# BEST ESTIMATE METHODS FOR SAFTEY ANALYSIS AND TRIP ASSESSMENT

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#### Abstract

Nuclear safety has moved away from deterministic conservative methods toward more probability based analysis. Advances in computer modeling and distributed computing have made possible the use of more advanced computational tools with quantifiable levels of accuracy. These improvements allow for more rigorous treatments of accident scenarios and lend themselves to statistical uncertainty analysis. This paper describes various methods for best estimate analysis ranging from conservative to more realistic assessments using Monte Carlo simulations, Wilk's method and extreme value statistics. Best Estimate and Uncertainty (BEAU) methodology is examined along with the use of probability and confidence intervals such as the 95/95 criterion in safety analysis and trip assessments. The examination details how best estimate methods can contribute to more realistic and robust safety analysis.

### 1. Introduction

Nuclear safety analysis encompasses a wide range of events and systems that effect the normal and emergency operation of nuclear reactors. The most prevalent area is the utilization of safety systems that are designed to trigger a rapid shutdown of the reactor in response to unwanted plant conditions or accident scenarios. The specific metric, such as neutron power or boiler level, is monitored continually against a previously determined setpoint. If the parameter passes this limit in an unsafe direction a trip is initiated and a rapid shutdown is performed. This trip must be fully analyzed to ensure that the emergency action is taken within an appropriate time frame to maintain plant integrity and avoid dangers to personnel and the surrounding community. Trip assessment is the study of a specific trip and the determination of a trip setpoint that is effective in avoiding or mitigating as much as possible any unwanted consequences of an accident scenario.

In order to better explain trip assessment and the methods utilized in its study, the loss of feedwater accident and the resultant rundown of the steam generator (SG) level will be used as an example case throughout this paper. In the event of a total loss of feedwater, all four SG levels would begin to drop. The level transient in a single SG would be similar to the transient generated by the thermalhydraulic modeling software known as Simulation of Primary Heat Transport (SOPHT). This transient is depicted in Figure 1, where 0 meters is the cold pressurized reference level and the normal operating level at 100%FP is 4.5m. Once the SG level drops below a pre-determined setpoint the reactor will trip on SG low level and initiate a rapid shutdown response. The full system is comprised of 3 logic channels (D, E and F) receiving 4 input signals (one from each SG) for a full complement of 12 redundant signals. The logic channel's measurement is taken as the minimum of the 4 SG signals. The trip logic registers a reactor trip when 2 of the 3 logic channels drop below the trip setpoint.



Figure 1: Theoretical SG Level Transient for Large Loss of Feedwater Accident [1]

Determining the trip setpoint for a specific system begins with the definition of the absolute safety limit. This is the limit of the specific system where the initiated shutdown is activated in such a time that the safety objectives are met. In our example case this limit refers to the minimum inventory in the SG for which 15 minutes of operator action time is available. This limit does not include any uncertainties in the system measurements, simulation or initial conditions and is usually determined by direct testing or extensive computer modeling.

The actual trip setpoint used must allow for variations inherent in the system. These variations include time delays in the execution of the trip, shutdown system (SDS) instrument uncertainties, system simulation uncertainties, and uncertainties in initial plant conditions. These variations push up the setpoint to its required level as seen in Figure 2. The space between the required trip setpoint (RTSP) and the actual operating envelope is known as the margin to trip (MTT).



Figure 2: Single Element Trip Assessment Breakdown

# 2. Deterministic Assessment

Historically, trip assessments and analysis have focused on deterministic events that are limiting cases which bound most accidents ensuring that the response of a system to an emergency condition will be able to encompass any of the uncertainties present. This conservative estimate maximizes all the uncertainties and places the RTSP at its highest level. This conservative analysis was utilized due to its bounding of all other cases, ensuring built in margin for the design. However, the high level of conservatism is leading to operational problems as the reactor designs begin to age. As the reactors and their instruments age their uncertainties will tend to increase expanding the normal operational envelope and that of periodic operations, such as online fuelling, reducing the MTT and in some cases bringing operational values very close to the deterministic trip setpoint. The reduction in margin increases the possibilities of spurious trips and may also require the reactor to derate its operating levels to ensure there is sufficient margin. The derating of systems such as limiting reactor power level to less than 100%FP is extremely costly to utilities as their plants are not running at peak output. Additionally, this ultra conservative assessment method promotes an unrealistic view of the plant and its systems, the simplifications of this method make determining the exact margin to safety limits impossible. In our example system, the limiting case states there is only enough water in the SG to allow for 15 minutes of operator decision time where the actual SG inventory is likely to be higher which will allow for more operator decision time. The search for more realistic trip assessment and more accurate estimates of margin has turned toward statistical assessments and best estimate predictions. There are several levels of statistical treatment and conservatism that range from simple statistical assessment using only a single trip element to the propagation of errors through multiple redundant systems and the use of extreme value statistics (EVS).

