

UNCERTAINTY MODELING ENHANCEMENT CONCEPTS IN QRA METHODOLOGY

Robert Baker; A-P-T Research, Inc. John Tatom; A-P-T Research, Inc. Paper 20706



OUTLINE

- Background: Explosive Risk Methodology
- Overview of Recent Analysis
- Results
 - Part 1
 - Part 2
 - Parts 3a, 3b, and 3c
 - Part 4
- Conclusions
- References



- The DDESB has developed and continuously improved its approved methodology for estimating explosives risks over a 20-year period.
 - This methodology is described in detail in DDESB Technical Paper 14 (TP-14).
 - Current edition is Revision 4a; Revision 5 is currently being drafted
- In 2002-2003, it was recognized that a state-of-the-art tool must incorporate the uncertainties involved in estimating risk.
- Various reviews during the last 15 years have suggested potential changes to the risk model:
 - Using different statistical distributions to model individual sub-elements of risk (currently all submodels are represented by lognormal distributions).
 - Shifting sub-model point estimates to the mean of each element distribution (currently point estimates are treated as the distribution median).
- In 2017, the Risk Assessment Program Team completed a task to confirm that the Analytical methodology currently in use could successfully incorporate these two changes. This paper reports the findings of this study.



Risk Methodology Background ANALYTICAL MODEL (REF. 1)

 $E_{\rm ep}(E{\sf F}) = E_{\rm ep}(\Delta t)^* E_{\rm ep}({\sf S})^* E_{\rm ep}[E(\lambda^*{\sf E})]^* E_{\rm ep}[E({\sf p}_{\rm f/e})]$

 $= \Delta t_o^* \exp(0.5\sigma_{\Delta t}^2)^* S_o^* \exp(0.5\sigma_S^2)^* E_{ep}[E(\lambda^* \mathsf{E})]^* E_{ep}[E(\mathsf{p}_{\mathsf{f}/e})]$

Where:

 $E_{\rm ep}(\Delta t) = \Delta t_{\rm o}^* \exp(0.5\sigma_{\Delta t}^2)$

 $E_{\rm ep}(S) = S_{\rm o}^* \exp(0.5\sigma^2_{\rm S})$

The Analytical Model computes risk as the product of elemental sub-models addressing the annual Probability of Event, Scaling Factors addressing handling conditions, the Probability of Fatality given an event, and the Exposure of personnel to the explosives hazard.

$$E_{\rm ep}[E(\lambda^*{\sf E})] = \lambda_{\rm oo}^*E_{\rm oo}^*\exp[0.5(\sigma_{\lambda o}^2 + \sigma_{\sf Eo}^2 + \sigma_{\sf NEW1}^2 + (r+1)^{2*}\sigma_{\rm e}^2 + 2(r+1)^*\rho_{\sf Ne}^*\sigma_{\sf NEW1}^*\sigma_{\rm e})]$$

 $E_{ep}[E(p_{f/e})] = \sum_{k} p_{f/k,oo} * exp[0.5(\sigma_{k1}^{2} + \sigma_{ko1}^{2})] - \sum_{i \neq k} p_{f/i,oo} * p_{f/k,oo} * exp[0.5(\sigma_{ik}^{2} + \sigma_{iko}^{2})] + \sum_{i \neq j \neq k} p_{f/i,oo} * p_{f/j,oo} * p_{f/k,oo} * exp[0.5(\sigma_{ijk}^{2} + \sigma_{iko}^{2})] - (\prod_{k} p_{f/k,oo})^{*} exp[0.5(\sigma_{1234}^{2} + \sigma_{12340}^{2})]$

