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Forecast Accuracy and Inventory Strategies©

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Forecast Accuracy - Abstract

Demand visibility is a vital component of an effective supply chain.

- Forecast accuracy at the primitive SKU level is critical for proper allocation of supply chain resources.
- Inaccurate demand forecasts often would result in supply imbalances when it comes to meeting customer demand.

In this paper, we will discuss the process of measuring forecast accuracy, the pros and cons of different accuracy metrics, and the time-lag with which accuracy should be measured. We will also discuss a method to identify and track forecast bias.

Download our Demand Metrics template for all formulas and calculations - http://demandplanning.net/DemandMetricsExcelTemp.htm

Demand Plan

- Demand Plan is a statement of expected future demand that is derived using a statistical forecast and enhanced with customer intelligence.
- Demand Plans need to be
  - Unbiased
  - Timely
  - In relevant detail
  - Covering the appropriate time horizon
- *What is different between Long-term and Short-term Planning?*

Short-term Planning

- Critical for tactical planning
- Limited flexibility to reschedule resources

So Make or Break it!

- Inaccurate forecast means
  - Lost sale
  - Lost customer
  - Excess inventory
  - Other inefficiencies

Long-term Forecasts

- Market or economy-oriented
- Useful for
  - Capacity Planning
  - Setting Strategic initiatives
- More flexibility to change and err
- Accuracy at an aggregate or macro level is more important
- **So mix matters less in Long-term forecasting!**

Right amount, wrong SKU!

	<u>**SKU A**</u>	<u>**SKU B**</u>	<u>**Total**</u>
Actual	25	75	100
Forecast	75	25	100
Accuracy	**0%**	**33%**	**100%**

Forecast Error

- Forecast Error is the deviation of the Actual from the forecasted quantity

$$\text{Error} \quad = \text{Absolute Value of } \{(\text{Actual} - \text{Forecast})\}$$

$$\text{Error \%} = \frac{\text{Absolute Value of } \{(\text{Actual} - \text{Forecast})\}}{\text{Actual}}$$

- Deviation vs. Direction
  - The first is the magnitude of the Error
  - The second implies bias, if persistent

Forecast Accuracy

- Forecast Accuracy is a measure of how close the Actual Demand is to the forecasted quantity.
  - Forecast Accuracy is the converse of Error
  - Accuracy (%) = 1 – Error (%)
- However we truncate the Impact of Large Forecast Errors at 100%. More formally
  - If Actual equals Forecast, then Accuracy = 100%
  - Error > 100% → 0% Accuracy
  - We constrain Accuracy to be between 0 and 100%
- Algebraically,
  - Accuracy = maximum of (1 – Error, 0)

Example (continued…)

	<u>**SKU A**</u>	<u>**SKU B**</u>	<u>**SKU X**</u>	<u>**SKU Y**</u>
Actual	25	50	75	74
Forecast	75	0	25	75
Absolute Error	**50**	**50**	**50**	**1**
Error (%)	**200%**	**100%**	**67%**	**1%**
Accuracy (%)	**0%**	**0%**	**33%**	**99%**

How do you measure value chain performance? Find out at the DemandPlanning.Net metrics workshop!

CALCULATION METHODOLOGY

- How to calculate a performance measure for forecast accuracy?
- How do we aggregate errors across products and customers?
- What are the different error measurements available?
- How do you define the Mean Absolute Percent Error?
- What is the weighted MAPE?

Aggregating Errors

To compute one metric of accuracy across a group of items, we need to calculate an Average Error

- Simple but Intuitive Method
  - Add all the absolute errors across all items
  - Divide the above by the total actual quantity
  - Define the average error as Sum of all Errors divided by the sum of Actual quantity
- This is known as WAPE or

Weighted Absolute Percentage Error!!!!

- *WAPE is also known as WMAPE, MAD/Mean ratio.*

Example of WAPE calculation

	SKU A	SKU B	SKU X	SKU Y	Total
Actual	25	50	75	74	$\boxed{224}$
Forecast	75	0	25	75	175
Absolute Error	**50**	**50**	**50**	**1**	$\boxed{\mathbf{151}}$
Error (%)	**200%**	**100%**	**67%**	**1%**	$\boxed{\mathbf{67\%}}$
Accuracy (%)	**0%**	**0%**	**33%**	**99%**	**33%**

WAPE

Different ways to err!