# **3.** Statistical Treatment of Uncertainties

Before we are able to move to a best estimate or EVS type of analysis a thorough investigation of the uncertainties affecting the trip parameters must be performed. For best estimate cases only some of the uncertainty terms are modeled in this fashion while the rest are held at their conservative bounding values. The EVS method seeks to produce the most realistic model of the system and hence requires intense uncertainty analysis for all components affecting the trip metric.

# 3.1 Probability Distributions and Monte Carlo Treatment

Each uncertainty parameter affecting the trip is treated as a probability distribution which has a specific range and mean value. The distribution can be modeled after any statistical curve depending upon the performance of the actual system. In practice, most systems are well represented by a Gaussian distribution that spans the component uncertainty ( $\pm X$  %) and has a mean of zero. This probabilistic approach sets up the system for a Monte Carlo statistical treatment running multiple simulations with random sampling of uncertainties. The Monte Carlo assessment utilizes two classes of uncertainties, epistemic and aleatory, defined below, to produce a realistic model. This assessment must be based on the realistic uncertainties inherent in the system and simulation model to produce an accurate representation of the system response.

# 3.1.1 Epistemic Uncertainties

The epistemic class of uncertainties describes the inabilities of the model used to accurately represent the real system and includes code and instrument uncertainties. A reduction in these uncertainties brings the model closer to a realistic representation of the system. In our example case, the code uncertainty results from inaccuracies in the thermalhydraulic simulation software such as SOPHT and is based upon validation work done matching code simulations with relevant experimental investigation. The instrument error follows the quoted uncertainty of the real component utilized as determined by the manufacturer or from extended operational experience.

#### 3.1.2 Aleatory Uncertainties

Aleatory uncertainties represent the variability of the real system in terms of initial conditions. The main components are related to the drift and calibration errors or offsets resulting from variations between different parts of the system. In the example case, this is seen in the offset between steam generators that is based upon operational fluctuations. Modulating the aleatory uncertainties allows the creation of multiple initial states that an emergency condition, such as a loss of feedwater, could propagate from.

### 3.1.3 Monte Carlo Simulation

Monte Carlo assessment seeks to determine the system response over a wide range of uncertainty and operating values to provide an accurate model. The simulation will first generate a random set of aleatory uncertainties that will produce an initial reactor state. For this given reactor state multiple emergency condition events are run with randomly selected epistemic uncertainties. In the example case, each reactor state is submitted to multiple rundown transients with random instrument and code uncertainty values to derive a distribution of trip times for the specific initial state. By running a significant number of different reactor states, with a sufficient number of transients for each, a robust representation of the response (i.e. trip time) of the system can be produced. The objective of EVS analysis and best estimate treatments is to assess the uncertainties of the systems and through multiple simulations establish a statistically determined response characteristic for a specific probability and confidence level.

#### 3.1.4 95/95 Probability and Confidence Interval

The determination of a distribution of responses over a range of initial reactor states and multiple accident transients is beneficial for analysis but must be further refined to provide proof of the satisfaction of regulatory limits. The accepted practice is to produce a bounding limit for a certain probability and confidence interval. Canadian and international standards for these statistical treatments such as ISA 67.04 and CNSC Regulatory Guide G-144 require that instrumentation and trip setpoints provide a 95% probability with a 95% confidence level. [2] This is known as the 95/95 approach and has been widely accepted as an acceptable demonstration of compliance with regulatory limits.

Specifically, for the example case, we must demonstrate that there is at least a 95% probability of a trip over 95% of the available reactor states. [2] In order to satisfy this criterion

the 95<sup>th</sup> percentile highest trip time must be taken for each set of transients run and then an overall 95<sup>th</sup> percentile trip time must be taken over the full range or reactor states studied. This result is the 95/95 trip time, which means that the reactor will trip before this time with a 95% probability for 95% of the possible reactor states.