And variances are respectively:

$$\begin{aligned} \sigma_{k1}^{2} &= \sigma_{k0}^{2} + \sigma_{y}^{2} + \sigma_{NEW2}^{2} \\ \sigma_{k01}^{2} &= \sigma_{k0}^{2} + \sigma_{y0}^{2} \\ \sigma_{ik}^{2} &= \sigma_{i}^{2} + \sigma_{k}^{2} + 2(\sigma_{y}^{2} + \sigma_{NEW2}^{2}) \\ \sigma_{ik0}^{2} &= \sigma_{i0}^{2} + \sigma_{k0}^{2} + 2\sigma_{y0}^{2} \\ \sigma_{ijk}^{2} &= \sigma_{i}^{2} + \sigma_{j}^{2} + \sigma_{k}^{2} + 3(\sigma_{y}^{2} + \sigma_{NEW2}^{2}) \\ \sigma_{ijk0}^{2} &= \sigma_{i0}^{2} + \sigma_{j0}^{2} + \sigma_{k0}^{2} + 3\sigma_{y0}^{2} \\ \sigma_{1234}^{2} &= \Sigma_{k}\sigma_{k}^{2} + 4(\sigma_{y}^{2} + \sigma_{NEW2}^{2}) \\ \sigma_{12340}^{2} &= \Sigma_{k}\sigma_{k0}^{2} + 4\sigma_{y0}^{2} \end{aligned}$$

- The DDESB-approved methodology directly calculates the Expected Value of Fatalities (EF) using an analytical approach.
- This analytical approach models the resulting risk using a lognormal distribution.



Risk Methodology Background MONTE CARLO EXPERIMENT (REF. 2)



Monte Carlo experiments provide another approach to combine the element distributions to estimate EF and the risk distribution.

A-P-T Research, Inc. | 4950 Research Drive, Huntsville, AL 35805 | 256.327.3373 | www.apt-research.com ISO 9001:2015 Certified



STANDARD TEST CASES

		Part 1: Or	iginal Values -	Point Estimate	e = Median
INPUT VARIABLES	S	Case 1	Case 2	Case 3	Case 4
median value of delta t	∆t₀	2.28E-02	2.28E-02	2.28E-01	2.28E-01
std dev of delta t	$\sigma_{\Delta t}$	6.93E-01	2.31E-01	2.23E-01	6.93E-01
median value of scale factor	S₀	3.00E+00	3.00E+00	1.00E+01	3.00E+00
std dev of SF	σ_{s}	1.70E-01	1.70E-01	7.68E-01	1.70E-01
median value of lambda	λο	1.00E-05	3.00E-06	1.00E-04	3.00E-05
std dev of lambda	σ_{λ}	5.36E-01	3.66E-01	5.36E-01	6.49E-01
Ep Median Daily Exposure	E _{oo}	2.28E-02	2.28E-02	2.28E+01	2.28E+02
Rand Var std dev Exposure	σ_{e}	9.99E-01	2.31E-01	7.68E-01	6.08E-02
Ep std dev of Exposure	σ_{Eo}	4.05E-01	0.00E+00	6.93E-01	0.00E+00
Ep Median Pf e blast	P _{f 100}	2.96E-09	2.96E-09	2.96E-09	2.96E-09
Ep Median Pf e bldg collapse	P _{f 200}	2.35E-10	1.00E-15	3.66E-10	4.87E-02
Ep Median Pf e debris	P _{f 300}	1.75E-08	2.00E-10	3.35E-03	1.06E-06
Ep Median Pf e glass	P _{f 400}	1.00E-10	1.00E-15	1.00E-10	1.00E-15
Std Dev Pf e due to Yield	σ _y	1.21E+00	0.00E+00	3.15E-02	1.60E-01
Ep std dev Pf e due to Yield	σ_{yo}	3.66E-01	3.66E-01	3.66E-01	3.66E-01
Std Dev Pf e due to NEW	σ_{NEW}	9.69E-01	0.00E+00	0.00E+00	1.36E-01
std dev for variation in o/p	σ1	7.15E-01	7.15E-01	7.15E-01	0.00E+00
std dev for variation in b/c	σ2	7.06E-01	7.06E-01	7.06E-01	2.55E-01
std dev for variation in debris	σ_3	8.66E-01	8.66E-01	8.66E-01	1.10E-01
std dev for variation in glass	σ_4	8.83E-01	8.83E-01	8.83E-01	0.00E+00
Ep std dev for overpressure	σ_{1o}	3.49E-01	3.49E-01	3.49E-01	3.49E-01
Ep std dev for bldg damage	σ_{2o}	5.71E-01	5.71E-01	5.71E-01	5.71E-01
Ep std dev for debris	σ_{30}	6.35E-01	6.35E-01	6.35E-01	6.35E-01
Ep std dev for glass	σ_{40}	8.83E-01	8.83E-01	8.83E-01	8.83E-01