- Mean Percent Error – MPE
- Mean Absolute Percent Error - MAPE
- Mean Absolute Deviation - MAD
- Weighted Absolute Percent Error – WAPE or WMAPE
- Root Mean Squared Error - RMSE

Different ways to err!

- Mean Percent Error (MPE) is an Average of the Percentage Errors. Mean Absolute Percent Error (MAPE) is an Average of the Percentage Errors.
  - These ignore the scale of the numbers.
  - MPE can be positive or negative, MAPE is always positive.
- Weighted Absolute Percent Error (WAPE or WMAPE) is the Sum of Absolute errors divided by the Sum of the Actuals

$$WMAPE = \frac{\sum \left| Actual - Forecast \right|}{\sum Actual}$$

  - WAPE gives you a true picture of forecast quality in an organization and how this will impact the business performance in both Sales and profits.
  - WAPE can also be construed as the Average Absolute Error divided by the Average Actual quantity

Root Mean Squared Error

- Mean Squared Error is the Average of the squared errors (hence positive).
- Root Mean Squared Error (RMSE) is the classic Statistical Error – very similar to Standard Deviation.

$$MSE = \frac{\sum (Actual - Forecast)^2}{N}$$

$$RMSE = \sqrt{MSE}$$

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Illustration of Error Metrics

	Actual	Forecast	Error	Abs. Error	Pct. Error	Sqrd. Error
Sku A	1	3	-2	2	200%	4
Sku B	50	0	50	50	100%	2,500
Sku X	75	25	50	50	67%	2,500
Sku Y	74	75	-1	1	1%	1
Sku Z	75	100	-25	25	33%	625
Total	**275**	**203**	**72**	**128**		**5,630**
Average	**55**	**40.6**	**14.4**	**25.6**	**80%**	**1,126**
					with A	w/o Sku A
	Mean Absolute Percent Error =				**80%**	**50%**
	Weighted Absolute Percent Error =				**47%**	**46%**
	Root Mean Squared Error =				**34**	**38**
	RMSE as % of Actuals =				**61%**	**55%**

Why WAPE?

- WAPE gives you the best read on how the quality of forecasting will affect the Organization – Top line results, Profitability and the general quality of life of the supply chain participants.
- MAPE/MPE
  - very unstable
  - will be skewed by small values
  - In the Example, SKU A drives most of the Error.
- WAPE is <u>simple and elegant</u> while <u>robust</u> as a computational measure!

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MAPE vs. WAPE

- The MAPE is un-weighted and hence commits the sin of averaging percentages.
  - Assumes the absolute error on each item is equally important.
  - Large error on a low-value item or C item can unfairly skew the overall error.
- WAPE is volume weighted but can be value weighted either by standard cost or list price
  - High-value items will influence the overall error
  - So it is better to use WAPE for volume weighted MAPE and WMAPE for dollar weighted or Cost-weighted measures.
  - We denote WMAPE_p to mean price weighted MAPE and
  - WMAPE_c to mean Cost weighted MAPE.

WMAPE

- Weighted MAPE or Value weighted MAPE
  - $WMAPE = \sum(w^*|(A-F))|/ \sum(w^*A)$
  - Both Error and Actuals are weighted
  - The weight can even be a subjective measure based on criticality of the item.
- High-value items will influence the overall error
- Highly correlated with safety stock requirements
- Very useful in setting safety stock strategies

LAG AND BIAS

- What is forecast bias?
- How to measure forecast bias?
- What is the forecast lag for evaluating forecasts?
- How do you determine forecast lags?

Absolute vs. Arithmetic!

	Actual	Forecast	Error	Abs. Error	Pct. Error
Sku A	1	3	-2	2	200%
Sku B	50	0	50	50	100%
Sku X	75	25	50	50	67%
Sku Y	74	75	-1	1	1%
Sku Z	75	100	-25	25	33%
Total	**275**	**203**	**72**	**128**	
Average	**55**	**40.6**	**14.4**	**25.6**	**80%**
	Wean Absolute Percent Error =				**47%**
	Absolute Accuracy (%)				**53%**
	Arithmetic Accuracy				**135%**

Absolute vs. Arithmetic

- Absolute accuracy is the converse of MAPE.
  - A 47% MAPE implies accuracy of 53%.
- Arithmetic Accuracy is a measure of total business performance regardless of the mix issues
  - Defined as a simple quotient of Actual vs. Forecast
  - Directionally offsetting errors result in accuracy close to 100%
  - Arithmetic Accuracy is also known as Forecast Attainment.

