Introduction to Operation Management

030 **Deliver**

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3 Forecasting

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Demand Forecasting

Forecasting is a critical component of an organization's Demand Planning, Forecasting, and Management process, serving as a bridge between planning and execution. It involves predicting future demand for products or services, allowing organizations to make informed decisions about production, inventory, and resource allocation. By employing a combination of subjective and objective methods, organizations can develop robust forecasts that guide strategic, tactical, and operational decisions. Continuous evaluation and refinement of forecasting techniques ensure that organizations remain responsive to market changes and maintain a competitive edge.

Here's a more detailed exploration of the concept:

Demand Planning

Demand Planning is the proactive aspect of managing demand, focusing on strategies to influence and shape customer demand. This involves decisions related to promotions, pricing strategies, packaging, and other marketing efforts designed to increase or stabilize demand for a product. The goal is to align the organization's capabilities with market opportunities, ensuring that the demand generated aligns with the company's strategic objectives.

Demand Forecasting

Demand Forecasting is the analytical process of estimating future customer demand based on historical data, market trends, and other relevant factors. It answers the question, "What should we expect demand for our product to be given the demand plan in place?" Forecasting is divided into three levels, each serving different organizational needs:

1. **Strategic Forecasts**: These long-term forecasts (spanning years) are used for high-level decisions such as capacity planning, investment strategies, and long-term resource allocation. They help organizations prepare for future market conditions and align their strategic goals with anticipated demand.

2. **Tactical Forecasts**: These medium-term forecasts (weeks to months to quarters) support sales planning, short-term budgeting, inventory management, and labor planning. They provide a framework for aligning operational activities with market demand, ensuring that resources are efficiently utilized.

3. **Operational Forecasts**: These short-term forecasts (hours to days) are crucial for day-to-day decision-making in production, transportation, and inventory replenishment. They help organizations respond quickly to changes in demand, minimizing disruptions and optimizing operational efficiency.

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Forecasting Principles

Forecasts Are Never Perfect: It's important to acknowledge that precise predictions are unattainable. Instead of relying solely on specific point forecasts, it's beneficial to incorporate a range of possible outcomes. Additionally, tracking and analyzing forecast errors can help identify trends or shifts over time.

Combined Forecasts Are More Reliable: When forecasts are aggregated, they tend to be more accurate than when they are broken down into smaller parts. This is because combining different elements can reduce overall variability, as fluctuations in one area may offset those in another. The coefficient of variation (CV), which is the ratio of the standard deviation to the mean, is often used to assess this variability. Forecasts can be aggregated by product category (e.g., a group of related products rather than a single item), by time period (e.g., monthly demand versus daily demand), or by location (e.g., regional demand versus demand at a specific store).

Short-Term Forecasts Are More Accurate: Predicting events in the near future is generally easier and more precise than making long-term forecasts. This principle highlights the importance of the time interval between making a forecast and the occurrence of the event. Shorter time frames typically yield better accuracy. Techniques like postponement and modularization can help reduce the forecasting time for a final product, thereby improving accuracy.

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Forecasting Methods

Forecasting methods are categorized into subjective and objective approaches:

Subjective Methods: Often used by marketing and sales teams, these methods rely on human judgment and intuition. They include:

- **Judgmental Methods**: Techniques like sales force surveys, Delphi sessions, and expert opinions, where insights are gathered from individuals with knowledge of the market.
- **Experimental Methods**: Techniques like customer surveys, focus groups, and test marketing, where data is collected from controlled experiments and extrapolated to predict broader trends.

Objective Methods: Typically used by production and inventory planners, these methods rely on data and statistical analysis. They include:

Causal Methods: These methods identify and utilize underlying relationships or reasons that affect demand. Examples include leading indicators and regression analysis, where external factors are used to predict demand changes.

Time Series Methods: These methods analyze historical demand data to identify patterns and trends. Techniques such as exponential smoothing and moving averages are used to forecast future demand based on past behavior.

Measuring Forecast Quality

In the realm of forecasting, it's crucial to strike a balance between the costs associated with forecast errors and the expenses incurred in producing high-quality forecasts. This balance is essential for optimizing resource allocation and ensuring efficient operations. To achieve this, forecasting metric systems should focus on capturing two key dimensions:

- **Bias**: This refers to a consistent tendency to overestimate or underestimate demand. A biased forecast can lead to systematic errors in planning and decision-making, resulting in either excess inventory or stockouts.
- **Accuracy**: This measures how close the forecasted values are to the actual observed demand. High accuracy indicates that the forecast closely matches real-world demand, enabling more effective planning and resource allocation.