## **3.2 Dealing with Increased Computing Demand**

The move towards statistical treatment of uncertainties and Monte Carlo simulations has significantly increased the computing and time demands of trip assessment. Deterministic methods avoided extensive simulation and multiple signal processing and had rather light computational demands. However, the key to an effective Monte Carlo analysis is ensuring there is a large and diverse sample set that is significantly random. In a numerical analysis of the example case, it was found that 1000 reactor states with 2000 transients was needed for a robust statistical treatment. [1] This amounts to 2 million simulation runs and when we factor in the fact that there are 12 transients being modeled during each simulation (3 logic channels with 4 SGs) when performing a true EVS analysis, the computational demands are quite high. Best estimate simulations are less demanding depending on their level of conservatism but still use up considerable resources.

The simulations performed in trip assessment generally utilize reactor physics or thermalhydraulic code models that in some cases are run for each transient. These codes are complex and may take a bit of time to run. In our example case, a suitable code used to predict the SG rundown transient is SOPHT. A simple SOPHT run, such as would be needed in this case, may take 5-10 seconds dictating a possible computing time of 20 million seconds (more than 5,500 hrs), not necessarily accounting for the multiple signals. Obviously, this is not viable in most cases of analysis and methods are needed to reduce this excessive computing time. Advances in such areas as distributed computing, the use of functional response surfaces and statistical treatments such as Wilk's method are able to provide sizeable computation reductions.

#### 3.2.1 Distributed Computing

The excessive demands of trip assessment modeling dictate the use of advanced data processing techniques such as distributed or parallel computing. The essence of distributed computing does not reduce the amount of computations performed it just spreads them out over multiple processors which each perform a small part of the calculation. For the example case the multiple transients run for a specific reactor state can be run by multiple computers. This cooperation significantly reduces the computing time necessary and utilizes the abilities of multiprocessor workstations, servers and computer clusters. The technique of distributed computing has led to the possibility of much more complex error propagation models, such as EVS. This distributed method reduces the overall time necessary but slightly increases the computational resources necessary, due to the demands of managing multiple worker computers. In conjunction with distributed computing other methods that reduce the individual transient run times can be applied.

## 3.2.2 Functional Response Surfaces

The most time consuming effort of each simulated transient is the running of the thermalhydraulic or physics modeling code. This problem can be remedied by generating an approximation of the modeling code using a functional response surface (FRS). In essence a FRS is a multivariable polynomial curve fit of the output of the modeling code which can take into account many parameters such as pressure, temperature and flux. The FRS approximates the real modeling code transient with sufficient accuracy, produces the necessary outputs and since it is a polynomial function runs much faster. In our example case, the SOPHT transient was fitted with a cubic polynomial that approximated the SG level rundown. Instead of 5-10s SOPHT simulations being run, the polynomial curve fit is simulated with times on the order of  $10^{-3}$ s. This significant reduction in transient computing time allows for full modeling of the 12 signals within our example system without extensive computing time. Using a FRS in conjunction with distributed computing, provides a robust method for proper statistical treatment of Monte Carlo type simulations with multiple signals while maintaining reasonable execution times. Time reductions through the use of better computing techniques and FRS approximations benefit the robust statistical analysis methods that require excess simulations. However, some statistical methods can achieve similar results with much less modeling effort.

#### 3.2.3 Wilk's Method

Generating the system response distribution using the full Monte Carlo simulation is quite time consuming and computationally intense but will generate an accurate overall response with a defined probability and confidence. However, there is a statistical analysis method that can be applied to determine a distribution free tolerance limit. Wilk's method, first proposed in 1941, allows the determination of a response with a specific probability and confidence interval while performing a fraction of the simulations originally thought necessary. The method states that if we produce N samples of a random system and order the results  $y_1, y_2, y_3 \dots y_N$  such that  $y_1 > y_2 > y_3 \dots > y_N$  the largest value,  $y_1$ , will bound all other responses with a given probability,  $\gamma$ , and confidence,  $\beta$ . The relation between the number of samples, N, and a given  $\gamma$  and  $\beta$  is defined using Equation 1 for a two sided tolerance and Equation 2 for a single sided tolerance.

