



Demand Forecasting and Managing Variability in a Supply Chain

Learning Objectives

- ▶ Role of forecasting in a supply chain
- ▶ Components of a demand forecast
- ▶ Demand forecasting using historical data
- ▶ Analysing forecast errors
- ▶ Managing demand/supply in a supply chain

- ▶ Forecasting with Excel

Role of forecasting

- ▶ Demand forecasts form the basis of all planning decisions in a supply chain
 - ▶ Push: produce to *anticipated* demand levels
 - ▶ Pull: set capacity and component *availability* levels
- ▶ Forecast time horizons
 - ▶ Short term (days, weeks): shift scheduling
 - ▶ Medium Term (weeks, months): workforce planning, materials purchasing, promotions
 - ▶ Long term (months, years): capacity expansion, capital/financial budget

Characteristics of Forecasts

- ▶ Forecasts are always wrong!
 - ▶ Expected value
 - ▶ Error/variability from the expected value
- ▶ Long-term forecasts are usually less accurate than short-term forecasts
- ▶ Aggregate forecasts are usually more accurate than disaggregate forecasts
- ▶ Mature products with stable demand are easier to forecast than seasonal goods or “fashion” items with short product-life

Influences on Customer Demand

“Predictions are usually difficult, especially about the future” – Yogi Berra

- Historical patterns
 - Past demand -> future demand
 - Seasonality? Trend?
- Externalities
 - Weather
 - State of the economy
- Internal factors
 - Planned promotional/discount campaigns
 - Display position and advertising efforts
- Competitors' actions

Components of Observed

Demand Observed demand (O) =
Systematic component (S) + Random
component (R)

- Forecasting should focus on identifying the systematic component
- Systematic component = *Expected value of demand*
- Time series model:
 - (Basic) demand **level**
 - **Trend**, rate of growth/decline in demand per period
 - **Seasonality**, (predictable) seasonal fluctuations

Forecasting Methods

- ▶ Qualitative
 - ▶ Subjective, human judgement and opinions
 - ▶ Little historical data available, e.g. new product, .com
- ▶ Time Series
 - ▶ Assume past history is good indicator of future demand
 - ▶ Best for stable environments
 - ▶ Easy to implement
- ▶ Causal
 - ▶ Assume other (measurable) factors that is correlated with demand
 - ▶ Models (e.g. regression) identify factors and quantifies the strength of the correlations
- ▶ Simulation
 - ▶ Assumes some underlying principles of customer behaviour and develop possible scenarios in the future to predict demand

