Comments on the
Office of Management and Budget Proposed Risk Assessment Bulletin
Prepared by the International Council on Systems Engineering
Risk Management Working Group
Mark A. Powell, Chair
Submitted: 15 July 2006

Page 6: *Actuarial Analysis of Real-World Human Data*

Change:

"When large amounts of historic data from humans are available, an actuarial risk assessment may be performed using classical statistical tools."

To:

"When large amounts of historic data from humans are available, an actuarial risk assessment may be performed using either classical statistical tools or Bayesian statistical tools. Both classical statistical tools and Bayesian statistical tools will provide coincidental results, although the interpretation will be different."

Reason:

The use of classical statistical tools for performing risk assessments has not proven to be as robust as Bayesian statistical tools. However, when large amounts of actuarial data are available, the results obtained using either classical statistical tools or Bayesian statistical tools produce the same results. The interpretation of those results is quite different, since the Bayesian results are interpreted as probabilities where the classical results are interpreted as frequencies from a hypothetical infinite ensemble. See Clemen and Reilly, "Making Hard Decisions," 2004; Berger, "Statistical Decision Theory and Bayesian Analysis," 1985; Raiffa and Schlaifer, "Applied Statistical Decision Theory," 1960; and Gelman et al, "Bayesian Data Analysis."

Page 7: *Failure Analysis of Physical Structures*

Change:

"Since these events are exceedingly rare (e.g., bridge failure or a major core meltdown at a nuclear reactor), it may not be feasible to compute risks based on historic data alone."

To:

"Since these events are exceedingly rare (e.g., bridge failure or a major core meltdown at a nuclear reactor), actuarial data are extremely rare and a combination of what actuarial data may be available, censored data, and surrogate analog data must be used."

Reason:

"Probabilistic Risk Assessment" is a process that is based on Bayesian statistical methods that allows use of censored data and surrogate analog data along with actuarial data if it is available. These methods fuse all of the data sources in producing the distribution of risk from the available data. See NASA Procedural Requirement 8705.5 and the referenced "NASA Probabilistic Risk Assessment Procedures Guide for Managers and Practitioners," 2002.

Page 13: *3. Standards Related to Characterization of Risk*

Change:

"(ii) the expected risk or central estimate of risk for the specific populations [affected];"

To:

"(ii) the median (50%) risk as a central estimate of risk for the specific populations [affected];"

Reason:

Properly performed risk assessments produce the entire distribution for the risk, and usually using numerical Monte Carlo methods. The "expected" or mean risk value may be at any quantile from near 0% to close to 100%. The median at 50% is a much better central estimate and is easier for decision makers to understand. Also, because such risk assessments may be performed using numerical Monte Carlo methods, the calculation of the "expected" or mean risk can experience numerical artifacts. Consider the case of computing a mean from a risk modeled using a Student-t distribution with one degree of freedom by means of Monte Carlo sampling. The mean is completely unstable and will produce spurious results with repeats of the process, the median will not.

Page 15: *5. Standards Related to Critical Assumptions*

Change:

"Whenever possible, a quantitative evaluation of reasonable alternative assumptions should be provided."

To:

"Whenever possible, a quantitative evaluation of reasonable alternative assumptions should be provided. This quantitative evaluation should reveal the sensitivity of the risk assessment results to changes due to small changes in the assumptions."

Reason:

A sensitivity analysis is always reasonable easy to perform and will identify any assumptions for which the risk assessment is sensitive. Many assumptions are relatively insensitive, and the sensitivity analysis can increase confidence in the results. This is simply good practice. See Clemen and Reilly, "Making Hard Decisions," 2004.

Page 16: *7. Standards Related to Regulatory Analysis*

Change:

"5) When a quantitative characterization of risk is made available, this should include a range of plausible risk estimates, including central estimates. A "central estimate" of risk is the mean or average of the distribution; or a number which contains multiple estimates of risk based on different assumptions, weighted by their relative plausibility; or any estimate judged to be most representative of the distribution.32 The central estimate should neither understate nor overstate the risk, but rather, should provide the risk manager and the public with the expected risk.33 "

To:

"5) When a quantitative characterization of risk is made available, this should include a range of plausible risk estimates, including central estimates. A "central estimate" of risk is the mean or average of the distribution; or a number which contains multiple estimates of risk based on different assumptions, weighted by their relative plausibility; or any estimate judged to be most representative of the distribution.32 The median (50%) is perhaps a better central estimate than the mean or average, especially for skewed risk distributions. The central estimate should neither understate nor overstate the risk, but rather, should provide the risk manager and the public with the expected risk.33

Reason:

Properly performed risk assessments produce the entire distribution for the risk, and usually using numerical Monte Carlo methods. The "expected" or mean risk value may be at any quantile from near 0% to close to 100%. The median at 50% is a much better central estimate and is easier for decision makers to understand. Also, because such risk assessments may be performed using numerical Monte Carlo methods, the calculation of the "expected" or mean risk can experience numerical artifacts. Consider the case of computing a mean from a risk modeled using a Student-t distribution with one degree of freedom by means of Monte Carlo sampling. The mean is completely unstable and will produce spurious results with repeats of the process, the median will not.

