Characterizing Epistemic Uncertainty for Launch Vehicle Designs

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ABSTRACT

NASA Probabilistic Risk Assessment (PRA) has the task of estimating the aleatory (randomness) and epistemic (lack of knowledge) uncertainty of launch vehicle loss of mission and crew risk, and communicating the results. Launch vehicles are complex engineered systems designed with sophisticated subsystems that are built to work together to accomplish mission success. Some of these systems or subsystems are in the form of heritage equipment, while some have never been previously launched. For these cases, characterizing the epistemic uncertainty is of foremost importance, and it is anticipated that the epistemic uncertainty of a modified launch vehicle design versus a design of well understood heritage equipment would be greater. For reasons that will be discussed, standard uncertainty propagation methods using Monte Carlo simulation produce counter intuitive results, and significantly underestimate epistemic uncertainty for launch vehicle models. Furthermore, standard PRA methods, such as Uncertainty-Importance analyses used to identify components that are significant contributors to uncertainty, are rendered obsolete, since sensitivity to uncertainty changes are not reflected in propagation of uncertainty using Monte Carlo methods.

This paper provides a basis of the uncertainty underestimation for complex systems and especially, due to nuances of launch vehicle logic, for launch vehicles. It then suggests several alternative methods for estimating uncertainty and provides examples of estimation results. Lastly, the paper describes how to implement an Uncertainty-Importance analysis using one alternative approach, describes the results, and suggests ways to reduce epistemic uncertainty by focusing on additional data or testing of selected components.

1. INTRODUCTION

Uncertainty is an important aspect of any PRA to reflect the level of confidence in the models and data used in the analysis, and to provide information used for engineering and management decisions. In launch vehicles, risks are typically considered high [1], compared to most industry applications. Uncertainty, especially the upper bounds, can aid in anticipated launch commit decisions for NASA.

As technology advances and new system designs populated with first launch hardware are developed for more ambitious space applications, estimating uncertainty of these designs becomes paramount to mission success. Additionally, the ability to characterize the contribution of components to the overall uncertainty provides a means for supporting testing plans and system development.

To perform a proper uncertainty analysis for new designs, the development of epistemic uncertainty (uncertainty due to lack of knowledge) represents a difficult task, both in assigning failure probability distribution bounds to new components, and in propagating this uncertainty through the PRA logic model.

One would believe that standard Monte Carlo simulation provides an appropriate methodology to propagate uncertainty through subsequent logic models. However, upon further investigation, this method appears to be highly questionable, and becomes more of a concern in logic models with structures like those that reflect launch vehicle designs.

2. UNCERTAINTY PROGAGATION

Monte Carlo simulation provides a process to propagate uncertainty through a reduced Boolean equation created by PRA software to solve logic trees, such as built in the Systems Analysis Programs for Hands-on Integrated Reliability Evaluations (SAPHIRE) tool [2]. Probability distributions, representing the uncertainty of component failure rates, can be randomly sampled using Monte Carlo simulation and combined to estimate an uncertainty distribution for the top event in the PRA fault-tree model.

Uncertainty propagation is affected by the logic of the tree and in general, AND gates tend to preserve or increase the bounds of two numerically similar combined basic events, while OR gates reduce this uncertainty. Sensitivity studies show the top event in a fault tree with many OR gates is insensitive to changes in the epistemic uncertainty of the tree's basic events. Although this phenomenon was known, we did not fully realize the resulting implications on PRA until fairly recently, which prompted this paper for peer discussion.

Several simple tests were performed to understand the nature and extent of uncertainty changes due to propagating in this manner. It was understood that when performing Monte Carlo routines on a Boolean expression, the mean results of the PRA mode top event could be determined by dominating basic events. Therefore in these test cases the basic event failure probabilities are all set to the same magnitude. Moderate variances in the magnitude of basic events, such as found in typical complex systems, will not significantly affect the results of these test cases. This also applies to uncertainty, where dominance by any basic event or small set of basic events will result in the uncertainty also being dominated by those same basic events.