Experimental Parameters					
Outer Loop: K Reps 50,000					
Inner Loop: Y Years	50,000				
Random Number Seed	35611				

In 2003, four standard test cases were devised to represent the four corners of the envelope:

- Low Risk, Low Uncertainty
- Low Risk, High Uncertainty
- High Risk, Low Uncertainty
- High Risk, High Uncertainty



ANALYSIS PROCESS OVERVIEW



The study was divided into four parts to examine the impacts on the model if various combinations of distributions and point estimate usage were implemented.



PART 1: ALL LOGNORMAL DISTRIBUTIONS, POINT ESTIMATES USED AS MEDIAN

Part 1 demonstrated that the Analytical and Monte Carlo tools used to validate original methodology produce the same results as in 2003.

Solution Method	Part 1, Case 1 (Low-Wide)			Part 1, Case 2 (Low-Narrow)		
Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method (2003)	5.26E-15	9.29E-15	1.83E-14	2.54E-17	1.93E-17	6.14E-17
Analytical Method (2017)	5.26E-15	9.29E-15	1.83E-14	2.54E-17	1.93E-17	6.14E-17
Monte Carlo (2003)	5.28E-15	9.39E-15	1.81E-14	2.55E-17	1.91E-17	6.08E-17
Monte Carlo (2017)	5.28E-15	9.39E-15	1.81E-14	2.55E-17	1.91E-17	6.08E-17

Solution Method	Part 1, Case 3 (High-Wide)			Part 1, Case 4 (High-Narrow)		
Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method (2003)	9.00E-05	2.20E-04	3.37E-04	4.85E-04	8.42E-04	1.68E-03
Analytical Method (2017)	9.00E-05	2.20E-04	3.37E-04	4.85E-04	8.42E-04	1.68E-03
Monte Carlo (2003)	9.01E-05	2.18E-04	3.38E-04	4.87E-04	8.45E-04	1.68E-03
Monte Carlo (2017)	9.01E-05	2.18E-04	3.38E-04	4.87E-04	8.45E-04	1.68E-03



PART 2: ALL LOGNORMAL DISTRIBUTIONS, POINT ESTIMATES USED AS MEAN

Part 2 repeated a previous study that demonstrated the Analytical uncertainty model is valid when sub-model point estimates are treated as the means of element distributions.

Solution Method	Part 2, Case 1 (Low-Wide)			Part 2, Case 2 (Low-Narrow)		
Solution Method	MethodPart 2, Case 3MethodExpect ValStdytical Method3.25E-165.67(Monte Carlo)3.26E-165.71A%0.31%0.7	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	3.25E-16	5.67E-16	1.12E-15	1.48E-17	1.13E-17	3.60E-17
Experimental (Monte Carlo)	3.26E-16	5.71E-16	1.13E-15	1.49E-17	1.13E-17	3.58E-17
Δ%	0.31%	0.71%	0.89%	0.68%	0.00%	0.56%

Solution Method	Part 2, Case 3 (High-Wide)			Part 2, Case 4 (High-Narrow)		
Solution Wethod	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	1.74E-05	4.27E-05	6.54E-05	2.29E-04	3.97E-04	7.93E-04
Experimental (Monte Carlo)	1.74E-05	4.23E-05	6.54E-05	2.30E-04	3.98E-04	7.90E-04
Δ%	0.00%	0.94%	0.00%	0.44%	0.25%	0.38%



COMPARISON - PARTS 1 AND 2

Part 2 also confirmed previous results demonstrating that the risk estimate is reduced when Point Estimates are applied as the Mean of elemental distributions rather than as the Median.

