



Developing Risk Adjusted Results with Limited Data

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The Problem

- Need to give decision makers the best available data
- Risk is important
 - Point estimate alone could provide misleading results
- You want to include risk in your analysis
 - Cost or Benefits
 - Schedule risk possibly also applicable
- Time is limited
- Currently only have a point estimate

What to Do?



Quick Risk Methodology

- Original concept developed by Dr. Steve Book, MCR LLC
- Provides a simple approach for applying risk
- Requires only a few assumptions
 - Point Estimate (value and probability)
 - Overall uncertainty range
 - Most-Likely (Mode) probability (for some distributions)
- NOT a substitute for a complete analysis



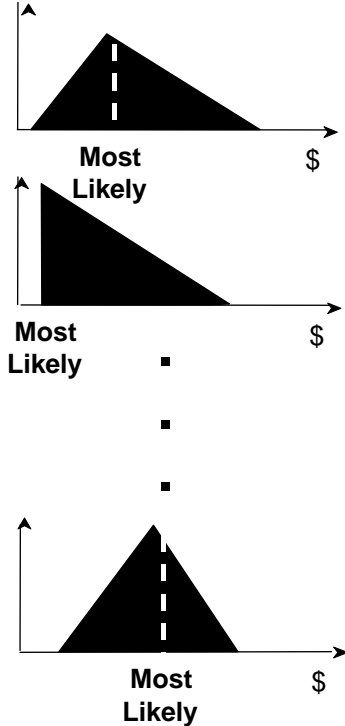
Conceptual Overview

- Risk Analysis is composed of assigning statistical distributions to individual components (e.g., WBS)
- Combine all these distributions into single total distribution
- “Quick Risk” skips these steps and creates the single “final” distribution directly
 - Based on typical results for the point estimate and range of the results
 - Initial development uses a simple Triangular distribution
 - Expanded to include Normal and Log-Normal
- Let’s now talk about the “typical” input values

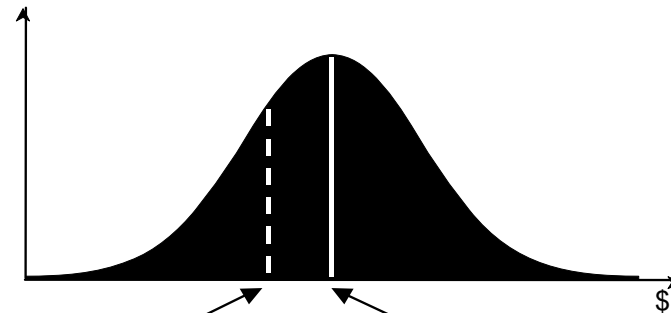


The "Point Estimate"

WBS -ELEMENT TRIANGULAR COST DISTRIBUTIONS



MERGE WBS - ELEMENT COST DISTRIBUTIONS INTO TOTAL - COST DISTRIBUTION



POINT ESTIMATE IS TYPICALLY ROLL -UP OF MOST LIKELY WBS -ELEMENT COSTS
(Historically and by Simulation between the 20th and 30th Percentiles)