No single metric can fully capture both bias and accuracy, so it is advisable to use multiple metrics to assess forecast quality comprehensively. Common metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), each providing different insights into the forecast's performance.

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Forecasting metrics

Notation

- A_t: Actual value of observation t
- F_t: Forecast value of observation t
- e_t: Error for observation t, $e_t = A_t - F_t$
- n: number of observations
- μ: mean
- σ: standard deviation
- CV: Coefficient of Variation – a measure of volatility - $CV = \frac{\sigma}{\mu}$

Formulas

- Mean Deviation: $MD = \frac{\sum_{t=1}^{n} e^t}{n}$
- Mean Absolute Deviation: $MD = \frac{\sum_{t=1}^{n} e^t}{n}$
- Mean Squared Error: $MSE = \frac{\sum_{t=1}^{n} {e_t}^2}{n}$
- Root Mean Squared Error: $RMSE = \sqrt{\frac{\sum_{t=1}^{n} {e_t}^2}{n}}$
- Mean Percent Error: $MPE = \frac{\sum_{t=1}^{n} \frac{e_t}{A_t}}{n}$
- Mean Absolute Percent Error: $MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{A_t}}{n}$
- Statistical Aggregation of n Distributions of Equal Mean and Variance

$$\sqrt{{\sigma_1}^2 + {\sigma_2}^2 + {\sigma_3}^2 + \cdots + {\sigma_n}^2} = \sigma_{ind}\sqrt{n}$$

$$\mu_{agg} = \mu_1 + \mu_2 + \mu_3 + \cdots + \mu_n = n\mu_{ind}$$

$$CV_{agg} = \frac{\sigma\sqrt{n}}{\mu n} = \frac{\sigma}{\mu\sqrt{n}} = \frac{CV_{ind}}{\sqrt{n}}$$

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Time Series Analysis

Time series forecasting is a widely utilized technique for predicting future values based on historical data, particularly effective for mid-range forecasts of items with extensive demand records. This method involves identifying and matching patterns in data distributed over time, requiring a substantial amount of historical data to accurately capture the underlying components or patterns. Time series forecasting is particularly useful for understanding business cycles, which are more suited to longer-range, strategic forecasting horizons. By understanding the components of time series data and employing strategies to enhance model accuracy, organizations can make more informed decisions, optimize their operations, and better align their resources with market demand. While time series models have limitations, particularly in the presence of non-stationary demand, they remain a valuable component of a comprehensive forecasting strategy. By integrating time series forecasting with other methods and continuously refining their approach, businesses can improve their forecasting capabilities and achieve greater operational efficiency.

Key Time Series Models

Cumulative Model:

This model considers all available historical data, resulting in a forecast that changes very slowly over time. It is characterized by its stability, as it smooths out short-term fluctuations and focuses on long-term trends. The cumulative model is less responsive to recent changes, making it ideal for stable environments where sudden shifts are unlikely.

Naïve Model:

The naïve model relies solely on the most recent data point to make forecasts. This approach is highly responsive, allowing forecasts to quickly adapt to recent changes in demand. However, this responsiveness comes at the cost of stability, as forecasts can become volatile and subject to dramatic shifts with each new data point.

Moving Average Model:

The moving average model strikes a balance between the cumulative and naïve models by allowing forecasters to select a specific number of recent periods (M) to include in the forecast. This model provides flexibility in determining how much historical data to consider, offering a generalized approach that can be tailored to specific forecasting needs. The moving average model assumes stationary demand and applies equal weighting to each data point within the selected period.

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Components of Time Series

Time series data can be decomposed into several key components, each contributing to the overall pattern observed in the data:

- **Level (a)**: Represents the average value around which demand fluctuates. It captures the scale of the time series and remains constant in the absence of other patterns.

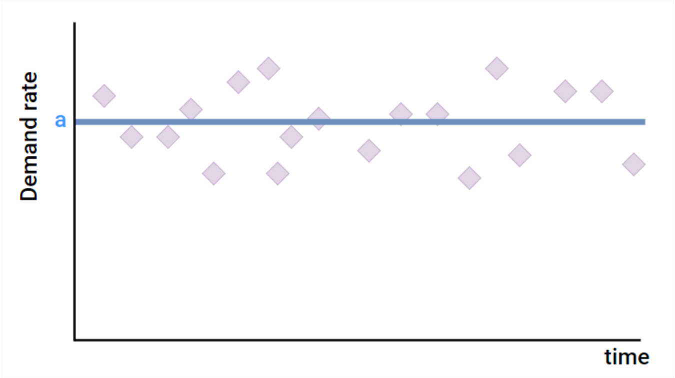

Figura 1. Level (a)

- **Trend (b)**: Indicates the rate of growth or decline in the data, reflecting a persistent movement in one direction. Trends can be linear, exponential, quadratic, or follow other mathematical forms, depending on the nature of the data.

