HP

Strategic Planning and Modeling Group

Forecasting for Short-Lived Products

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Jim has been with HP for 21 years. He spent most of this time in Vancouver, Washington working with HP's ink-jet printer products, He has made significant contributions in the areas of power electronics design, motion control systems design, nonlinear modeling /physical characterization and design tool development. He holds legacy designs in linear encoders on DeskJet carriage axis and the closed-loop control of paper axis systems. Jim has also held positions of responsibility in R&D, procurement engineering, process engineering, and supply chain modeling during his tenure at HP.

Jim's academic background includes a degree in Electrical Engineering from University of Washington (emphasis in Analog Electronics and Control Systems) His graduate study includes digital signal processing, digital control systems and system architecting at Stanford University and the University of Southern California.

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Forecasting for Short-Lived Products

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Along with all its competitors in the technology arena, HP faces the challenges of high demand uncertainty, short product life cycles, steep price competition, and high inventory costs. To contain the cost of inventory on the one hand, and capture all possible sales on the other, it is essential for planning purposes to know as closely as possible what the sales expectations will be. This is done through forecasting.

In the electronics industry, it is the medium-term forecasts (3-6 months) that ultimately drive the business. However, the forecasting methods in use today are often poorly suited to the consumer electronics industry. Their main assumptions are that products have essentially infinite life cycles, and that univariate forecasting (use of one source of data) is sufficient to produce accurate forecasts.

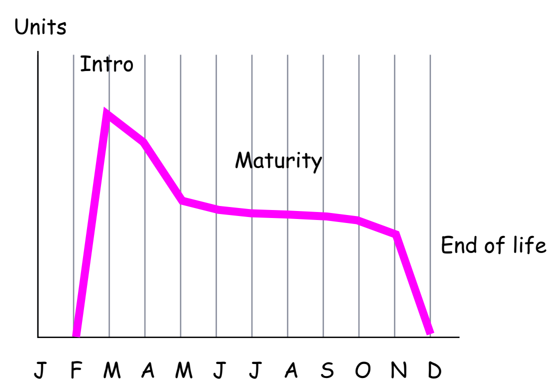
Microprocessor speeds are increasing constantly, along with new functionality, standards, and features. Therefore, technology companies must actively plan the end-of-life for their products, including related capacity planning, marketing, distribution, and rollover activities.

Because of these shortcomings, HP's Strategic Planning and Modeling group (SPaM) has developed a new forcasting methodology called the Product Life Cycle or PLC method. This method is specifically designed to forecast products with high uncertainty, steep obsolescence curves and short life cycles. The SPaM team has also implemented this methodology in a software tool, currently in use by HP's own forecasters.

General Electronic Product Life Cycle Characteristics

The typical electronic consumer products discussed here are those with life cycles ranging from 3 to 18 months. The shipment profiles for such products typically exhibit common life cycle characteristics. Figure 1 shows an example of a normalized product life cycle profile. Notice the steep introduction spike, the gradually sloping plateau at maturity, and the end-of-life drop-off.

Figure 1: Product life cycle template



Although individual products may vary in terms of life cycle duration and the shape of the curve, they also exhibit some important commonalities:

- Well-defined life cycle phases for introduction, maturity, and end-of-life.
- Steep spike during product introduction, sometimes the result of channel stuffing, followed by a decline or plateau during maturity.

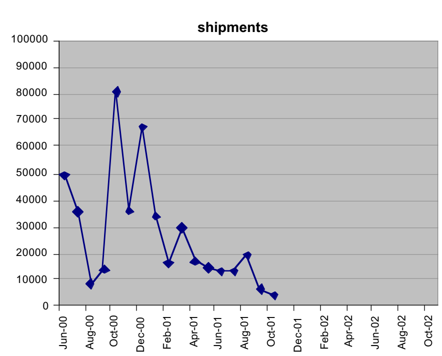
- Steep end-of-life (EOL) drop-off often caused by planned product rollovers.