MOST LIKELY TOTAL COST

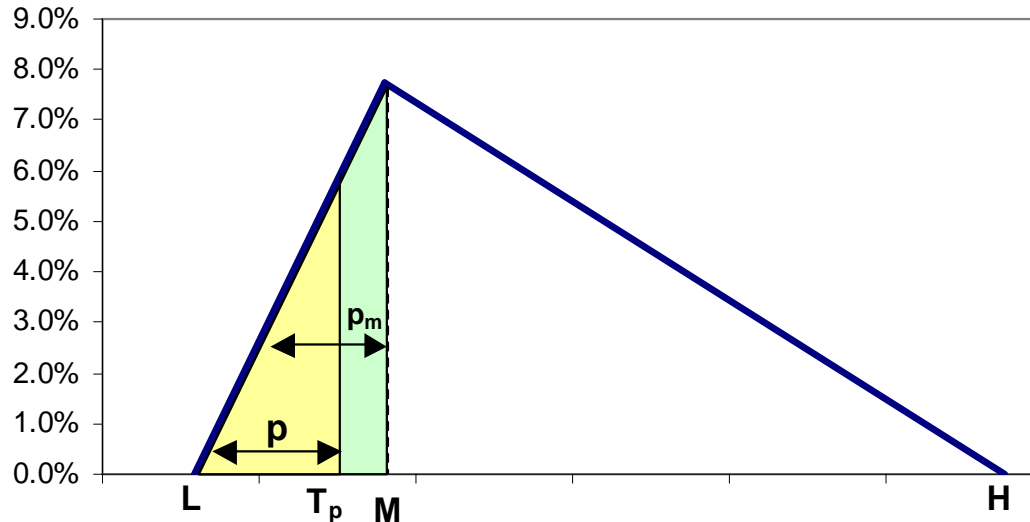


Uncertainty Range

- Basic uncertainty range defined by the ratio of the “high” and the “low” estimates
 - “High” is a reasonable upper bound
 - “Low” is a reasonable lower bound
 - Does not use the absolute difference (i.e., High – Low)
 - A Triangular Distribution has a built-in Upper & Lower limits
 - Normal Distribution (and similar) is infinite in extent (not reasonable for limits)
- Let’s start with the basic Triangular Distribution



Triangular Distribution



T_p is the point estimate (given)

P is the cumulative probability at the point estimate (assumed)

k is the ratio of high to low (assumed)

$$k = H/L$$

$$M = (1 - p_m)L + p_mH$$

M is the Mode or Most - Likely

p_m is the probability at the mode of the distribution (assumed)



Summary Triangular Equations

- Given the assumed values we can solve for the Triangular distribution parameters (L,M,H)

Two conditions apply:

$$L = \frac{T_p}{\left\{k - (k - 1)\sqrt{(1 - p)(1 - p_m)}\right\}} \quad \text{if } p \geq \frac{M - L}{H - L} = p_m$$

$$L = \frac{T_p}{\left\{1 + (k - 1)\sqrt{p \cdot p_m}\right\}} \quad \text{if } p \leq \frac{M - L}{H - L}$$