$$\beta = 1 - \gamma^{N} - (N - 1)(1 - \gamma)\gamma^{N - 1}$$
(1), [3]

$$\beta = 1 - \gamma^N \tag{2},$$

In most trip assessment cases the desire is for the single sided tolerance with a probability of  $\gamma = 0.95$  and a confidence interval of  $\beta = 0.95$ , the 95/95 criterion. Using Equation 2 a single sided tolerance that follows the 95/95 criterion would require N = 59 samples, achieving a response value y<sub>1</sub> that bounds all responses with a 95% probability and a confidence of 95.15%. Obviously this is a drastic reduction in the number of simulations necessary and can save much computing time. In the case of the EVS method for our example instead of running 1000 reactor states with 2000 transient we could use Wilk's method and achieve a similar result with 59 states and 59 transients each. However, it is recommended in most cases that the full set of inner transients is still run to ensure that the 95% probability limit is accurately met. Our example case is quite simple in that it has only one output variable to track, SG level. Wilk's method has been analyzed and expanded for use in cases with multiple output variables by Guba et. al. (2003) allowing its statistical gains to be applied to more complex assessment scenarios. For a one sided confidence where the number of output variables is defined by p the relation follows Equation 3.

$$\beta = \sum_{j=0}^{N-p} {N \choose j} \gamma^{j} (1-\gamma)^{N-j}$$
(3), [3]

Wilk's method allows for robust analysis with definable statistical benchmarks without the need for the definition of a full response distribution. This saves valuable computing time and makes the switch to BE and EVS type analysis more economical. However, the user must remain vigilant in their careful consideration of uncertainty propagation to ensure these statistical methods are employed properly to yield the desired results.

### 4. Best Estimate Statistical Assessments

The term Best Estimate is referred to frequently and not always with proper clarification. In general Best Estimate refers to the most likely value for a specific element such as SG level or neutron power. Best Estimate and Uncertainty (BEAU) involves taking the best estimated value for a certain parameter while considering its variability due to the uncertainties within the system. However, values are meaningless without a given probability and confidence level. As described earlier, the most common strategy is to use the 95/95 criterion accomplished using modeling software that runs multiple simulations which then undergo statistical analysis to produce a definitive parameter value. The concept of statistical 95/95 BEAU analysis is becoming accepted the standard method for trip assessment by most national regulators and the IAEA.

The BEAU terminology must be qualified with which portions of the system are treated using best estimate and which are assumed to be a conservative value. In most BEAU analysis a large portion of the system is still treated conservatively. As we move away from the conservative cases features such as redundant systems are credited. There are two main stages of the BEAU analysis explained in this paper with varying degrees of conservation. They involve the inclusion of multiple signals in error propagation in various ways. They are described in Table 1 along with the deterministic and extreme value statistics cases.

Table 1. Description of Statistical Analysis Wethous			
	Logic Channel	Multiple Logic	Multiple Signals
Case	Uncertainty	Channels	in a Logic Channel
Deterministic	Ignored	Ignored	Ignored
SBE	Included	Ignored	Ignored
BE Logic Channel	Included	Included	Ignored
EVS	Included	Included	Included

 Table 1: Description of Statistical Analysis Methods

# 4.1 Simplified Best Estimate

The first case, known as simplified best estimate (SBE), does not model redundant signals in its error propagation. In the context of our example system the SBE case performs a best estimate by running multiple transients and choosing to recognize only the worst channel

overall. Therefore if channel D is limiting the entire trip is based on when D will drop below the trip setpoint. The uncertainty in a specific logic channel is modeled in the SBE case rather than just taking on the worst value possible as per the deterministic case. This case pushes away from the ultra conservative slightly but still models the system as if it was one single SG with 3 of 3 trip logic rather than the 4 SG system with 2 of 3 trip logic that is actually employed.

## 4.2 Best Estimate Logic Channel

The second BE case is referred to as Best Estimate Logic Channel (BELC) and does partially propagate errors through the redundancy inherent in the system. This case takes the worst signal for each logic channel D, E and F and then computes the trip with standard 2 of 3 channel logic. This case recognizes the inherent logic channel uncertainties and includes the multiple logic channels present in its analysis. This is a more realistic case that generally represents a single SG system with 2 of 3 logic. The BELC method is rarely used at this time but may find a niche due to its bridging of the gap between the SBE method and a full EVS type analysis. Propagation of errors through redundant signals will decrease uncertainties as with more signals it is more likely that one will be biased lower and trip early.