Basic Approach to Demand Forecasting

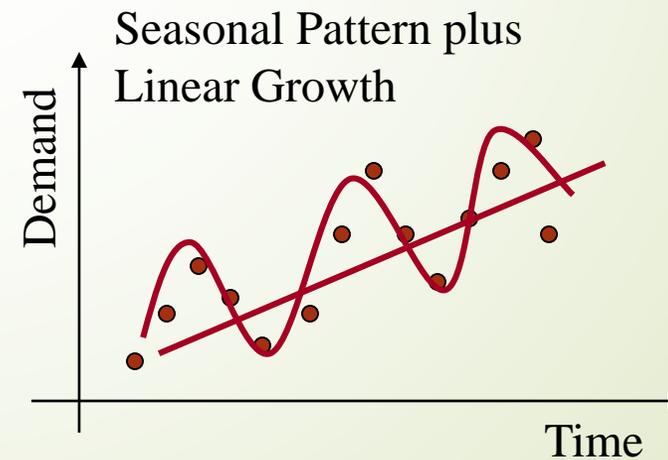
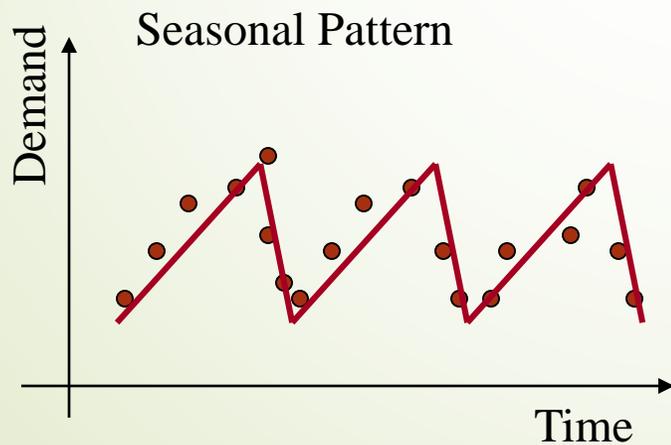
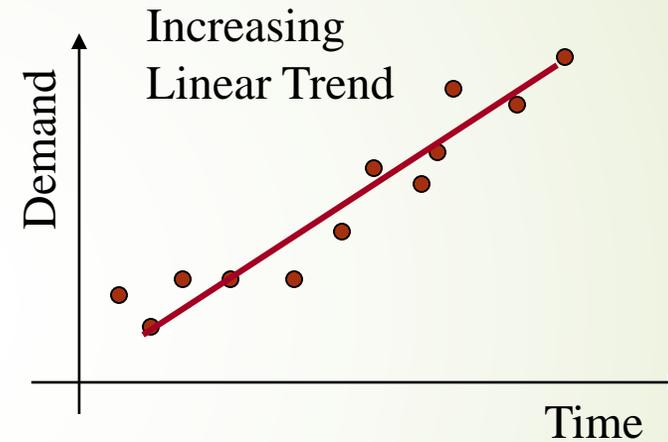
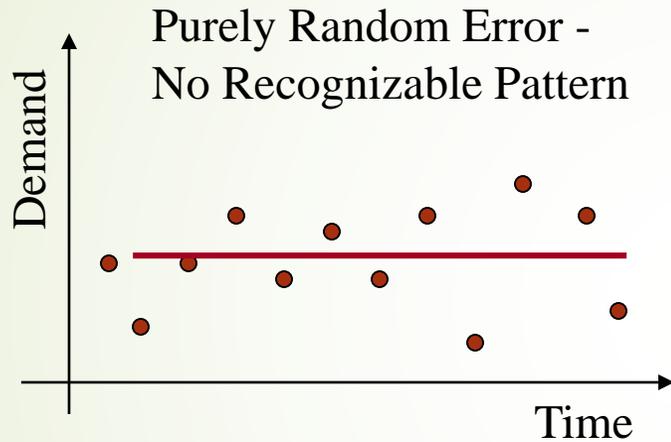
- ▶ Understand the objective of forecasting
 - ▶ Forecast horizon; affected by suppliers' lead times
- ▶ Integrate demand planning and forecasting
 - ▶ Co-ordination between marketing, production and suppliers
- ▶ Identify major factors that influence the demand forecast
 - ▶ Growth Trend? Seasonality?
 - ▶ Substitutes and complementary products?
- ▶ Understand and identify customer segments
 - ▶ Levels of aggregation
- ▶ Determine the appropriate forecasting technique
 - ▶ Geographical location, product life-cycle, etc.
- ▶ Establish performance and error measures for forecasts
 - ▶ Assess cost impacts; consider investments in improving forecasts accuracies

No forecast is perfect; system must be flexible and have contingency plans to handle forecast errors