To facilitate understanding of the nature and extent of this reduction, several sample sets were run in SAPHIRE. Each sample set was selected to minimize the effect of other variables in the solution of the top event and emphasize the changes in uncertainty. Initial test cases focused on determining the number of similar events with specific logic potentially causing this decrease in uncertainty.

To set up the test cases, two small logic trees of ten similar events were developed. Each independent basic event was given the same probability distribution. One logic tree contained all OR gates and the other contained all AND gates. All basic-event probabilities for these test cases used a lognormal distribution with a mean of 1.0E-5 and an Error Factor (EF) and were uncorrelated (The EF for the lognormal distribution is defined as the 95th percentile divided by the median.*)* The EF was varied for each test case as was the number of basic events in the fault tree logic. For each case, 99999 random SAPHIRE trials were run using a random seed, and in all of the cases the top event converged. In each case, the uncertainty distribution of the top event was a good fit to a lognormal distribution that we parameterized using moment matching. Tables 1 and 2 below show the test cases and top event uncertainty results for the OR gate tree and the AND gate tree, respectively.

Table 1: EF Results from OR Logic Uncertainty Test Cases

	Error Factor				
Number of Basic Events	5	10	15	20	100
2	3.4	6.1	8.6	11.1	44.5
5	2.3	3.8	5.1	6.3	21.3
10	1.9	2.8	3.7	4.5	13.8
20	1.6	2.2	2.8	3.3	9.5

As can be seen from Table 1, the EF significantly decreases as the number of similar basic events increases under the top event. Even as the EF is increased to 100, a very large and potentially unreasonable EF, the reduction in uncertainty of uncorrelated events added together in the Boolean expression reduces significantly and is essentially diminished compared to the basic event uncertainty after ten such events. Test runs were also conducted at a higher mean value (5.0E-5) showing similar results.

Table 2: EF Results from AND Logic Uncertainty Test Cases

	Error Factor				
Number of Basic Events	5	10	15	20	100
2	9.6	26.5	47.1	70.9	700.3
3	17.5	NA	NA	NA	NA
4	NA	NA	NA	NA	NA
20	NA	NA	NA	NA	NA

Table 2 shows some of the AND logic test cases. As the number of basic events increases, the ability to characterize the uncertainty becomes more difficult, since the result of combining the basic events using Monte Carlo becomes unbounded.

3. CORRELATION AND PRACTICAL APPLICATIONS

Correlation effects were as anticipated in the test cases. By correlating some of these events using 100 percent positive correlation, the effect was essentially to reduce the number of distributions, therefore; the number of basic events used by SAPHIRE to determine the uncertainty of the top event; Table 1 and Table 2 applies accordingly. In our launch vehicle design PRA models, the degree of correlation between similar component types (e.g., different cable and connector pairs) had some minor effects in increasing uncertainty. However, the increase was not enough to show sensitivity to increased epistemic uncertainty at the component level.

Our belief is that due to the launch vehicle environments, for example in ascent, most components at least at the system level are partially correlated in some manner. Partially correlating all of these components would result in greater uncertainty in the logic model. The possibility of adding partial correlation was investigated, considering the complexity and number of component basic events affected. Even at a system level, this approach was both beyond the standard current tool set available and introduced additional model uncertainty in ascertaining the appropriate partial correlation factors. In addition, even if we developed alternative tools and addressed the added model uncertainty in assigning partial correlation factors, the method of applying partial correlation and creating an N-by-N basic event matrix would be daunting to develop and apply. Therefore, alternative methods were sought to capture epistemic uncertainty. These methods are introduced below.

4. LAUNCH VEHICLES AND COMPLEX SYSTEMS WITH MULTIPLE SAFETY BARRIERS DIFFERENCES

One pertinent question arises concerning uncertainty bounds when comparing Monte Carlo simulations used in solving complex systems employing multiple safety systems and launch vehicle PRAs. Namely, why is this uncertainty reduction effect not as apparent in these PRAs and is it an issue?