Lead vs. Lag

- Setting measurement standards will be influenced by
  - Production Lead time
  - Batch Size
- Production Lead time dictates the Forecast Lag to be used in computing accuracy
  - Longer the lead time, larger is the forecast Lag
  - Larger the Lag, lower the forecast accuracy

Lag Analysis

	March	April	May	June	July
March	125	130	175	210	225
Lag	0	1	2	3	4
April		135	185	220	235
Lag		0	1	2	3
May			170	225	225
Lag			0	1	2
Actuals	**128**	**135**	**172**	**225**	

Lag 2 Forecast

Evolution of forecast

Forecast Bias

Bias is the tendency for error to be persistent in one direction. Most bias can be classified into one of two main categories:

- Forecaster bias occurs when error is in one direction for all items.
- Business Process Bias occurs when error is in one direction for specific items over a period of time.

Forecast Bias – Case 1

	Actual	Forecast	Error	Abs. Error	Pct. Error	Accuracy
Sku A	1	3	-2	2	200%	0%
Sku B	25	50	-25	25	100%	0%
Sku X	25	75	-50	50	200%	0%
Sku Y	74	75	-1	1	1%	99%
Sku Z	75	100	-25	25	33%	67%
Total	**200**	**303**	**-103**	**103**	**52%**	48%
Average	**40**	**60.6**	**-20.6**	**20.6**		
	Absolute Accuracy				**48%**	
	Arithmetic Accuracy				**66%**	

Type 1 Bias

- This is a subjective bias. Occurs due to human intervention (often erroneous) to build unnecessary forecast safeguards. Examples:
  - Increase forecast to match Division Goal
  - Adjust forecast to reflect the best case volume scenario in response to a promotion
  - Building a forecast component to reflect production uncertainty (in effect, doubling the safety stock)
  - Organization’s natural tendency to over-forecast due to high visibility of product outs compared to excess inventory
- This bias results in
  - Increased inventories and
  - Higher risk of obsolescence.

Forecast Bias – Case 2

SKU A	110%	118%	121%	101%	112%	+
SKU B	88%	92%	90%	81%	88%	-
SKU X	95%	104%	101%	100%	97%	No
SKU Y	65%	135%	70%	130%	95%	No
Sku Z	70%	72%	85%	99%	102%	-

The key is to statistically measure the bias. To establish that a forecast is biased, you have to prove that the net bias is statistically significant using standard confidence intervals.

Type 2 Bias

- This bias is a manifestation of business process specific to the product.
- This can either be an over-forecasting or under-forecasting bias. This bias is hard to control, unless the underlying business process itself is restructured.
- Examples:
  - Items specific to a few customers
  - Persistent demand trend when forecast adjustments are slow to respond to such trends
  - Distribution changes of an item over time
    - Either item getting distribution across new customers over time or
    - Item slowly going through an attrition with delistments over time.

Bias – Is there a remedy?

- If bias is type 1, correcting the forecast is easy but making the organization adjust to unbiased forecasting is the harder sell.
  - Since Arithmetic accuracy conveys similar information as absolute accuracy, using a mass counter-adjustment is the easiest solution.
  - In Case 1, slashing the forecast across the board by 33% would dramatically increase the accuracy.
- If bias is type 2
  - Each item bias needs to examined for specific process reasons.
  - Process needs to be re-adjusted

Cut forecast by 33% in Case 1

	Actual	Original Forecast	Rev. forecast	Abs. Error	Pct. Error	Accuracy
Sku A	1	3	2.0	1	101%	0%
Sku B	25	50	33.5	9	34%	66%
Sku X	25	75	50.3	25	101%	0%
Sku Y	74	75	50.3	24	32%	68%
Sku Z	75	100	67.0	8	11%	89%
Total	**200**	**303**	**203**	**67**	**33%**	67%
Average	**40**	**61**	**41**	**13**		
	Absolute Accuracy				**67%**	
	Arithmetic Accuracy				**99%**	

Industry Benchmark Measurement

- We measure item level absolute accuracy using an one-month bucket and a three-month bucket.
- The one-month accuracy is measured using a two-month lag forecast ie. May actuals measured using March forecast
- The three-month accuracy is measured using an one-month lag forecast ie. May-July actuals using April forecast.
- Business policy issue
  - Quarter close effects
  - Unannounced business deals
- The above have an effect on one-month accuracy but NOT on three-month accuracy.