# 4.3 Other Best Estimate Analysis

Another type of Best Estimate analysis can focus on the single element trip assessment breakdown provided earlier in Figure 2. This strategy uses an analysis that is broken up over the four major error input parameters and allows for varying degrees of conservation. This provides a built in safety factor and allows for reduced uncertainty analysis efforts in not vital areas of the trip parameter. This approach has a single trip element base which can be expanded by collecting multiple single elements into a network resembling the actual system. This would help account for the redundancy gains possible with the real system. However, the fact that the errors are not separated into their epistemic and aleatory classes makes the definitive establishment of a confidence interval impossible. In the extreme realistic method where all the single element uncertainty values are included, properly classed between epistemic and aleatory and all redundancy is modeled we reach the method of extreme value statistics.

# 5. Extreme Value Statistics

The method of extreme value statistics (EVS) is designed to provide the most realistic account of actual reactor operations. It is a branch of BEAU that seeks to accurately determine statistical benchmarks by propagating uncertainties through the reactor system. The propagation is designed to properly model all uncertainty areas and any redundancy inherent within the system. In order to accomplish this analysis, a thorough investigation of the uncertainties affecting the trip parameters must be performed. The uncertainties must be classified as epistemic or aleatory to determine their position in the analysis. The heart of EVS is the Monte Carlo analysis which selects random values for the uncertainties from a probabilistic distribution. The aleatory uncertainties are used to produce a specific initial reactor state for which multiple accident transients are run. The transients each have randomly selected epistemic uncertainties. As described in Section 3.1 running a significant number of transients for a wide range of reactor states will produce a system response distribution. Analyzing the distribution determines the 95/95 response of the system. EVS provides the most robust statistical treatment for trip

assessment with definitive bounds and confidence. The realistic modeling of systems provides analysts and operations personnel with the best information possible on the state of their system.

The shift from conservative analysis to best estimate and EVS approaches provides the ability to prove compliance through the demonstration that for a given confidence, the system will yield results below the prescribed limits. This avoids operating restrictions imposed by using the overly conservative standards and promotes a more realistic method of evaluation.

Extreme value statistics and best estimate methods have a major effect on the perceived trip assessments and can provide significant perspective on real plant operations. For our example case, the conservative trip time was defined to be 130.4s while the SBE and EVS trip times were 111.3s and 100.8s respectively. The seconds gained in trip time translate to several Mg worth of SG inventory since the earlier than expected trip means the reactor is at 100%FP for less of the transient. This change in assessment methods provides a much more realistic view of the plant conditions and shows that the operator decision time available is no longer the bounding 15 minutes but in the case of EVS is closer to 46 minutes. Even in this simple example case the use of EVS analysis has shown that the operators have 30 minutes of extra decision time available than was previously believed.

### 6. Conclusions

As described, the move towards robust statistical analysis methods with proper treatment and propagation of uncertainties provides detailed assessment with accurately defined probabilistic tolerances. The study of trip assessment can benefit significantly from the use of these methods in providing more realistic modeling of the actual state of the system and uncertainty analysis that can help identify vulnerable areas. Despite the demands of these methods on analysis time and computing resources there are new methods and technologies that are able to maintain reasonable execution times. The use of distributed computing and functional response surfaces make the detailed analysis methods much more efficient. Bv utilizing Wilk's method, the treatments necessary to achieve results with definitive statistical benchmarks become much simpler and less time and resource intensive. The benefits provided in these more realistic analysis methods justify the increased resources necessary and highlight the inaccuracies present in deterministic trip assessments. The level of built in conservation and the reduced analysis and computational requirements of methods such as the simplified best estimate (SBE) will likely make them the choice for continued use in system assessments. However, caution must be taken to ensure that the conservative estimates of the 95/95 level are still valid. The EVS approach is the most realistic model of real system performance and makes full use of detailed error propagation and uncertainty analysis.

There is a clear movement towards the use of best estimate methodology and robust statistical treatments such as BEAU and EVS in the analysis of reactor operations. Regulatory bodies are increasing the amount of design basis regulations for which they will accept probabilistic analysis. This is promoting a more realistic approach to analysis throughout the industry with renewed focus on uncertainty analysis and statistical methods.

# 7. References

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