Traditional forecasting techniques don't always serve us well when used as standalone methods because they can't anticipate these life cycle phase transitions. Their weaknesses with regard to short-lived products such as those produced in the fashion and technology industries can be summarized as follows:

- Many only use historical data from the current product being forecasted. For technology products that must be forecasted in advance, this data may not be available at the time the forecast is generated for planning purposes.
- They assume essentially infinite life cycles, whereas technology products have well-defined and often very short life cycles.
- They don't consider life cycle phase transitions such as introduction and end-of-life effects. In the technology arena, anticipating these transition phases correctly is critical to the success and profitability of the product.
- They can't predict end of life curves from historical data for the same product.
- They are confused by short-term order swings.
- They can't incorporate events aside from seasonality very well.

Some of the weaknesses of traditional methods as applied to consumer electronic products are shown in the next few figures. We start with a demand profile for a typical consumer electronic product. Figure 2 shows shipments from the manufacturer to the sales channels for the life of this product (June 2000 through November 2001).

Figure 2: Shipment profile example



This example shows an initially high demand peak as the channel stocks up on the product. Subsequent shipment values for the third and fourth month are low due to the relatively high inventory level in the channel. In October 2000, the marketing group drops the price to help spur demand.

Figure 3 shows what happens when we apply a commonly used method, simple exponential smoothing, to this shipment profile, at various points during the product's life cycle. This method projects a series of horizontal lines, none of which capture the actual shipment profile.

Figure 3: Simple exponential smoothing

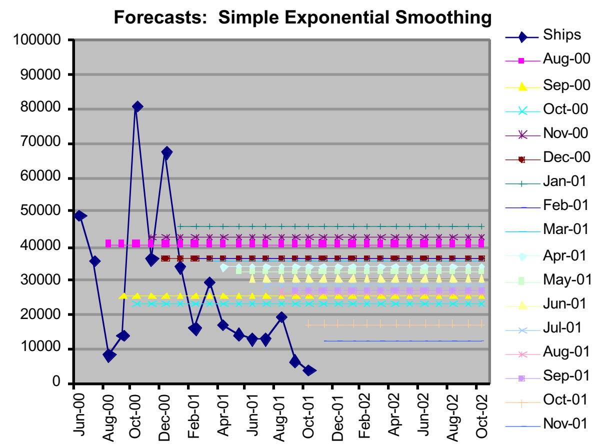
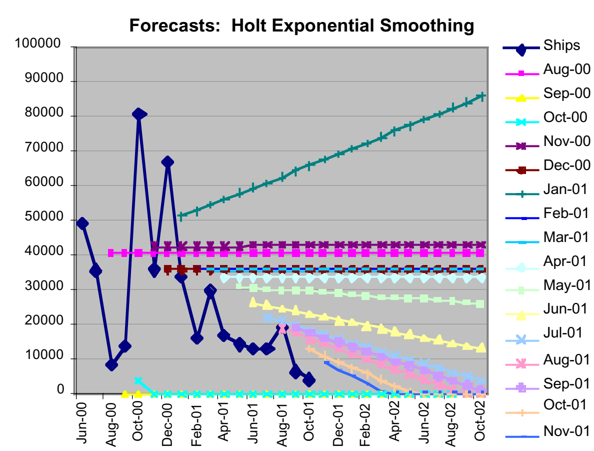


Figure 4 shows another closely related method, Holt exponential smoothing. The results are similar except that some of the forecasts slope up or down when the Holt method projects a non-zero trend. Again, none of them match reality except perhaps towards the very end of the product's life.

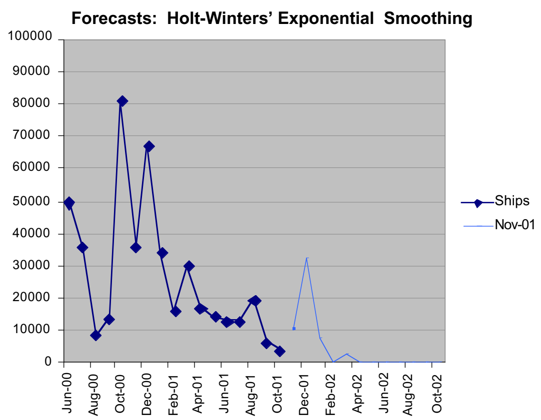
Figure 4: Holt exponential smoothing



Neither of these methods recognizes life cycle transitions. Also, they require 2 actual shipment data points before any forecast is generated, whereas for planning purposes, most of these forecasts have to be created 6-12 months in advance of product introduction.