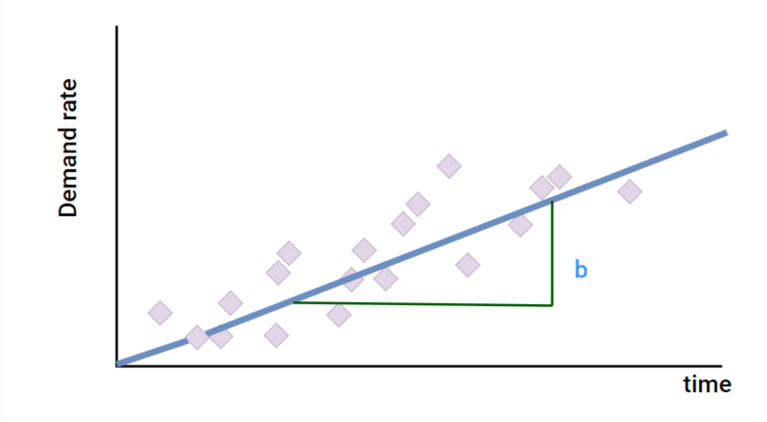

Figura 2. Trend (b)

- **Seasonal Variations (F)**: These are recurring patterns that occur at regular intervals, such as hourly, daily, weekly, monthly, or quarterly cycles. Seasonal variations can be driven by natural factors (e.g., weather) or man-made factors (e.g., holidays, promotions). Understanding these variations is crucial for accurately capturing the cyclical nature of demand.

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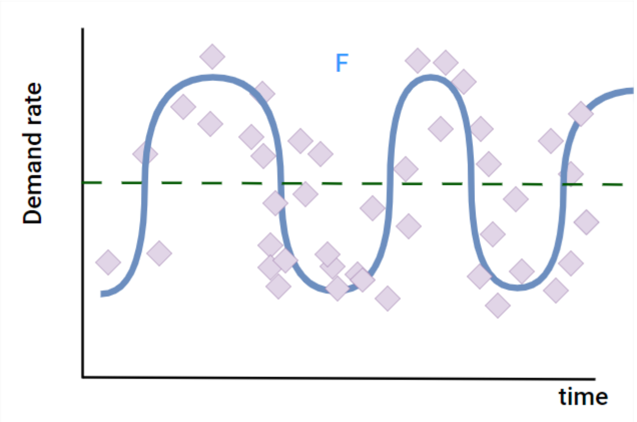

Figura 3. Season Variations (F)

- **Random Fluctuation (e or ε)**: This component accounts for irregular and unpredictable variations in the data, often referred to as "noise." These fluctuations are not explained by the level, trend, or seasonal components and represent the inherent uncertainty in the data.

Notation

- x_t: Actual demand in period t
- $\hat{x}_{t,\ t+1}$: Forecast for time $t+1$ made during time t
- a: Level component
- b: Linear trend component
- F_t: Season index appropriate for period t
- e_t: Error for observation $t, e_t = A_t - F_t$
- t: Time period $(0,1,2,\dots n)$
- Level Model: $x_t = a + e_t$
- Trend Model: $x_t = a + bt + e_t$
- Mix Level-Seasonality Model: $x_t = aF_t + e_t$
- Mix Level-Trend-Seasonality Model: $x_t = (a + bt)F_t + e_t$

Formulas

Time Series Models (Stationary Demand Only):

Cumulative Model: $\hat{x}_{t,t+1} = \frac{\sum_i^t x_i}{t}$

Naïve Model: $\hat{x}_{t,t+1} = x_t$

M-Period Moving Average Forecast Model: $\hat{x}_{t,t+1} = \frac{\sum_{i=t+1-M}^{t} x_i}{M}$

- If $M = t$, we have the cumulative model where all data is included
- If $M = 1$, we have the naïve model, where the last data point is used to predict the next data point.

Exponential Smoothing

Exponential smoothing is a powerful forecasting technique used to predict future values based on past observations. Unlike other methods such as Cumulative, Naïve, and Moving Average, exponential smoothing assigns exponentially decreasing weights to older observations, giving more importance to recent data. This approach is particularly useful in time series forecasting where the most recent data points are more relevant for predicting future values.