Page 17: ***Section V: Special Standards for Influential Risk Assessments***

Change:

"3. Standard for Presentation of Numerical Estimates

When there is uncertainty in estimates of risk, presentation of single estimates of risk is misleading and provides a false sense of precision. Presenting the range of plausible risk estimates, along with a central estimate, conveys a more objective characterization of the magnitude of the risks. Influential risk assessments should characterize uncertainty by highlighting central estimates as well high-end and low-end estimates of risk. The practice of highlighting only high-end or only low-end estimates of risk is discouraged.

This Bulletin uses the terms "central" and "expected" estimate synonymously. When the model used by assessors is well established, the central or expected estimate may be computed using standard statistical tools. When model uncertainty is substantial, the central or expected estimate may be a weighted average of results from alternative models. Formal probability assessments supplied by qualified experts can help assessors obtain central or expected estimates of risk in the face of model uncertainty.35*”*

To:

“3. Standard for Presentation of Numerical Estimates

When there is uncertainty in estimates of risk, presentation of single estimates of risk is misleading and provides a false sense of precision. Presenting the range of plausible risk estimates, along with a central estimate, conveys a more objective characterization of the magnitude of the risks. Influential risk assessments should characterize uncertainty by highlighting central estimates as well high-end and low-end estimates of risk. The practice of highlighting only high-end or only low-end estimates of risk is discouraged.

The median (50%) is an excellent central estimate that will demonstrate no artifactual tendencies due to use of numerical methods. When the model used by assessors is well established, the central estimate may be computed using standard statistical tools. When model uncertainty is substantial, the central estimate may be a weighted average of results from alternative models. Formal probability assessments supplied by qualified experts can help assessors obtain central or expected estimates of risk in the face of model uncertainty.35*”*

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Properly performed risk assessments produce the entire distribution for the risk, and usually using numerical Monte Carlo methods. The “expected” or mean risk value may be at any quantile from near 0% to close to 100%. The median at 50% is a much better central estimate and is easier for decision makers to understand. Also, because such risk assessments may be performed using numerical Monte Carlo methods, the calculation of the “expected” or mean risk can experience numerical artifacts. Consider the case of computing a mean from a risk modeled using a Student-t distribution with one degree of freedom by means of Monte Carlo sampling. The mean is completely unstable and will produce spurious results with repeats of the process, the median will not.

Page 18: ***Section V: Special Standards for Influential Risk Assessments***

Change:

“When the model used by assessors is well established, the central or expected estimate may be computed using classical statistics. When model uncertainty is substantial, the central or expected estimate may be a weighted average of the results from alternative models.38 Judgmental probabilities supplied by scientific experts can help assessors obtain central or expected estimates of risk in the face of model uncertainty.39 Central or expected estimates of risk play an especially critical role in decision analysis and cost-benefit analysis.40”

To:

“When the model used by assessors is well established, the central estimate may be computed using classical statistics. The median (50%) is an excellent central estimate that will demonstrate no artifactual tendencies due to use of numerical methods. When model uncertainty is substantial, the central estimate may be a weighted average of the results from alternative models.38 Judgmental probabilities supplied by scientific experts can help assessors obtain central estimates of risk in the face of model uncertainty.39 Central estimates of risk play an especially critical role in decision analysis and cost-benefit analysis.40"

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Properly performed risk assessments produce the entire distribution for the risk, and usually using numerical Monte Carlo methods. The "expected" or mean risk value may be at any quantile from near 0% to close to 100%. The median at 50% is a much better central estimate and is easier for decision makers to understand. Also, because such risk assessments may be performed using numerical Monte Carlo methods, the calculation of the "expected" or mean risk can experience numerical artifacts. Consider the case of computing a mean from a risk modeled using a Student-t distribution with one degree of freedom by means of Monte Carlo sampling. The mean is completely unstable and will produce spurious results with repeats of the process, the median will not.