Want to improve your process? DemandPlanning.Net Diagnostic consulting is a good place to start!

SIMPLE SAFETY STOCK

- Why do we need safety stock?
- Is safety stock related to Forecast Accuracy?
- How do you calculate safety stock levels?

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Safety stock

- Safety stock is defined
  - as the component of total inventory needed to cover unanticipated fluctuation in demand or supply or both
  - As the inventory needed to defend against a forecast error
- Hence Forecast error is a key driver of safety stock.
- Here we illustrate the basic safety stock concept that covers demand volatility but not deviations in supply lead time or variability.

Safety Stock Calculation

- Using all three determinants of Safety stock,
  - SS = SL * Forecast Error * √Lead Time
- SL is Customer Service Level
  - Generally set at 98% (why?)
  - Which translates into a multiple of 2.054 (why?)
- Forecast Error used is the Root Mean Squared Error
- Lead time is either weeks or months, consistent with the forecast measurement period.
- However we do not consider variability in lead time or the supply quantity.
- Also we do not consider the interaction between lot size, variability as well as the effect of order frequency.

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Importance of Forecast Error

- Lead times are externally determined
  - Supplier Considerations
  - Structure of your Supply Chain
- Service Level Targets are typically in a narrow band between 95% and 99.5%
- Hence Forecast Error is the big driver of safety stock.

Example of Safety Stock Calculation

		Nuts	Bolts	Rings
Lead-Time	Months	0.75	2	2
Service Level	98%	2.05	2.05	2.05
Standard Deviation	Monthly	16	11	5
Standard Deviation % on Avg. Volume		16%	50%	5%
Average volume		100	22	100
Safety Stock	Units	28	32	15
Safety Stock in Days		**8.7**	**44.1**	**4.4**

Forecast Bias

- Does Bias affect Safety stock?
  - Depends on whether it is type 1 or type 2 bias.
  - If bias can be quantified, then there is no uncertainty and hence no need for additional safety stock
- If this is a type 1 bias, adjustment is easy
  - Add or subtract the bias to the forecasted quantity to arrive at your supply
  - Safety stock needs to be adjusted down to match the error contributed by the bias

ABOUT US

- Who is the author?
- What is Demand Planning LLC?
- Who are Demand Planning LLC clients?
- How can you contact the author of this paper?

About The Author

Dr. Mark Chockalingam is Founder and President, Demand Planning LLC, a Business Process and Strategy Consultancy firm. The author specializes in research and consulting in the areas of Demand Forecasting, Supply chain optimization and Inventory Management.
He has worked with a variety of clients including Fortune 500 companies such as Pfizer, Honeywell, Miller Coors, FMC, Pepsi Foods, Schlumberger, Abbott to small and medium size companies such as Au Bon pain, Keter, Celanese AG etc.

Prior to establishing his consulting practice, Mark has held important supply chain positions with several manufacturing companies. He was Director of Market Analysis and Demand Planning for the Gillette Company (now part of P&G), and prior to that he led the Sun care, Foot care and OTC forecasting processes for Schering-Plough Consumer HealthCare.
Mark has a Ph. D. from Arizona State University, an MBA from the University of Toledo and is a member of the Institute of Chartered Accountants of India.

About Demand Planning LLC

Demand Planning LLC is a consulting boutique comprised of seasoned experts with real-world supply chain experience and subject-matter expertise in demand forecasting, S&OP, Customer planning, and supply chain strategy.

We provide process and strategy consulting services to customers across a variety of industries - pharmaceuticals, CPG, High-Tech, Foods and Beverage, Quick Service Restaurants and Utilities.

Through our knowledge portal DemandPlanning.Net, we offer a full menu of training programs through in-person and online courses in Demand Forecast Modeling, S&OP, Industry Forecasting, collaborative Forecasting using POS data.

DemandPlanning.Net also offers a variety of informational articles and downloadable calculation templates, and a unique Demand Planning discussion forum.

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