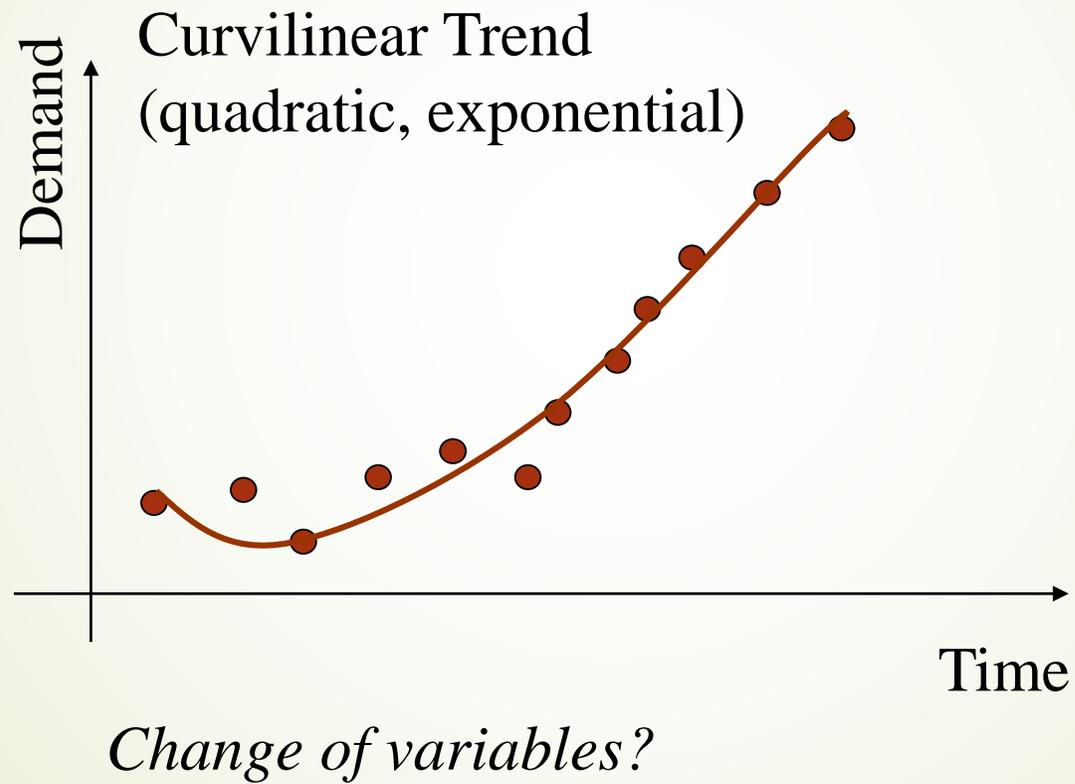
Common Time Series Patterns

- ▶ Constant (stationary)
- ▶ Increasing/decreasing linear trend
- ▶ Seasonal variations
- ▶ Non-linear (e.g. exponential) trend
- ▶ Combinations
 - ▶ Additive
 - ▶ Multiplicative
 - ▶ Mixed

Common Time Series Patterns



Other Time Series Patterns



Underlying model and definitions

Systematic component = (level + trend) x seasonal factor

L = estimate of level for period 0 (de-seasonalised demand)

T = estimate of trend (increase/decrease in demand per period)

S_t = Estimate of seasonal factor for period t

D_t = Actual demand observed for period t

F_t = Forecast of demand for period t

$$F_{t+k} = [L + (t+k)T] S_{t+k}$$

De-seasonalising Demand

- De-seasonalised demand is the demand that would have been observed in the absence of seasonal fluctuations
- The **periodicity** p is the number of periods after which the seasonal cycle repeats itself
(e.g. if period length = 3 months, $p = 4$)

$$\bar{D}_t = \begin{cases} \frac{1}{p} \left(\sum_{i=t-\lfloor \frac{p}{2} \rfloor}^{i=t+\lfloor \frac{p}{2} \rfloor} D_i \right) & \text{for } p \text{ odd} \\ \frac{1}{2p} \left(D_{t-\frac{p}{2}} + D_{t+\frac{p}{2}} + 2 \sum_{i=t-\frac{p}{2}+1}^{i=t+\frac{p}{2}-1} D_i \right) & \text{for } p \text{ even} \end{cases}$$

Estimating Model Parameters

- ▶ Seasonal factors:
- ▶ Seasonal factor for a given period (in the future) can be estimated by averaging seasonal factors of periods of corresponding seasons

$$\bar{S}_t = \frac{D_t}{D_t} = \frac{\text{actual demand}}{\text{de - seasonalised demand}}$$

Static Forecasting

- ▶ Values of L and T estimated based on a set of data
- ▶ Methods:
 - ▶ Simple averaging
 - ▶ Linear regression
- ▶ These (static) values of L and T are used for future forecasts

Example: Natural Gas

Period t	Season	Demand Dt	Deseasonalised demand	Seasonal factor	Deseas. Forecast	Actual Forecast	Avg. Seasonal factor	L	T
1	spring	8000							
2	summer	13000							
3	autumn	23000	19750	1.16			1.09	18439	524
4	winter	34000	20625	1.65			1.68		
5	spring	10000	21250	0.47			0.50		
6	summer	18000	21750	0.83			0.68		
7	autumn	23000	22500	1.02					
8	winter	38000	22125	1.72					
9	spring	12000	22625	0.53					
10	summer	13000	24125	0.54					
11	autumn	32000							
12	winter	41000							
13	spring				25251	12638			
14	summer				25775	17610			
15	autumn				26299	28755			
16	winter				26823	45143			
17	spring				27347	13687			

Adaptive forecasting

- The estimates of level, trend and seasonality are updated after each demand observations

L_t = estimate of level at end of period t (de-seasonalised)