Analytical Solution Method	Case 1 (Low-Wide)			Case 2 (Low-Narrow)		
Analytical Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Part 1: Point Estimate = Median	5.26E-15	9.29E-15	1.83E-14	2.54E-17	1.93E-17	6.14E-17
Part 2: Point Estimate = Mean	3.25E-16	5.67E-16	1.12E-15	1.48E-17	1.13E-17	3.60E-17
% Reduction	93.82%	93.90%	93.88%	41.73%	41.45%	41.37%

Appletical Colution Mathed	Case 3 (High-Wide)			Case 4 (High-Narrow)		
Analytical Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Part 1: Point Estimate = Median	9.00E-05	2.20E-04	3.37E-04	4.85E-04	8.42E-04	1.68E-03
Part 2: Point Estimate = Mean	1.74E-05	4.27E-05	6.54E-05	2.29E-04	3.97E-04	7.93E-04
% Reduction	80.67%	80.59%	80.59%	52.78%	52.85%	52.80%



PART 3A: ALL TRIANGULAR DISTRIBUTIONS, POINT ESTIMATES USED AS MEDIAN

- Part 3a explored the validity of using non-lognormal element distributions. In 3a, each sub-model distribution was represented by a triangular distribution.
- Results show excellent agreement in modeled Expected Value and comparable values for Standard Deviation and 95th percentiles.

Solution Method	Part 3a, Case 1 (Low-Wide)			Part 3a, Case 2 (Low-Narrow)		
Solution Wethod	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	6.00E-11	6.46E-11	1.73E-10	2.29E-15	2.16E-15	6.19E-15
Experimental (Monte Carlo)	5.96E-11	7.08E-11	1.99E-10	2.28E-15	2.44E-15	7.15E-15
۵%	0.72%	9.58%	14.85%	0.43%	13.20%	15.47%

Solution Method	Part 3a, Case 3 (High-Wide)			Part 3a, Case 4 (High-Narrow)		
Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	1.01E-02	1.13E-02	2.97E-02	7.42E-04	7.48E-04	2.07E-03
Experimental (Monte Carlo)	1.01E-02	1.29E-02	3.41E-02	7.37E-04	9.31E-04	2.58E-03
۵%	0.74%	13.72%	14.93%	0.72%	24.41%	24.46%



PART 3B: ALL NORMAL DISTRIBUTIONS, POINT ESTIMATES USED AS MEDIAN

- Part 3b explored the validity of using another non-lognormal distribution. In 3b, each sub-model distribution was represented by a normal distribution.
- Results again show excellent agreement in modeled Expected Value and comparable values for Standard Deviation and 95th percentiles.

Solution Method	Part 3b, Case 1 (Low-Wide)			Part 3b, Case 2 (Low-Narrow)		
Solution Wethod	ethod Expect Val Std Dev cal Method 3.25E-16 1.21E-10 onte Carlo) 3.25E-16 1.22E-11 Δ% 0.10% 0.58%	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	3.25E-16	1.21E-16	5.51E-16	1.48E-17	5.61E-18	2.53E-17
Experimental (Monte Carlo)	3.25E-16	1.22E-16	5.47E-16	1.48E-17	5.00E-18	2.40E-17
۵%	0.10%	0.58%	0.64%	0.31%	10.81%	5.23%