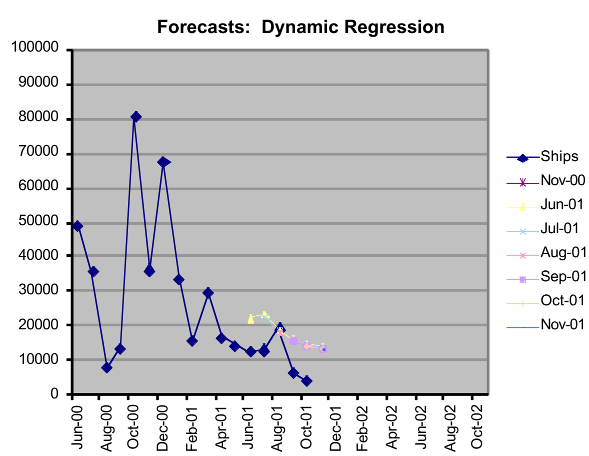
Most of the other commonly used statistical forecasting methods do no better. Most of them, like the Box-Jenkins method, produce results similar to the exponential smoothing examples shown in Figure 3 and Figure 4. The Holt-Winter's method of exponential smoothing, shown in Figure 5, has the drawback of showing no data at all until 17 actual data points are available, limiting its usefulness as a planning tool for short-lived products.

Figure 5: Holt-Winter's exponential smoothing



There is one traditional method, dynamic regression, that seems to produce better results, as shown in Figure 6. However, this method requires 12 actual shipment data points before it can generate a forecast, and there is no forecast unless causal variables are available. If causal variables (lagged actual data in this case) are not available, forecasts of causal variables are required. This further burdens the forecaster to forecast these input variables as well as the original variable of interest.

Figure 6: Dynamic regression



Another method that is not a standard statistical method is the "like-modeling" method used in SAP's Advance Planner and Optimizer Demand Planning module (APO DP). The like-modeling method allows the user to select one or multiple past products as reference products and create history data based on these "like products."

The like-modeling method is slightly better suited to electronic products than some of the other methods. However, it is still overly sensitive to the actual demand data points that don't come in close to the corresponding forecasted values. Figure 7 shows the forecast source data for the first forecast. When we move up one period to August 2001, as shown in Figure 8, we see that the like-modeling forecast method is overly sensitive to the addition of the single actual data point for July 2001. The forecast shows a sharp negative trend because the first actual data point (red dot in Figure 8) came in far below the "like-products" forecasted value for this period.

Figure 7: Like-modeling historical trend example

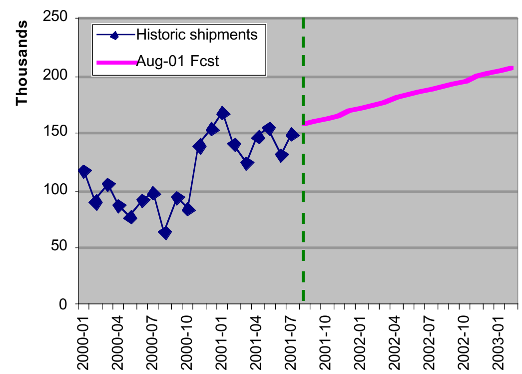
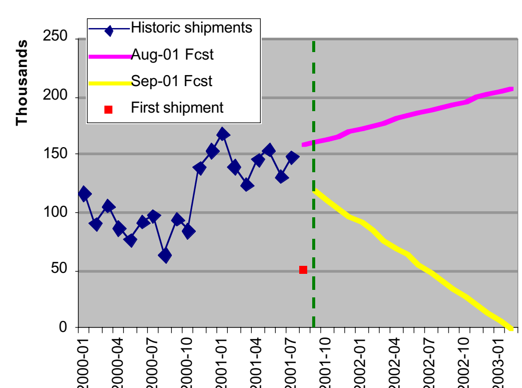


Figure 8: Like-modeling, one more period



In addition, pure time-series methods cannot incorporate known upcoming market events such as competitive product introductions, price drops, promotions, or account-specific big deals and bundles. These various events can dramatically alter a product's actual demand profile. While we cannot forecast with certainty the precise impact of such events, we generally have a very good idea of their direction and a reasonable estimate of their magnitude. Thus, incorporation of such knowledge can improve forecast accuracy significantly.