The answer probably lies in the nature of functionality and safety design in these complex systems. If multiple safety barriers can be called on to mitigate accident transients, then this redundancy is at the system level and results in AND logic (safety redundancy) at the top of the fault tree logic. Launch vehicle design, due to weight reduction, optimized aerodynamics/volume, and cost considerations, usually features single fault tolerance (redundancy) at the subsystem level. Loss of the avionics system, for example, will result in loss of the launch vehicle. In other words, launch vehicle redundancy is built-in typically at the subsystem level rather than the system or element level. This will be reflected in redundancy, or AND gates at a lower level in the logic tree, while the upper portion of the tree will have multiple OR gate logic, depicting that any loss at the system or element level results in loss of the vehicle. After the discussion in Section 2, one can see where the differences in the tree logic structure between complex systems with multiple safety barriers and launch vehicles result in differences in epistemic uncertainty propagation. Furthermore, dividing the logic trees into phases to ascertain functional and environmental differences, as is experienced with launch vehicle missions, can only perpetuate the uncertainty reduction problem.

Although these complex systems typically preserve or increase some uncertainty due to the logic structure of these designs using Monte Carlo simulation, it was suspected that the uncertainty and uncertainty-importance results are as sensitive as needed to be for analytical purposes. In any case, the reduction in epistemic uncertainty for systems that have redundancy at a lower level using Monte Carlo uncertainty propagation techniques in PRA, may be occurring to some extent. PRA analysts should be aware of this potential. It is very apparent that this reduction is occurring in PRA models of launch vehicle designs.

5. IMPLICATIONS TO LAUNCH VEHICLE PRA UNCERTAINTY AND RELATED ANALYSES

One of the main implications of this reduced uncertainty effect is the reduced ability to determine which basic events, and thus components, in the model represent a significant contributor to uncertainty due to lack of knowledge about that component. This is an artifact of the propagation of the logic tree for launch vehicles and basic events become insensitive to changes in the uncertainty. Often in cases where new equipment is used and demonstrated historical data is unavailable, PRA component reliability information may reflect like equipment or the use of a component in a different environment by assigning an increase in the component epistemic uncertainty. This increase would reflect use of the component in a different environment, a different purpose, or a modified function. The magnitude of the increased uncertainty should provide insight into how much the “like” component differs from the design component and how much lack of knowledge exists related to that piece of the design.

Uncertainty-Importance analyses can often identify and prioritize components, especially in a design setting, where reduced component uncertainty could substantially reduce the system-level uncertainty and, therefore; improve the credibility bounds of the model. This can be accomplished by further investigation and using more applicable failure rate sources for the component, or invoking focused component testing. It can be time consuming and expensive to research every component in a complex system to reduce the level of uncertainty. Minimizing the number of components that require further investigation could prove to be a time and cost saving method, which would avoid performing this for every component.

6. ALTERNATIVE APPROACHES TO ESTIMATE EPISTEMIC UNCERTAINTY

Alternative approaches [3] were explored to estimate and maintain uncertainty and express sensitivity to changes in component or components groups' epistemic uncertainty.

6.1 Partial Correlation Based On Environmental Factors

One such method explored was to apply a partial correlation factor across physical or interactive systems. The concept is based on environmental factors coupling failure rates of unlike components together either due to a similar location or similar environmental stress factors. Thus partially correlating failure rates would have the effect of increasing uncertainty by not treating the events as completely independent.. A launch vehicle will often have co-located systems due to limited space and volume requirements. For example, the engine compartment may include the engine, portions of the main propulsion system, and some avionics electronics hardware. All these systems may have some correlated failures associated with being co-located in a launch vehicle.

The challenge with this approach is assigning a generic partial correlation factor and then implementing the correlation. Implementing a generic correlation factor in a custom code to build matrices for a reduced Boolean expression was explored. This was a more straight forward approach then applying multiple partial correlation factors. However, it was found that there was a lack of defensible engineering basis to establish generic correlation factors for specific systems at this time. Although this approach was not finalized, it still remains a potential option for improving accuracy of uncertainty estimates. The true test of this approach will be determined when modifications to the assigned epistemic uncertainty are propagated through the logic model and exhibit sensitivity to these changes.