Solution Method	Part 3b, Case 3 (High-Wide)			Part 3b, Case 4 (High-Narrow)		
Solution Wethod	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	1.75E-05	6.69E-06	3.00E-05	2.28E-04	8.76E-05	3.92E-04
Experimental (Monte Carlo)	1.75E-05	6.02E-06	2.85E-05	2.29E-04	7.84E-05	3.72E-04
۵%	0.18%	10.00%	5.07%	0.45%	10.46%	5.09%



MIXED DISTRIBUTIONS – PARTS 3C AND 4

Input Distribution	Variable	Normal	Lognormal	Triangular
D-11-1	Median of delta t	~		
Delta t	Std dev of delta t	×		
Coolo Footor	Median of Scale Factor	bleNormalLognormtXXFactorXFactorXFactorXlaXdaXExposureXposureXv ExposureXblastXastXbldg collapseXdg collapseXtion in bldgXdebrisXstsXtion in bldgXXXtion in glassXtion in glassXtion in glassXto YieldXto NEWX		v
Scale Factor	Std dev of Scale Factor			^
l analada	Median of lambda	X 29 10 10 10 10 10 10 10 10 10 10 10 10 10		
Imput Distribution Delta t Scale Factor Scale Factor Sambda Daily Exposure Blast Building Collapse Debris Glass Yield	Std dev of lambda		^	
	Ep Median Daily Exposure	×	X X X X	
Daily Exposure	Ep std dev of Exposure	^		
Blast	Rand Var std dev Exposure			X
	Ep Median Pfle blast		v	
Blast	Ep std dev for blast		~	
	Std dev for variation in blast	X		
	Ep Median Pfle bldg collapse		v	
Puilding Collance	Ep std dev for bldg collapse		^	
building Collapse	Std dev for variation in bldg collapse	x		
	Ep Median Pfle debris		×	
Debris	Ep std dev for debris		*	
	Std dev for variation in debris	X	-	
	Ep Median Pfle glass			
Glass	Ep std dev for glass		~	
	Std dev for variation in glass	X		
Viald	Ep std dev Pfle due to Yield		X	
TIEIU	Std dev Pfle due to Yield	X		
NEW	St dev Pfe due to NEW		X	

A mixture of Normal, Lognormal, and Triangular distributions was used for study Parts 3c and 4.



PART 3C: MIXTURE OF DISTRIBUTIONS, POINT ESTIMATES USED AS MEDIAN

- Part 3c explored the validity of using a mixture of elemental distributions. In Part 3c, element models used lognormal, normal, or triangular distributions.
- The Analytical and Monte Carlo approaches produced comparable values for Expected Value, Standard Deviation, and 95th percentiles.

Solution Method	Part 3c, Case 1 (Low-Wide)			Part 3c, Case 2 (Low-Narrow)		
	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	5.51E-15	4.57E-15	1.39E-14	1.30E-16	8.35E-17	2.88E-16
Experimental (Monte Carlo)	5.80E-15	6.30E-15	1.68E-14	1.38E-16	1.02E-16	3.30E-16
Δ%	5.27%	37.78%	20.57%	5.90%	22.49%	14.48%

Solution Method	Part 3c, Case 3 (High-Wide)			Part 3c, Case 4 (High-Narrow)		
	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	3.66E-04	4.87E-04	1.16E-03	3.23E-04	3.70E-04	9.57E-04
Experimental (Monte Carlo)	3.85E-04	5.53E-04	1.30E-03	3.38E-04	4.26E-04	1.04E-03
Δ%	5.26%	13.51%	11.94%	4.63%	15.21%	8.50%



PART 4: MIXTURE OF DISTRIBUTIONS, POINT ESTIMATES USED AS MEAN

- Part 4 validated that the two changes could be successfully used together. In this part, point estimates were used as means for a mixture of distributions.
- The Analytical and Monte Carlo approaches produced comparable values for Expected Value, Standard Deviation, and 95th percentiles.