The PLC Method

The Product Life Cycle (PLC) Forecasting Method can be summarized as follows. First, it considers life-cycle aspects of early growth, maturity, and end of life. Second, it includes seasonality factors and future events such as big deals, promotions, and price drops Third, it establishes an initial forecast based on an approximate life cycle shape, applies other factors, and then employs the latest actual data to update that forecast over time.

The way the life cycle shapes are created and applied is through templates. For our purposes, we have defined a template as "a general approximate shape." Examples of forecast templates are shown in this section. Templates can represent a general life cycle shape; they can also represent events such as economic booms or slumps, product promotions, product bundling, price drops, and competitive product introductions.

The steps to generate a PLC forecast are as follows:

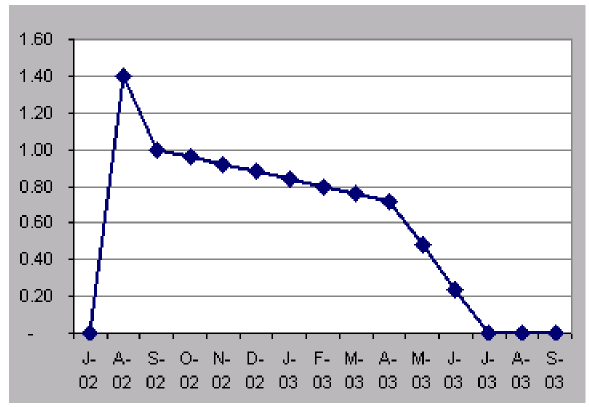
1. Analyze historical data and generate a basic PLC shape for each product family or product group for which you plan to generate new forecasts.
2. Multiply the PLC template by mature volume estimates to create the volume-scaled PLC template.
3. Apply templates with long-term future effects, such as seasonality or price drops. These are multiplied against the PLC template baseline. For example, multiply the initial forecast by a seasonality template to account for seasonal ups and downs.
4. Apply templates that can be quantified on a product-quantity basis , such as specific-quantity big deals, end-of-life sell-offs, and bundles.
5. Update the forecast periodically during the product's life using actual data.

In addition to the theoretical process described here, HP's Strategic Planning and Modeling group (SPaM) has developed a software tool that incorporates the principles of the PLC forecast method for use by HP's consumer products divisions. The next section uses examples from the HP SPaM forecast generation tool to illustrate the forecast generation process.

Forecast Generation Example

We start by applying the most basic templates, which are the normalized product life cycle and seasonality templates. Figure 9 shows an example of a normalized product life cycle template. Note the clearly defined introduction, maturity, and end-of-life phases.

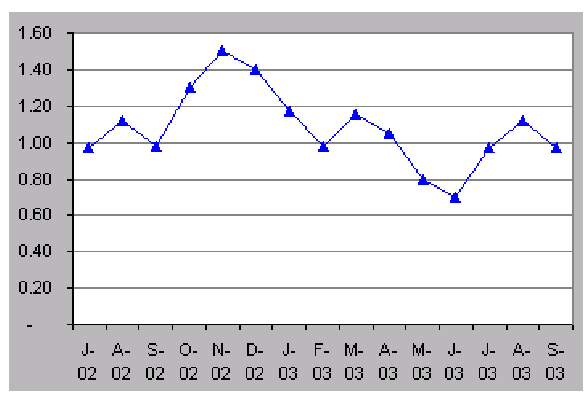
Figure 9: Normalized product life cycle template



When this template is applied to a particular product forecast, the start date is set. The example shows a start date of July 2002 and an end date of July 2003. This becomes the baseline for the new product forecast.

Next, the forecaster applies common factors such as seasonality. Figure 10 shows a seasonality profile with an expected demand surge around the Christmas season. Since the seasonality templates can influence the forecast either up or down on a multiplying bias, the individual values vary around a value of 1.0 on the y-axis.