T_t = estimate of trend at end of period t

S_t = estimate of seasonal factor for period t

D_t = actual demand observed for period t

F_t = forecast of demand for period t (made in period $t-1$ or earlier)

$$F_{t+k} = (L_t + kT_t)S_{t+k}$$

Moving Average

$$L_t = (D_t + D_{t-1} + \dots + D_{t-(N-1)}) / N$$

$$L_{t+1} = (D_{t+1} + D_t + D_{t-1} + \dots + D_{t-(N-2)}) / N$$

$$F_{t+k} = L_t \quad \text{for all } k$$

- ▶ Assumes no trend and no seasonality
- ▶ **Level** estimate is the average demand over most recent N periods
- ▶ Update: add latest demand observation and drop oldest
- ▶ Forecast for all future periods is the same
- ▶ Each period's demand equally weighted in the forecast
- ▶ *How to choose the value of N ?*
 - ▶ N large =>
 - ▶ N small =>

Simple Exponential Smoothing (No trend, no seasonality)

$$L_{t+1} = \alpha D_{t+1} + (1 - \alpha)L_t$$

$$F_{t+k} = L_t \quad \text{for all } k$$

- Rationale: recent past more indicative of future demand
- Update: **level** estimate is weighted average of latest demand observation and previous estimate
- α is called the **smoothing constant** ($0 \leq \alpha \leq 1$)
- **Forecast for all future periods is the same**
- Assume systematic component of demand is **the same** for all periods (L)
- L_t is the best guess at period t of what the systematic demand level is

Simple Exponential Smoothing - Example

$$L_0 = 22083 \quad \alpha = 0.1$$

$$F_1 = L_0$$

$$D_1 = 8000$$

$$E_1 = F_1 - D_1 = 22083 - 8000 = 14083$$

$$\begin{aligned} L_1 &= \alpha D_1 + (1 - \alpha)L_0 \\ &= (0.1)(8000) + (0.9)(22083) = 20675 \end{aligned}$$

$$F_2 = L_1 = 20675, \quad F_{10} = L_1 = 20675$$

Simple Exponential Smoothing

$$L_{t+1} = L_t - \alpha \underbrace{\left(\overbrace{L_t}^{F_{t+1}} - D_{t+1} \right)}_{E_{t+1}}$$

- Update: new **level** estimate is previous estimate adjusted by weighted forecast error
- *How to choose the value of the **smoothing constant** α ?*
 - Large $\alpha \Rightarrow$ responsive to change, forecast subject to random fluctuations
 - Small $\alpha \Rightarrow$ may lag behind demand if trend develops
- Incorporates more information but keeps less data than moving averages
 - Average age of data in exponential smoothing is $1/\alpha$
 - Average age of data in moving average is $(N+1)/2$

Understanding the exponential smoothing formula

$$\begin{aligned}
 L_{t+1} &= \alpha D_t + (1-\alpha)L_t \\
 &= \alpha D_t + (1-\alpha)(\alpha D_{t-1} + (1-\alpha)L_{t-1}) \\
 &= \alpha D_t + \alpha(1-\alpha)D_{t-1} + (1-\alpha)^2 L_{t-1} \\
 &\quad \vdots \\
 &= \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + \dots + \alpha(1-\alpha)^k D_{t-k} + \dots
 \end{aligned}$$

- Demand of *k-th* previous period carry a weight of $(1-\alpha)^k$ hence the name exponential smoothing
- Demand of more recent periods carry more weight

Exponential Smoothing with Seasonality (no trend)

- De-seasonalise demand data
- Apply exponential smoothing update
- Seasonalise forecast

$$\overline{D}_t = D_t / S_t$$

$$L_t = \alpha \overline{D}_t + (1 - \alpha) L_{t-1}$$

$$F_{t+k} = L_t S_{t+k} \quad \text{for all } k$$

Trend corrected exponential smoothing (Holt's model)

Update :

$$L_{t+1} = \alpha D_{t+1} + (1 - \alpha)(L_t + T_t)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t$$

Forecast :

$$F_{t+k} = L_t + kT_t$$

- ▶ β is the smoothing constant for trend updating
- ▶ If β is large, there is a tendency for the trend term to “flip-flop” in sign
- ▶ Typical β is α^2