Weighting of Observations:

- Exponential smoothing applies weights that decrease exponentially over time. This means that newer observations have a higher weight compared to older ones.
- The rate at which the weights decrease is determined by the smoothing parameter, often denoted as (α).

Smoothing Parameter (α):

- The smoothing parameter (α) ranges between 0 and 1.
- $(\alpha \to 1)$: The forecast becomes more sensitive to recent changes, making it more volatile and similar to a Naïve forecast.
- $(\alpha \to 0)$: The forecast becomes smoother and more stable, resembling a cumulative average.
- In practice, (α) is typically chosen between 0 and 0.3 to balance responsiveness and stability.

The simplest form of exponential smoothing, known as the Simple Exponential model, is based on the assumption that demand remains constant over time. In contrast, Holt's Model is an enhanced version that incorporates both the level and the trend of the data. This model introduces an additional smoothing parameter, similar to the one used for the level, to adjust for trends. Furthermore, exponential smoothing can be applied to dampen trend models, acknowledging that trends typically do not persist indefinitely. This approach helps in producing a more stable and reliable estimate of forecast errors.

Notation

- x_t: Actual demand in period t
- $x_{t,t+1}$ Forecast for time $t+1$ made during time t
- α: Exponential smoothing factor for <u>level</u> $0 \leq \alpha \leq 1$
- β: Exponential smoothing factor for <u>trend</u> $0 \leq \beta \leq 1$
- φ: Exponential smoothing factor for <u>dampening</u> $0 \leq \varphi \leq 1$
- ω: Mean Square Error trending factor $0.01 \leq \omega \leq 0.1$

Formulas

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Simple Exponential Smoothing Model (Level Only) is designed for situations where demand remains constant over time. In this model, the "new" information is simply the most recent observation, while the "old" information is represented by the latest forecast, which incorporates all previous data. The formula for updating the forecast is given by

$$\hat{x}t, t+1 = \alpha x_t + (1-\alpha)\hat{x}t-1, t$$

Damped Trend Model with Level and Trend: This approach uses exponential smoothing to moderate a linear trend, reflecting the natural slowing of trends over time. The forecast for future periods is calculated as follows:

$$\hat{x}_{t,t+\tau} = \hat{a}t + \sum i = \phi^i \widehat{b_t}$$

- $\hat{a}_t = \alpha x_t + (1-\alpha)\left(\hat{a}_t - 1 + \phi\hat{b}_{t-1}\right)$
- $\hat{b}_t = \beta(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta)\phi\hat{b}_{t-1}$

Exponential Smoothing with Holt-Winter: Exponential Smoothing for Level & Trend, also known as Holt's Method, is designed to handle data with a linear trend. The forecast for a future time period (t+k), made at time (t), combines the most recent estimates of both the level and the trend.

For the level component, the "new" information is the latest observation, while the "old" information is the most recent forecast for that period. This forecast is derived from the previous period's level estimate plus the trend estimate from that same period.

For the trend component, the "new" information is the difference between the latest level estimate and the one before it. The "old" information is simply the trend estimate from the last period.

The formulas used are:

$$\widehat{x_{t,t+\tau}} = \widehat{a_t} + \tau\widehat{b_t}$$

- $\hat{a}t = \alpha\, x_t + (1-\alpha)\left(\hat{a}t - 1 + \widehat{b_{t-1}}\right)$
- $\hat{b}t = \beta(\,\hat{a}_t - \hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1}$

Mean Square Error Estimate: Exponential smoothing can also be applied to derive a more consistent and stable estimate of the mean square error for forecasts. The formula used is:

$$\mathrm{MSE}t = \omega(x_t - \hat{x}t - 1, t)^2 + (1-\omega)\mathrm{MSE}_{t-1}$$

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Exponential Smoothing with Holt-Winter

- For multiplicative seasonality, consider each (F_i) as representing the "percentage of average demand" for a specific period (i).
- The total of all (F_i)) values across a complete season must equal a constant (P).
- It's crucial to regularly update the seasonality factors to prevent significant drift. This requires extensive record-keeping, which can be challenging to manage in a spreadsheet, but it's essential to grasp this concept.

Notation

- x_t: Actual demand in period t
- $x_{t,t+1}$ Forecast for time $t+1$ made during time t
- α: Exponential smoothing factor for level $0 \leq \alpha \leq 1$
- β: Exponential smoothing factor for trend $0 \leq \beta \leq 1$
- φ: Exponential smoothing factor for dampening $0 \leq \varphi \leq 1$
- F_t: Multiplicative seasonal index appropriate for period t
- P: Number of time periods within the seasonality (note: $\int_{i=1}^{P} \hat{F}_i = P$

Formulas

Holt-Winter Exponential Smoothing Model (Level, Trend, and Seasonality)

This model incorporates a linear trend along with a multiplicative seasonal effect on both the level and trend components.

