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Forecasting

I. Learning and Experience Curves
- a. Concept
  - i. A company or person gets more efficient as he/she/it gains experience with a task or product
  - ii. Experience curves = At the company / industry level, measuring dollars instead of hours spent on a task
  - iii. $Y(u) = au^{-b}$ = number of hours it takes to produce the uth unit
    1. a = number of hours to produce the first unit
    2. b = learning coefficient / learning rate
  - iv. That's the most common representation but not the only form of learning curve
  - v. Can also express in terms of cumulative time or average time to produce a unit
- b. Types of Learning
  - i. Individual: People continue doing a job repeatedly; they gain efficiency
  - ii. Organizational: Management changes, better materials, et cetera
- c. Learning Percentage
  - i. For a 90% learning curve, what does that mean?
  - ii. The time it takes to produce the second unit is 90% of the time it took to produce the first unit.
  - iii. Unit 200 takes 90% as long as unit 100
  - iv. $Y(2u) / Y(u) = a(2u)^{-b} / au^{-b} = 2^{-b} = -90\%$
  - v. Learning coefficient thus corresponds to the percentage
  - vi. $b = -\log_2(0.9) = -\ln(0.9) / \ln(2)$ so $b = 0.152$
- d. Estimating the Learning Curve
  - i. Sometimes can lookup a "known" curve for a particular job
  - ii. Can also establish from your own performance data – fit a curve to the data
  - iii. Linear Relationship: $\ln(Y(u)) = \ln(a) – b \ln(u)$
  - iv. Or do simple regression analysis
- e. Using Learning Curves
  - i. The firm that grabs the largest market share early in the lifespan of a new generation of product will have the lowest cost (even if it's on the same percentage learning curve)
  - ii. Being on a lower percentage experience curve gives an advantage even at the same volume
  - iii. A firm with more experience can offer lower prices to get a bigger advantage
  - iv. Aggressive operations improvement: cost reductions due to experience
  - v. You initially want more flexibility (like a job shop). As volumes increase, move up the diagonal on the product-process matrix (up to line flow if you get high enough volumes)
  - vi. If you focus too much on the learning curve you may miss a chance to switch to a new product warranted by a radial shift in consumer tastes

II. Forecasting
- a. Introduction
  - i. Forecasting by and large is done for strategic, financial, marketing, sales, …
  - ii. Needed in order to undertake any business planning activity
  - iii. Different techniques work well for different types of forecasting
  - iv. Short-range forecasts are needed to plan operations; tend to be worthless everywhere else in the firm
  - v. Want objective techniques (regression-based or time series forecasts); those are good within Operations
- b. Gauging Accuracy
  - i. Say you're considering two methods of forecasting
    1. Method 1 is off by +/- 100 in alternate years
    2. Method 2 is off by +50 / -150.

        ii. Forecast Error is Actual Demand – Forecast
        iii. Mean Forecast Error: Method 1 looks better. Mean1 = 0, Mean2 = -50
        iv. Example
            1. Method 1 is +/- 100, Method 2 is +/- 50
            2. MFE = 0 for both, yet Method 2 obviously looks better
        v. Average Error Size (MAD – Mean Average Deviation)
            1. For Method 1 = 100
            2. For Method 2 = 50
        vi. Mean Squared Error: Now a large number (a large error) is made much worse than a smaller error
        vii. There are obviously tradeoffs between methods
    c. Time Series Forecasting
        i. Only historical data are considered; no other factors
        ii. There's always some randomness in actual demand. $D = \mu + \varepsilon_t$
        iii. Demand = Pattern(Mean) + Randomness
        iv. We don't want to even try forecasting actual demand; we just want to forecast the pattern
    d. Moving Averages
        i. Time series technique that works well when you're not worried about trend or seasonality
        ii. Average (mean) previous periods (say 3 months worth) and call that he forecast for all future periods
        iii. Selecting the number of periods
            1. Tradeoff stability and responsiveness
            2. Can't have both
            3. More periods = more stable
            4. Fewer periods = more responsive
            5. If you expect gradual changes, allow more responsiveness.
            6. If you expect lots of randomness, shoot for more stability.
        iv. Good when demand is stable over time
    e. Exponential Smoothing
        i. This is really a whole class of smoothing methods
        ii. We'll consider "simple" or "regular" smoothing
        iii. Forecast based on the previous forecast and on demand
        iv. $F_t = \alpha D_{t-1} + (1 - \alpha)F_{t-1}$
        v. $F_{t+k} = F_t$ for $k > 0$
        vi. Here α is the smoothing constant: the weight of each component
        vii. $F_t = F_{t-1} + \alpha(D_{t-1} – F_{t-1})$ where $D_{t-1} – F_{t-1}$ is the forecast error
        viii. You're changing your forecast by some fraction of the previous error
        ix. A third way to think about it:
            1. $F_t = \alpha D_{t-1} + \alpha(1-\alpha)^1 D_{t-2} + \alpha(1-\alpha)^2 D_{t-3} + \ldots$
            2. $F_t = \mathrm{SUM}(n=1, \infty, \alpha(1-\alpha)^{n-1} D_{t-n})$
        x. Just a weighted average of past demand, where weights just come from a formula
        xi. By choosing α correctly you can effectively weight, say, the first three periods as X% of the forecast
        xii. It's not quite a moving average but it's an average of past demand
        xiii. Choosing α: The Parameter
            1. Same stability vs. responsiveness decision again
            2. Small α means more stability (less weight on recent demand)
            3. Big α is more responsive
            4. There are software methods of picking α that gives the smallest MSE (or some other error)
        xiv. To get the "first" forecast, you need a forecast for the previous period. Using moving averages or something else to get that.

f. Can calculate the α and N that will give equivalent results
   i. $\alpha = 2 / (N + 1)$
   ii. $N = (2 - \alpha) / \alpha$
   iii. If you try both methods, they should perform equally well *in the long run*.
   iv. That doesn't mean they'll work the same in the short run
g. Trend Analysis
   i. The way you'd naturally do it in Excel
   ii. Good when you don't need to recomputed too often. Intense computations
   iii. Keep in mind:
      1. More sophistication is not necessarily better
      2. How much accuracy do we need?
   iv. Hult's method is an alternative to regression for trend analysis.

III. Seasonality
a. Want to reflect that demand swings in a sinusoidal way over seasons
b. Probably more important than trend
c. Could use sin/cos to estimate a curve
d. Could generate seasonal factors (multiplicative vs. additive)
e. Multiplicative
   i. Calculate the average of all periods
   ii. Then take each season's average / overall average
   iii. Tends to be long-run phenomenon: May not notice a trend in day-to-day data but might notice in longer time spans
   iv. May additionally have a trend within the seasonal data
   v. Compute demand / average to a ratio: how far above/below the average is each period?
   vi. Compute seasonal factors = straight average of ratios across all similar periods
   vii. Trend
      1. Average change in percentage in average yearly demand
      2. Use that as the increase to the forecast year T (from the (T – 1) average
      3. Then apply seasonal factors to get each period's forecast
   viii. Regression
      1. First deseasonalize demand
      2. Then do regression on all *those* data
      3. Then you've got only the trend data
f. Imagine a perfect trend data: 10, 11, 12, 13, 14
   i. The 5-period average will match where demand was right in the middle
   ii. With an even number of periods, the average belongs in between the middle *two* periods
   iii. Then take the two adjacent averages, average *them*, and that number belongs right in the middle