Holt's model - Example

$$L_0 = 12015 \quad T_0 = 1549 \quad \alpha = 0.1 \quad \beta = 0.2$$

$$F_1 = L_0 + T_0 = 12015 + 1549 = 13564$$

$$D_1 = 8000$$

$$E_1 = F_1 - D_1 = 13564 - 8000 = 5564$$

$$\begin{aligned} L_1 &= \alpha D_1 + (1 - \alpha)(L_0 + T_0) \\ &= (0.1)(8000) + (0.9)(13564) = 13008 \end{aligned}$$

$$\begin{aligned} T_1 &= \beta (L_1 - L_0) + (1 - \beta)T_0 \\ &= (0.2)(13008 - 12015) + (0.8)(1549) = 1438 \end{aligned}$$

$$F_2 = L_1 + T_1 = 13008 + 1438 = 14446,$$

$$F_{10} = L_1 + 9 T_1 = 13008 + 9(1438) = 25950$$

Trend and seasonality corrected exponential smoothing (Winter's model)

Update :

$$L_{t+1} = \alpha \left(\frac{D_{t+1}}{S_{t+1}} \right) + (1 - \alpha)(L_t + T_t)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t$$

$$S_{t+1+p} = \gamma \left(\frac{D_{t+1}}{L_{t+1}} \right) + (1 - \gamma)S_{t+1}$$

Forecast :

$$F_{t+k} = (L_t + kT_t)S_{t+k}$$

Winter's model - Example

$$L_0 = 18439 \quad T_0 = 524 \quad S_1 = 0.47, S_2 = 0.68, S_3 = 1.17, S_4 = 1.67,$$

$$\alpha = 0.1, \quad \beta = 0.2, \quad \gamma = 0.1,$$

$$F_1 = (L_0 + T_0) S_1 = (18439 + 524)(0.47) = 8913$$

$$D_1 = 8000, \quad E_1 = F_1 - D_1 = 8913 - 8000 = 913$$

$$\begin{aligned} L_1 &= \alpha (D_1 / S_1) + (1 - \alpha)(L_0 + T_0) \\ &= (0.1)(8000 / 0.47) + (0.9)(18439 + 524) = 18769 \end{aligned}$$

$$\begin{aligned} T_1 &= \beta (L_1 - L_0) + (1 - \beta)T_0 \\ &= (0.2)(18769 - 18439) + (0.8)(524) = 485 \end{aligned}$$

$$\begin{aligned} S_5 &= \gamma (D_1 / L_1) + (1 - \gamma)S_1 \\ &= (0.1)(8000 / 18769) + (0.9)(0.47) = 0.465 \end{aligned}$$

$$F_2 = (L_1 + T_1)S_2 = (18769 + 485)(0.68) = 13093,$$

$$F_{11} = (L_1 + 10 T_1)S_{11} = (18769 + 10(485))(1.17) = 27634$$

Analysing Forecast Errors

- ▶ Monitor if current forecasting methods accurate
 - ▶ Consistently under-predicting? Over-predicting?
 - ▶ When should we adjust forecasting procedures?
- ▶ Understand magnitude of forecast error
 - ▶ In order to make appropriate contingency plans
- ▶ Assume we have data for n historical periods

$E_t = F_t - D_t =$ forecast error in period t

$A_t = |E_t| =$ absolute deviation for period t

Measures of Forecast Error

- Mean Square Error (MSE)
 - Estimate of variance (σ^2) of random component
- Mean Absolute Deviation (MAD)
 - If random component normally distributed, $\sigma=1.25 \text{ MAD}$
- Mean Absolute Percent Error (MAPE)

$$MSE_n = \frac{1}{n} \sum_{i=1}^n E_t^2$$

$$MAD_n = \frac{1}{n} \sum_{i=1}^n A_t$$

$$MAPE_n = \frac{100}{n} \left(\sum_{i=1}^n \left| \frac{E_t}{D_t} \right| \right)$$

Tracking Errors

- ▶ Errors due to:
 - ▶ Random component
 - ▶ Bias (wrong trend, shifting seasonality, etc.)
- ▶ Monitor quality of forecast with a tracking signal
- ▶ Alert if signal value exceeds threshold
 - ▶ Indicates underlying environment changed and model becomes inappropriate
- ▶ Tracking signal sometimes used as smoothing constant
 - ▶ Reactive, but often unstable in practice

$$bias_n = \sum_{i=1}^n E_t$$

$$TS_t = \frac{bias_t}{MAD_t}$$

Summary so far

- Importance of forecasting in a supply chain
- Forecasting models and methods
- Exponential smoothing
 - Stationary model
 - Trend
 - Seasonality
- Measures of forecast errors
- Tracking signals
- Regression models

Regression Analysis

- ▶ Statistical technique to determine the *degree of association* between set of variables and demand.
- ▶ Given values of the *predictor (independent)* variables, the regression equation provides a forecast of demand.