- **Level Estimate**: The "new" information is the latest observation adjusted to remove seasonality, while the "old" information includes the previous estimates of both level and trend.
- **Trend Estimate**: This follows the same approach as in the Holt model.
- **Seasonality Estimate**: This is similar to the Double Exponential Smoothing model.

The forecast equation is:

$$\widehat{x_{t,t+\tau}} = \left(\hat{a}_t + \tau\hat{b}_t\right) \cdot \widehat{F_{t+\tau-P}}$$

- $\hat{a}t = \alpha\left(\frac{x_t}{\hat{F}_{t-P}}\right) + (1-\alpha)\left(\hat{a}_{t-1} + \widehat{b_{t-1}}\right)$
- $\hat{b}t = \beta(\hat{a}_t - \widehat{a_{t-1}}) + (1-\beta)\hat{b}_{t-1}$
- $\hat{F}_t = \varphi\left(\frac{x_t}{\hat{a}_t}\right) + (1-\varphi)\hat{F}_{t-P}$

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Double Exponential Smoothing (Seasonality and Level)

This model uses a multiplicative approach where the seasonality for each period is the product of the level and the seasonality factor for that period.

- **Level Estimate**: The "new" information is the latest observation adjusted to remove the seasonality factor, while the "old" information is the previous level estimate.
- **Seasonality Estimate**: The "new" information is the latest observation adjusted to remove the level factor, while the "old" information is the previous seasonality estimate for that period.

$$\widehat{x_{t,t+\tau}} = \hat{a}_t \cdot \widehat{F_{t+\tau-P}}$$

- $\hat{a}_t = \alpha(\frac{x_t}{\hat{F}_{t-P}}) + (1 - \alpha)(\hat{a}_{t-1})$
- **Seasonality Estimate**: $\hat{F}_t = \gamma\left(\frac{x_t}{\hat{a}_t}\right) + (1-\gamma)\hat{F}_{t-P}$

Normalizing Seasonality Indices

After each forecast, it's important to normalize the seasonality indices to ensure they remain accurate and do not drift over time. If these indices are not updated, they can become significantly misaligned. Most software packages handle this automatically, but it's advisable to verify.

The normalization process is:

$$\widehat{F_t^{NEW}} = \widehat{F_t^{OLD}} \times \frac{P}{\sum_{i=t+1-P}^{t} \widehat{F_i^{OLD}}}$$

This adjustment ensures that the sum of the seasonality indices over a complete cycle remains consistent, maintaining the integrity of the model's seasonal adjustments.

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Application and Limitations

Time series models are particularly effective when the demand is stationary, meaning that the statistical properties of the series do not change over time. However, if there is a trend in the underlying data, these models may lag behind actual changes, as they assume equal weighting for all included data points. This can lead to inaccuracies if the demand pattern shifts significantly.

Despite these limitations, time series forecasting remains a powerful tool for businesses, especially when combined with other forecasting methods to account for non-stationary demand or when used in conjunction with qualitative insights. By understanding and leveraging the components of time series data, organizations can make more informed decisions, optimize inventory levels, and improve overall operational efficiency.

Enhancing Time Series Forecasting

To maximize the effectiveness of time series forecasting, businesses can employ several strategies and techniques:

1. **Data Enrichment**: Incorporating additional data sources can enhance the accuracy of time series models. This might include external factors such as economic indicators, weather data, or social media trends that could influence demand patterns.

2. **Hybrid Models**: Combining time series models with other forecasting techniques, such as causal models or machine learning algorithms, can help address the limitations of each method. Hybrid models can capture complex patterns and non-stationary demand more effectively.

3. **Adaptive Methods**: Implementing adaptive forecasting techniques allows models to adjust dynamically to changes in the data. Methods like exponential smoothing can provide more weight to recent observations, improving responsiveness to shifts in demand.

4. **Scenario Analysis**: Conducting scenario analysis can help businesses prepare for various potential future states. By simulating different scenarios, organizations can assess the impact of various factors on demand and develop contingency plans.

5. **Regular Review and Adjustment**: Continuously monitoring and adjusting forecasting models is crucial for maintaining accuracy. Regularly reviewing model performance and incorporating feedback can help identify areas for improvement and ensure that forecasts remain relevant.

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