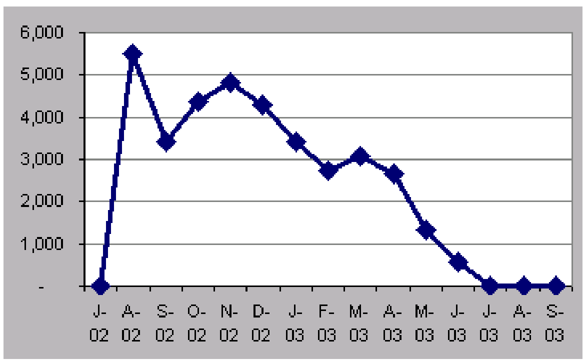
Figure 10: Seasonality template



The seasonality template is an example of what is known as a multiplicative template. In a multiplicative template, the baseline forecast is multiplied by a scaling factor represented over time by a profile that extends above or below a horizontal 1.0 line. A straight line right at the 1.0 line is the same as multiplying by one (no effect). A straight-line template just below the 1.0 line would have the effect of lowering the overall curve. A template that consisted of a single value greater than 1.0 in the middle with all other values equal to 1.0 would have the effect of causing an extra bump in the forecast in the place where the spike fell on the PLC curve for that particular product.

Figure 11 illustrates how the PLC template and the seasonality template would be combined to produce a product forecast. This graph shows the results of multiplying the templates together to produce an initial volume-scaled product forecast that ends in July 2003.

Figure 11: Combined PLC and seasonality templates



Another type of multiplicative template is the "price drop" template. Figure 12 shows an example of a price drop template. Note that this template shows the anticipated volume increase from a price drop that is planned for October 2002, in the fourth month of this product's life.

Figure 12: Price drop template example

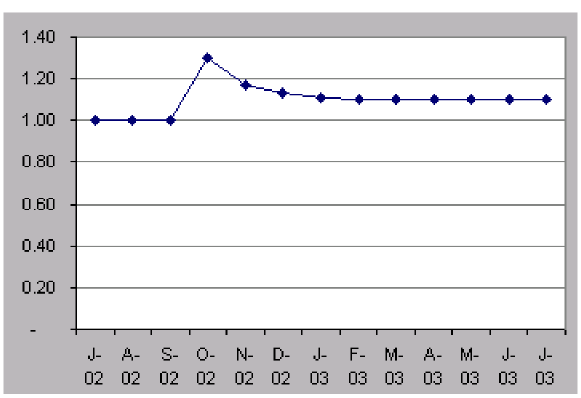
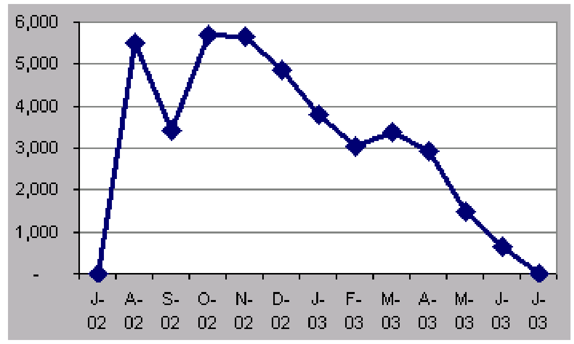


Figure 13 shows the result of combining the PLC, seasonality, and price drop templates.

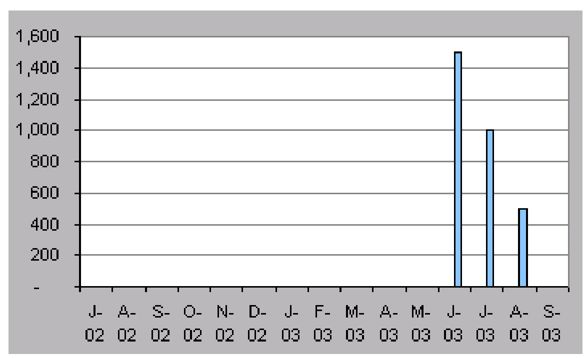
Figure 13: Combined PLC, seasonality, and price drop



After applying the multiplicative templates, the next step is to factor in unit-quantity, event-specific, additive templates. Additive templates are used to include unit quantities that are essentially "known" and which do not fit into the multiplicative concept. Examples of additive templates include bundles, big deals, and left-to-sell units at the end of a product's life.