Simple Linear Regression

- Only one independent variable
- Time series:
 - how demand (dependent variable) changes over time (independent variable)
- Scatterplots

Dependent Variable	Independent Variable
Sales of wallpaper	No. of new apartments
Hang Seng Index level	No. of times Cheng Siu Chow appears on TV
No. of patients at CUHK clinic	No. of students taking exams

(Pearson's) Sample Correlation Coefficient

$$\underline{X} = (\sum x_i)/n \quad \underline{Y} = (\sum y_i)/n$$

$$S_x = \text{sqrt}(\sum (x_i - \underline{X})^2 / (n-1))$$

$$S_y = \text{sqrt}(\sum (y_i - \underline{Y})^2 / (n-1))$$

$$S_{xy} = \sum (x_i - \underline{X})(y_i - \underline{Y}) / (n-1)$$

$$r = S_{xy} / S_x S_y \quad -1 \leq r \leq 1$$

r measures how good the linear relationship is between the variables

Watch out for induced correlation trap!

Linear Regression

Find the relationship: $Y = a + b X$

For each data point (x_i, y_i) , the residual error is

$$e_i = y_i - (a + b x_i)$$

Choose a and b to minimise $\sum e_i^2$

$$b = \frac{SXY}{SX^2}, \quad a = \bar{Y} - b \bar{X}$$

Forecast: a new situation yields x' and the predicted value for Y is $a+bx'$

Least Squares Regression

$$y_c = a + bx$$

where

y_c = Predicted (dependent) variable

x = Predictor (independent) variable

b = Slope of the line

a = Value of y_c when $x = 0$ (i.e., y -intercept)

and

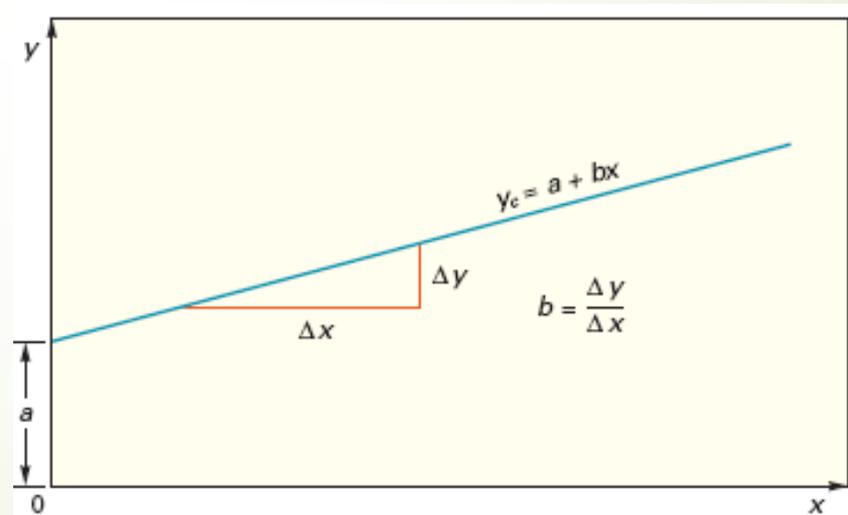
$$b = \frac{n \sum xy - \sum x \sum y}{n \sum x^2 - (\sum x)^2}$$