$$H = kL$$

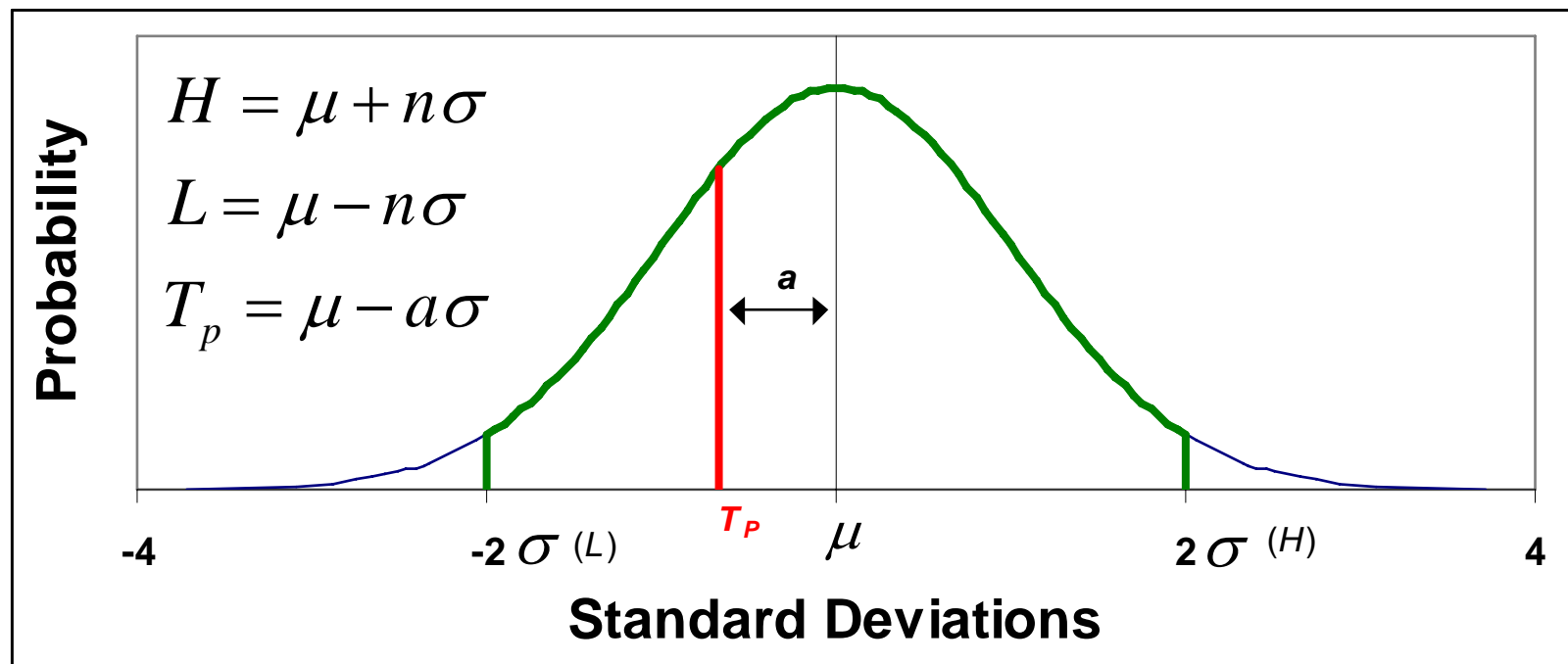
$$M = (1 - p_m)L + p_m H$$



Quick Risk – Normal Distribution

In a similar fashion we develop the method for a Normal Distribution using the concept of high and low values

* An important distribution due to the Central Limit Theorem



Note that the point estimate (T_p) is at the 25th percentile as a typical example only. Similarly the H and L are shown at $\pm 2\sigma$



Develop the Quick Risk Equations

- The Assumptions

T_p is the point estimate (given)

n is the number of standard deviations the "High/Low" are off the mean (assumed)

P is the cumulative probability at the point estimate (assumed)
thus a is simply the inverse normal at P

in Excel $a = -\text{norminv}(P,0,1)$

x is the ratio of high to low (assumed)

$x = H/L$



Normal Quick Risk Equations

- Given the previous assumptions we can solve for the unknowns (H , L , μ , σ):

$$L = \frac{2n T_p}{nx - ax + a + n}$$

$$H = xL = x \frac{2n T_p}{nx - ax + a + n}$$

$$\mu = \frac{(H + L)}{2}$$

$$\sigma = \frac{(H - L)}{2n}$$

The full development is provided in the backup along with the log-normal



Application

- Typical Values:
 - $p = 25\%$ with $n = 2$ (standard deviations)
 - for Triangular a $p_m = 30\%$
 - H/L can range from 2 to 8 depending on the program complexity
- Assess, based on the historical record of cost experience, the ratio H/L
 - Hardware: $H = 3L$
 - Software: $H = 8L$
 - Testing: $H = 2L$



Quick Risk Example

As an example here are the inputs for each of the methods developed here:

Normal: $n = 2$, $H/L = 3$, $T_p = 100$, $p = 25\%$

Triangular: $H/L = 3$, $T_p = 100$, $p = 25\%$, $P_m = 30\%$

Lognormal: $n = 2$, $H/L = 3$, $T_p = 100$, $p = 25\%$

Results at the 80% confidence level are:

Normal: 145.6

Triangular: 145.5

Lognormal: 151.6

We need a minimum of 46% more funding than at the point estimate.



What if it's a High Risk Project?