6.2 Interval Approach

Another approach that we discovered when investigating epistemic uncertainty sensitivity was the Interval Analysis technique [4]. Interval Analysis claims to characterize epistemic uncertainty, as distinguished from variability or randomness that is propagated through Monte Carlo routines. Although we do not necessarily adhere to this aspect of the concept, we have found the Interval Analysis method in our case to be useful in characterizing uncertainty and in showing responsiveness to assigned changes in epistemic uncertainty of our logic models.

Interval Analysis uses a reduced Boolean expression to solve a logic model for the top event. It does this by calculating the uncertainty ranges as an upper and lower bound (5^{th} and 95^{th}) for each basic event, and then using these bounding values to estimate an upper and lower bound for the top event [5].

Results from an example complex launch vehicle system showed an uncertainty EF (The EF is specific to the lognormal distribution and is only used as an approximation of the uncertainty) of about 1.5. Furthermore, applying a large EF to all basic events in this system, such as an EF of 10, showed minimal effects on the propagated uncertainty (i.e., EF~2). This effect was apparent in all major systems models of the launch vehicle.

Epistemic uncertainty for basic events ranged from EFs of 4 to 15 with many basic events having an uncertainty of around 6. Using the Interval Analysis technique, the uncertainty results showed an uncertainty value of 5.1. Uncertainty-Importance measurements [6] were run to identify dominant basic event contributors to uncertainty. These were grouped according to similarity to each other (e.g., Electrical Power, Navigation, and Flight Computer Software) and the EF modified for sensitivity to epistemic uncertainty.

The Interval Analysis approach responded to changes in the initial epistemic uncertainty in a reasonable manner. As one important group of basic events were increased from an EF of 5 to 10, the EF of the Interval approach went from 5.1 to 7.5. When this same group's EF was decreased to 3, the resulting EF was 3.5. Less important groups, as determined by the Uncertainty-Importance routines, had much smaller effects on the uncertainty as anticipated.

7. SUMMARY AND CONCLUSIONS

Uncertainty Analysis plays an important role in any PRA by describing the confidence around risk estimates. Much of the uncertainty in the design of launch vehicles is due to epistemic uncertainty or "lack of knowledge" either due to new equipment or technology, or from use of heritage equipment in a new environment. In either case, the ability to estimate uncertainty at the basic event level and establish a method for targeting this uncertainty requires an approach that is sensitive to changes in uncertainty levels.

Unfortunately, standard methods of uncertainty propagation using Monte Carlo techniques do not provide this sensitivity for typical launch vehicle design PRA models, due to the inherent logic structure that represents launch vehicle risks. While this is not a new phenomenon, it becomes very apparent when attempting to apply sensitivity studies to better understand the uncertainty.

Alternative options were suggested to support implementing sensitivity strategies. We found partial correlation between unlike components could potentially solve this issue and result in an increase in uncertainty while maintaining the standard Monte Carlo uncertainty propagation methods. However, after further investigation, this option was hindered due to the lack of engineering data and derivation to estimate partial correlation and the lack of tools to accomplish this task.

The Interval Analysis option was also introduced as an alternative that may aid in epistemic uncertainty approximation and support sensitivity studies on the uncertainty to help focus component failure rate data investigation, testing, and collection. This analysis methodology was shown to have reasonable uncertainty results on a test system PRA model, and be sensitive to modifications of the epistemic uncertainty at the basic event level.

It is recognized the preferred uncertainty propagation approach is to implement partial correlation and use Monte Carlo routines. However, implementation of this approach will likely require integration of physics-based risk models within PRA and advancement of PRA techniques to accommodate these models. Although further testing is warranted, the Interval Analysis option is a good alternative to provide uncertainty bounds for launch vehicle design PRA models and appropriate for uncertainty sensitivity studies.

8. REFERENCES

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