$$a = \frac{\sum y - b \sum x}{n} \text{ or } \bar{y} - b\bar{x}$$

where

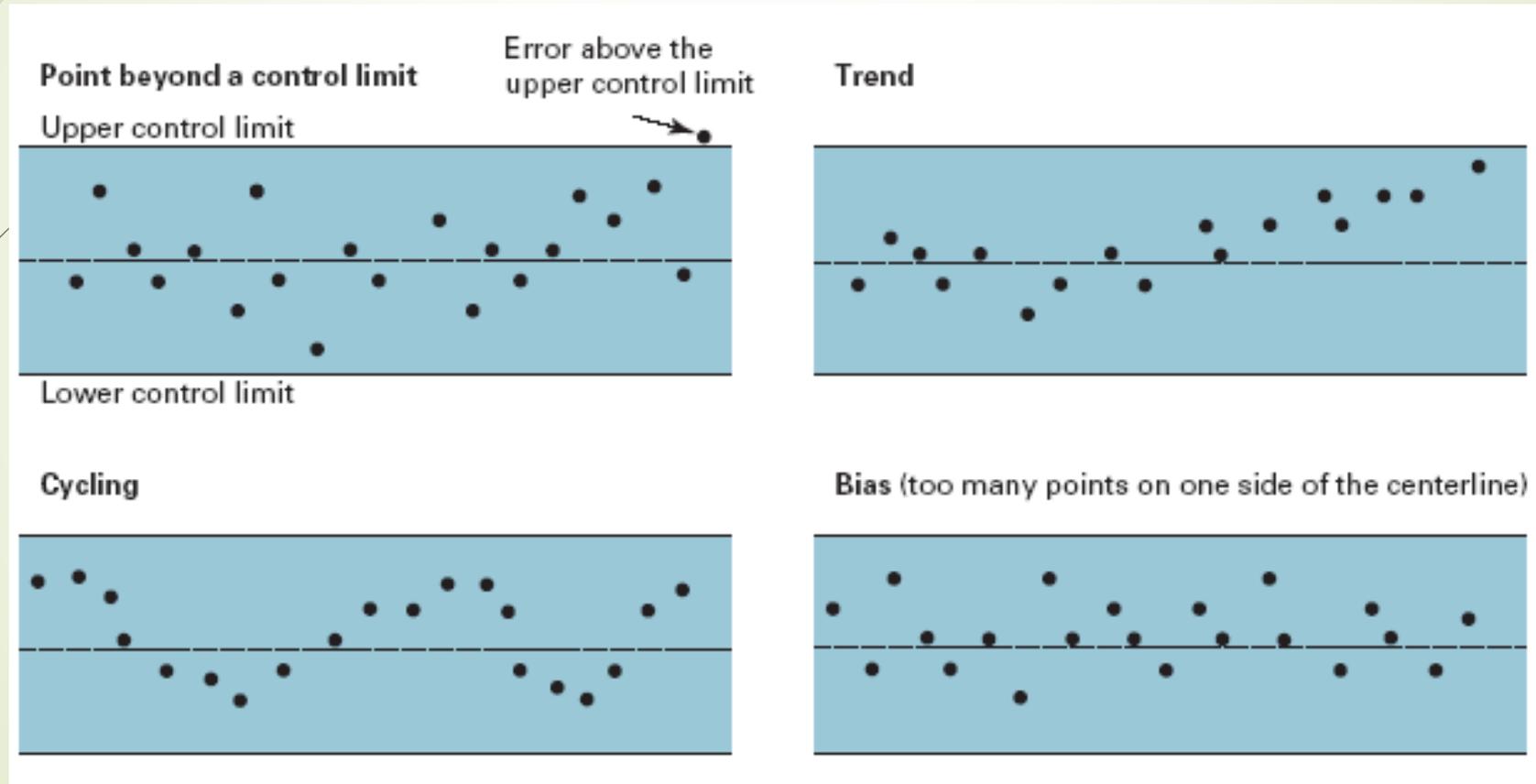
n = Number of paired observations

Forecasting



The line intersects the y axis where $y = a$. The slope of the line = b .