Solution Method	Part 4, Case 1 (Low-Wide)			Part 4, Case 2 (Low-Narrow)		
	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	3.92E-15	3.24E-15	9.90E-15	1.12E-16	7.22E-17	2.49E-16
Experimental (Monte Carlo)	4.13E-15	4.44E-15	1.19E-14	1.19E-16	8.85E-17	2.85E-16
Δ%	5.34%	36.92%	19.78%	5.93%	22.62%	14.37%

Solution Mothod	Part 4, Case 3 (High-Wide)			Part 4, Case 4 (High-Narrow)		
Solution Method	Expect Val	Std Dev	95th %	Expect Val	Std Dev	95th %
Analytical Method	2.35E-04	3.12E-04	7.42E-04	2.19E-04	2.51E-04	6.49E-04
Experimental (Monte Carlo)	2.47E-04	3.54E-04	8.32E-04	2.29E-04	2.89E-04	7.04E-04
Δ%	5.01%	13.50%	12.11%	4.70%	15.22%	8.55%



SHOULD THE RESULTING DISTRIBUTION BE MODELED AS LOGNORMAL?

- The final risk distribution is modeled as lognormal because Risk is the product of the element distributions [Central Limit theory].
- Histograms of the Monte Carlo experiments for the four test cases in Part 4 are comparable to lognormal curves computed using the mean and standard deviation computed by both the Analytical and Monte Carlo approaches.





CONCLUSIONS

- 1. Use of non-lognormal distributions to represent input variables does not "break" the TP-14 Analytical model of uncertainty which assumes the output risk results in a lognormal distribution.
 - Monte Carlo experiment does not assume a form for the output distribution.
 - Histograms demonstrate that the results follow a lognormal distribution.
- 2. Assigning elemental model point estimates as the mean rather than the median of the input distributions does not "break" the TP-14 Analytical model of uncertainty.
 - Agreement of Analytical and Monte Carlo results for Part 2 compares well to that of Part 1.
 - Risk estimates are reduced when Point Estimates are applied as the Mean.
 - Agreement between the two methods for Part 4 compares well to that of Part 3c.
 - Part 4 to Part 3c comparison demonstrates that the shift from median to mean does not depend on use of lognormally distributed element variables.

- 3. Agreement between Analytical and Monte Carlo results for Expected Value was significantly better than that observed for the standard deviation and 95th percentile.
 - This is due to the more straightforward modeling of expected values in the Analytical method. Variance equations are much more extensive, requiring additional study.
- 4. Use of a mix of distributions, including non-lognormal distributions, to model input variables does not "break" the ability to develop an analytical model to directly calculate parameters of the output risk distribution.
 - Results showed that Analytical results compare well with Monte Carlo experiments using a variety of distribution types.



REFERENCES

- 1. Mensing, Richard W., PhD. 2004. "An Analytical Approach for Treating Uncertainty in Probabilistic Risk Assessments." Analytics International Corp.
- 2. Baker, Bob, Dr. John Hall, Tom Pfitzer, Kristy Newton. 2004. "Uncertainty as Modeled in SAFER 3.0." APT Research, Inc.
- 3. Hardwick, Meredith J, Dr John Hall, John Tatom, Robert Baker. 2008. "Approved Methods and Algorithms for DoD Risk-based Explosives Siting." DDESB/APT Research, Inc.
- 4. van Bavel, Gregory H. 2011. "Uncertainty and the Safety Assessment for Explosives Risk (SAFER)." Defence R&D Canada, Center for Operational Research and Analysis.
- 5. Hall, John D, PhD, Bob Baker, Mary Robinson, and Dustin Nix. 2017. "TP-14 Rev 4a Uncertainty Task Final Report – Quantitative Risk Assessment (QRA) Methodology Enhancement." APT Research, Inc.
- 6. Flores, Jorge, et al. 2012. "Uncertainty Treatment in Risk Based Explosives Safety Modeling White Paper." APT Research, Inc.