners pick the best method, spot trends and forecast demand signal changes more quickly, and sense the best time to change methods when a more appropriate approach is indicated. Superior predictive power and real-time reflexes are the keys to coming out ahead of the competition during uncertain business cycles.



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