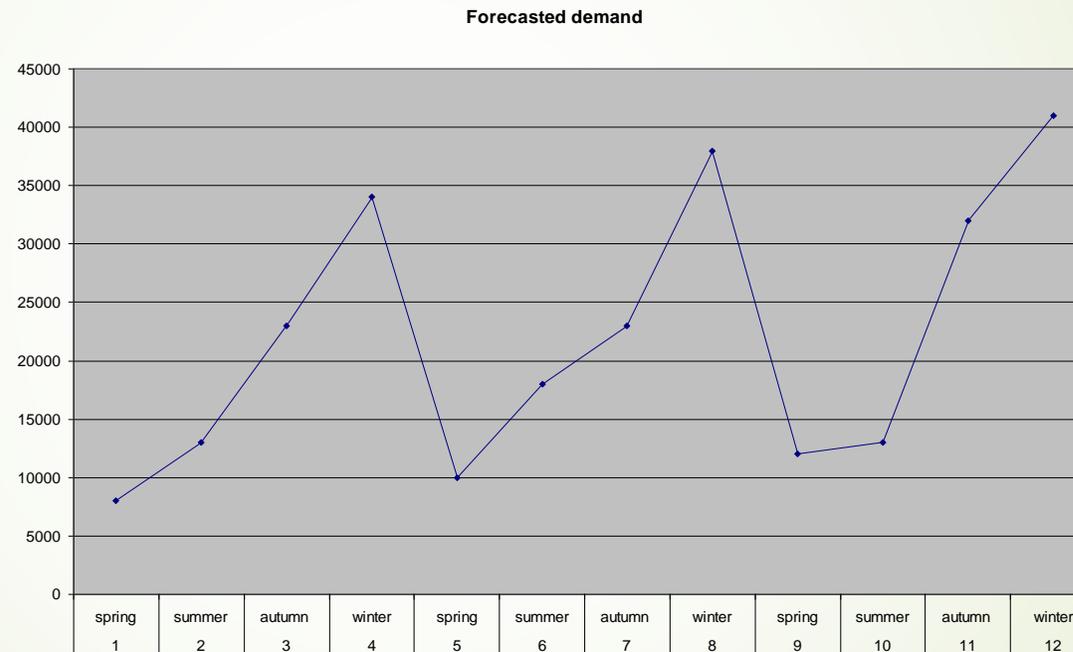
Nonrandom Errors



Special Forecasting Difficulties for Supply Chains

- New products and service introductions
 - No past history
 - Use qualitative methods until sufficient data collected
 - Examine correlation with similar products
 - Use a large exponential smoothing constant
- Lumpy derived demand
 - Large but infrequent orders
 - Random variations “swamps” trend and seasonality
 - Identify reason for lumpiness and modify forecasts
- Spatial variations in demand
 - Separate forecast vs. allocation of total forecasts

Managing (Predictable) Variability



How should we plan production to meet forecasted demand?

Managing Supply

- ▶ Chase strategy: production matches demand
 - ▶ No inventory
 - ▶ Capacity under-utilised during low demand periods
- ▶ Level (stable) production
 - ▶ High capacity utilisation
 - ▶ Personnel management/training simpler
 - ▶ Inventory build up in anticipation of seasonal demand variations; obsolescence risk
 - ▶ Order backlog; loss of goodwill
- ▶ Capacity vs. Inventory trade-off

Managing Capacity

- ▶ Time flexibility from workforce
 - ▶ More shifts during busy season
 - ▶ Overlapping shifts
 - ▶ Seasonal/Temporary workforce
- ▶ Subcontracting (Use of dual facilities)
 - ▶ Internal or main facility: focus on efficiency (low cost), level production
 - ▶ Peak demands subcontracted out or produced on more flexible facilities
- ▶ Designing product flexibility into the production process
 - ▶ Production lines re-configurable for different production rates
 - ▶ Complementary products produced in same facility (e.g. snowblowers and lawnmowers)

Managing Inventory

- ▶ Use common components across multiple products
 - ▶ Aggregate demand more stable (forecast more accurate)
 - ▶ Less obsolescence risk
- ▶ Build inventory of high demand or predictable demand items
 - ▶ Delay production of “fashion” items until closer to selling season

Managing Demand

- Promotion/Discount pricing
- Impact on demand
 - Market growth (attract new customers)
 - Increase overall demand
 - Stealing market shares (attract competitors' customers)
 - Increase overall demand
 - Forward buying (own customers buy earlier)
 - Demand "smoothing"?
- Timing of promotion: peak vs. non-peak
- Change in revenue vs. change in costs

Factors affecting promotion timing

<i>Factor</i>	<i>Favoured promotion time</i>
High forward buying	Low demand period
High stealing market share	High demand period
High market growth	High demand period
High margin product	High demand period
High inventory holding costs	Low demand period
Low production flexibility	Low demand period

Demand management

- Changes in demand impact production scheduling and inventory levels
 - Promotion at peak demand periods increases demand variability
 - Promotion at non-peak “smooths” demand
- Pricing and production planning must be done jointly
- **Preempt**, don't just react, to predictable variability
- Actively managing predictable variability can be a strategic competitive advantage

Flexibility and Quick Response

No forecast is perfect ...

There is no better forecast than the actual order!

- ▶ If supply chain is responsive, then effect of forecast errors is minimised
- ▶ Especially important when demand is unpredictable
- ▶ Example: National bicycle
 - ▶ Difficult to predict styles in sports bikes
 - ▶ Re-engineer supply chain
 - ▶ Customers design their own bike on Internet
 - ▶ Bike produced in Kashiwara and delivered in 2 weeks!

Summary

- Importance of forecasting
- Exponential smoothing models
 - Level, Trend, Seasonality
- Measuring forecast error; tracking
- Predictable variability
 - Managing supply
 - Managing demand
- Unpredictable variability?
- Co-ordinated management of supply and demand optimises profit
- Forecasting with Excel