- Results at the 80% confidence level for $H/L = 8$, are :
- Normal: 180
- Triangular: 184.5
- Lognormal: 220

We need a minimum of 80 % more funding than the original estimate



Conclusions

- We developed a quick and “dirty” methodology for performing a “quick-risk” analysis given a simple point estimate and some simple assumptions
- Equations for using three different statistical distributions (Triangular, Normal & Log-Normal) have been developed and provided
- When combined with the assumptions, this methodology allows the decision maker to estimate the high-confidence cost or benefits and make a more informed decision
- Not a substitute for the detailed analysis



Questions?



Backup



Backup - Triangular

BACK UP Notes: “How to Make Your Point Estimate Look Like a Cost-Risk Analysis”

Triangular Distribution

For a quick risk analysis we begin solving below the triangular distribution equations.
We assume:

T_p = Point Estimate with p = to the cumulative probability at the point estimate

$H = kL$ where H is the High value in the triangular distribution and L is the Low value
 $M = xL + (1-x)H$ where M is the Mode or Most-Likely

where

$$x = 1 - p_m$$

and p_m is the cumulative probability at the mode of the distribution



Backup - Triangular

The two general equations for a Triangular Distribution are as follows:

$$T_p = H - \sqrt{(1-p)(H-L)(H-M)} \quad \text{if } p \geq \frac{M-L}{H-L} \quad 1)$$

and

$$T_p = L + \sqrt{p(M-L)(H-L)} \quad \text{if } p \leq \frac{M-L}{H-L} \quad 2)$$

where T_p is value of the distribution at cumulative probability²

In order to use these two equations we need to solve for one of the variables as a function of the given information. We have chosen to solve for L.

a) Starting with the triangular equation in case 1 we can solve for L:

First substitute for H and M into equation 1:

$$T_p = kL - \sqrt{(1-p)(H-L)(H-M)} = kL - \sqrt{(kL-L)(1-p)\{kL-xL-(1-x)kL\}}$$

Factor the L:

$$= kL - \sqrt{L(k-1)(1-p)L\{k-x-(1-x)k\}} = kL - L\sqrt{(k-1)(1-p)(k-x-k+qx)}$$

Simplify by factoring the (k-1):

$$= kL - L\sqrt{(k-1)(1-p)x(k-1)} = kL - L(k-1)\sqrt{x(1-p)} = L\{k - (k-1)\sqrt{x(1-p)}\}$$



Backup - Triangular

Finally solve for L:

$$L = \frac{T_p}{\left\{k - (k-1)\sqrt{(1-p)(1-p_m)}\right\}} \quad 3)$$

b) Starting with the triangular equation in case 2 we can solve for L:

First substitute for H and M into equation 1:

$$\begin{aligned} T_p &= L + \sqrt{p(M-L)(H-L)} = L + \sqrt{p\{xL + (1-x)kL - L\}(kL - L)} \\ &= L + \sqrt{pL\{x + (1-x)k - 1\}L(k-1)} = L + L\sqrt{p(x + k - kx - 1)(k-1)} \\ &= L + L\sqrt{p\{x(1-k) - (1-k)\}(k-1)} = L + L(k-1)\sqrt{p(1-x)} = L + \left\{1 + (k-1)\sqrt{p(1-1+p_m)}\right\} \end{aligned}$$

$$L = \frac{T_p}{\left\{1 + (k-1)\sqrt{p \cdot p_m}\right\}} \quad 4)$$



Backup - Normal

The more general form of the equations, allowing H & L to be any $n\sigma$ off the mean yields:

$$H = xL \quad (1)$$

$$H = \mu + n\sigma \quad (2)$$

$$L = \mu - n\sigma \quad (3)$$

$$T_p = \mu - a\sigma \quad (4)$$

$$a = -\text{norminv}(T_p, 0, 1)$$

In order to use these equations we need to solve for one of the variables as a function of the given information. We have chosen to solve for L. We begin by replacing H into L's equation (3) from above:

$$xL = \mu + n\sigma$$

$$\mu = xL - n\sigma$$

Then,



Backup - Normal

$$L = \frac{(\mu + n\sigma)}{x} = T_p + a\sigma - n\sigma$$

From equation (2) we know:

$$\mu = L + n\sigma$$

It follows that:

$$\mu = xT_p + xa\sigma - n\sigma x - n\sigma$$

$$L = xT_p + xa\sigma - n\sigma x - 2n\sigma \stackrel{T_p}{=} + a\sigma - n\sigma$$

$$xT_p + xa\sigma - n\sigma x - 2n\sigma - a\sigma + n\sigma \stackrel{T_p}{=} - \cancel{T_p}$$

$$a\sigma(x-1) - n\sigma x - n\sigma = T_p - \cancel{T_p}$$

$$a\sigma(x-1) - n\sigma x - n\sigma = T_p - \cancel{T_p}$$

$$\sigma = \frac{(T_p - xT_p)}{a(x-1) - nx - n}$$

$$L = T_p + a \frac{(T_p - xT_p)}{a(x-1) - nx - n} - n \frac{(T_p - xT_p)}{a(x-1) - nx - n} = \frac{2nT_p}{nx - ax + a + n}$$

$$L = \frac{2nT_p}{nx - ax + a + n}$$



Backup - Normal

$$H = x \frac{2n T_p}{nx - ax + a + n}$$

Summing the following equations from above:

$$H = \mu + n\sigma$$

$$L = \mu - n\sigma$$

We determine:

$$\mu = \frac{(H + L)}{2}$$

Therefore,

$$\sigma = \frac{(H - \mu)}{n} = \frac{H}{n} - \frac{H + L}{2n} = \frac{H - L}{2n}$$

$$\sigma = \frac{(H - L)}{2n}$$



Quick-Risk LogNormal Distribution

•The Assumptions:

$z = \text{Ratio of } H / L$

$H = zL$

T_P : Point Estimate @ $c = \text{Selected Percentile (e.g., 25\%)}$

and $n = \text{implicit confidence level}$

let

$\alpha = \text{mean in Normal Space}$

$\beta = \text{Standard Deviation in Normal Space}$

then

$\ln(H) = \alpha + n\beta$ in Normal Space

$\ln(L) = \alpha - n\beta$ in Normal Space

$\ln(H) - \ln(L) = \ln(z)$

$a = -\text{norminv}(c, 0, 1)$

$\ln(T_P) = \alpha - a\beta$



Summary Quick-Risk LogNormal Equations

Solving :

$$\beta = \ln(z) / 2n$$

$$\alpha = \ln(T_P) + a \ln(z) / 2n$$

$$\mu = \exp\left(\alpha + \frac{\beta^2}{2}\right)$$

$$\sigma^2 = \exp(2\alpha + \beta^2) (\exp(\beta^2) - 1)$$



Backup - LogNormal

Extending the method to a Log-Normal distribution is only a little more complicated than the Normal distribution.

The first step is to convert to “Normal” space by taking the natural logarithm of the values. Thus if your point estimate is 100 then in “Normal” space value is $\ln(100)$ or 4.60517.

Given:

$z = \text{Ratio of } H / L$

$H = zL$

P : Point Estimate @ $c =$

Selected Percentile (e.g., 25%)

and $n =$ implicit confidence level

let

$\alpha =$ mean in *Normal Space*

$\beta =$ Standard Deviation in *Normal Space*

then

$\ln(H) = \alpha + n\beta$ in *Normal Space*

$\ln(L) = \alpha - n\beta$ in *Normal Space*

$\ln(H) - \ln(L) = \ln(z)$

$a = -\text{norminv}(c, 0, 1)$

$\ln(P) = \alpha - a\beta$

solving :

$\ln(H) - \ln(L) = 2n\beta = \ln(z) \Rightarrow \beta = \ln(z) / 2n$

$\ln(P) + a\beta = \alpha \Rightarrow \alpha = \ln(P) + a \ln(z) / 2n$

$\mu = \exp\left(\alpha + \frac{\beta^2}{2}\right)$

$\sigma^2 = \exp(2\alpha + \beta^2)(\exp(\beta^2) - 1)$