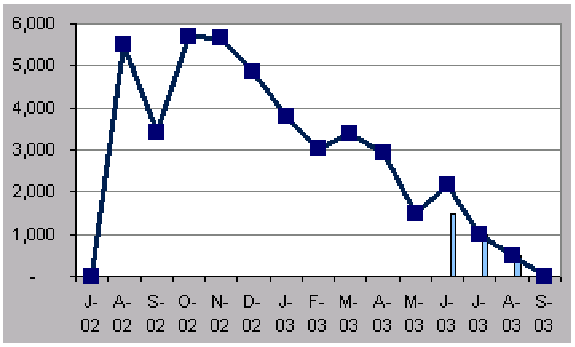
Figure 14 illustrates a left-to-sell template showing 3,000 units left towards the end of the product's life. We expect that these units will sell over a time period of three months for June, July, and August of 2003.

Figure 14: Left-to-sell template example



Putting everything together results in the final forecast shown in Figure 15. Note that the forecast now shows an extra spike and life cycle extension from July 2003 through September 2003.

Figure 15: Final forecast example



Updating a PLC Forecast

The previous section showed how we would use the PLC method to generate a new forecast. We also need a method to update our forecast over time, as the actual, observed demand data becomes available. To do this, we compare the values of actual shipments to the corresponding composite forecast values and magnitude-scale the composite forecast up or down in order to more accurately represent our future demand expectations on the basis of what we have observed in actual demand. For example, if demand is consistently higher than we had anticipated by our original composite forecast, we should adjust the forecast up to reduce the forecast error.

Mathematically, this is done as follows:

1. Divide each monthly demand data value by the corresponding originally-scaled composite forecast value.
2. Calculate a simple moving average of this ratio and feed the result into an exponential-smoothing algorithm.
3. Use the exponential-smoothing result as the scaling factor to update the composite forecast looking forward.

Additional Refinements

In practice, the PLC forecast method as employed by HP's SPaM group is more sophisticated than what is shown in these examples. For example, the forecast update process can be modified to factor in channel inventory adjustments and sell-through as well as shipments. However, the principles can be applied by any forecasting organization to suit the needs of any particular business that also has short-lived products.

PLC Implementation at HP

Prior to implementation of the PLC forecast method at HP, individual forecasters used a variety of home-grown methods and Excel spreadsheets. Nothing was standardized; the final forecasts from the Excel spreadsheets were uploaded into a central database to consolidate the forecast on a worldwide level.

Gaining Support for Pilot

When we developed the PLC method, we needed to demonstrate its usefulness in a pilot program. To implement a pilot, we needed to find group of participants who were willing to risk learning a new and untried method – not an easy thing, given the time and resource constraints faced by most forecasters. Challenges we had to overcome included persuading the forecasters to use the PLC method as a common forecasting approach, and ensuring data availability in the right format (especially actuals for the updating algorithm. This data needed to be collected from various sources. We also needed to gain commitment and trust from the forecasters, who were under time and resource constraints, in order to persuade them them to try this new method.

Keys to Gaining Acceptance

The following factors were keys to gaining acceptance through completion of the pilot period.

- Involve forecasters early on, and keep them involved in the ongoing design process. We had a 1.5-hour phone conference with our forecasters every week.
- A good user interface is key. If the user interface is cumbersome, then is far tougher to get acceptance. We were able to increase acceptance by responding to forecaster's feedback on the user interface and making the changes available to them quickly.
- Use rapid prototyping so that users can see something tangible, and let them play with it. We developed our first prototype in 6 weeks. It was still rough, but gave the users a good idea what the final version would look like. We started the tool development in January 2002, and took the first product line live in April 2002.
- When demonstrating your tool, use real data that the forecasters can relate to. If they recognize their data, you will get much better feedback.

Benefits

Current estimated savings for multiple product lines are approximately $15M a year. Based on forecaster feedback, the PLC forecasting tool has benefited the forecasting process in the following ways:

- Enables forecasters to quantify specific elements of the forecasts, by product, to independently track and change these forecast elements, and to see the cumulative effect.
- Applies a better methodology (the PLC forecast method) to improve forecast accuracy.
- Simplifies process of rolling up the forecasts along common aggregation vectors, such as platform, price band, and across product lines.
- Saves the forecasters time through simplfication and automation of certain database load tasks that used to take hours each month.
- Enables forecasters to fill in for one another more easily, and will result in more consistency among the different product lines.

Summary

The PLC Forecasting Method is specifically designed for products with short, well-defined product life cycles. By combining the template concept with more finely tuned updating and correction mechanisms, we capture sources of predictability that are not addressed by traditional statistical forecasting methods.