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PHASER 2.10 Methodology for Dependence, Importance, and Sensitivity: The Role of Scale Factors, Confidence Factors, and Extremes

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PHASER 2.10 Methodology for Dependence, Importance, and Sensitivity: The Role of Scale Factors, Confidence Factors, and Extremes

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Abstract

PHASER (Probabilistic Hybrid Analytical System Evaluation Routine) is a software tool that has the capability of incorporating subjective expert judgment into probabilistic safety analysis (PSA) along with conventional data inputs. An earlier report described the PHASER methodology, but only gave a cursory explanation about how dependence was incorporated in Version 1.10 and about how "Importance" and "Sensitivity" measures were to be incorporated in Version 2.00. A more detailed description is given in this report.

The basic concepts involve scale factors and confidence factors that are associated with the stochastic variability and subjective uncertainty (which are common adjuncts used in PSA), and the safety risk extremes that are crucial to safety assessment. These are all utilized to illustrate methodology for incorporating dependence among analysis variables in generating PSA results, and for Importance and Sensitivity measures associated with the results that help point out where any major sources of safety concern arise and where any major sources of uncertainty reside, respectively.

Acknowledgments

This work was especially stimulated by a great number of consultations with Scott Ferson, Applied Biomathematics; Doug Cooper, Analogy, Inc.; Tom Edrington, Bob Roginski and Dave Carlson, Sandia National Laboratories; and George Klir, State University of New York at Binghamton.

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I. Introduction

In 1993, an effort was initiated to help supplement traditional probabilistic safety analysis (PSA) methodology with a mathematically systematic way of incorporating expert judgment inputs. This work was based on fuzzy mathematics for processing subjective information and hybrid mathematics for combining subjective and probabilistic information. This led to the development of a software tool, PHASER (Probabilistic Hybrid Analytical System Evaluation Routine), which has the capability for incorporating subjective judgment into PSA. An earlier report [Ref. 1] described the methodology used. Some subjects addressed in the report were intentionally treated in overview fashion, since they were not yet incorporated in the software. For example, the report gave only a cursory explanation about how dependence was to be incorporated in Version 1.10 and about how "Importance" and "Sensitivity" measures were to be incorporated in Version 2.00. A more detailed description is given in this report, which along with Ref.1 provides a complete methodology description for the PHASER 2.10 software. The PHASER 2.10 User's Manual [Ref. 2] gives a definitive description of the software and its use.

One of the basic concepts covered in this report depends on scale factors and confidence factors that are associated with known (data-based or physical-first-principle-based) stochastic variability and subjective (engineering judgment) uncertainty. (The latter is an important constituent of PSAs.) The other basic concept is that the safety risk extreme is the most crucial area for safety assessment. These concepts are utilized to illustrate methodology for incorporating dependence among analysis variables in generating PSA results, and for "Importance" and "Sensitivity" measures associated with the results, which help point out where any major sources of safety concern arise and where any major sources of uncertainty reside, respectively.

II. Dependence

Fault tree and event tree construction can explicitly account for some forms of dependence among input variables. Some PSA codes (e.g., LHS) also allow the introduction of correlation (positive, negative, or zero). However, these capabilities are only a subset of subjective dependence, which must be accounted for in a variety of applications. After a substantial investigation[1], development of a subjective dependence algorithm was initiated for introduction into PHASER. This capability first became available in Version 1.10.

The method for addressing dependence is derived from the classical Frechet bounds. These specify two general relationships (Eqn.1). One gives bounds for the probability of the logical *and* of two variables A and B and the other gives bounds for the probability of the logical *or* of the two variables.

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[1] References 3 and 4 describe SNL contract work done in association with this project. The subject of dependence was addressed in both of these reports as one aspect of the contract work, and dependence research was also carried out at Sandia National Laboratories.

$$\max(0, \Pr(A) + \Pr(B) - 1) \le \Pr(AandB) \le \min(\Pr(A), \Pr(B))$$
$$\max(\Pr(A), \Pr(B)) \le \Pr(AorB) \le \min(1, \Pr(A) + \Pr(B)) \quad (1)$$

These bounds allow for positive or negative dependence. Based on the safety analysis problems we have observed, we elected to restrict relations to positive dependence.[2] With this modification, the Frechet bounds become:

$$\Pr(A)\Pr(B) \le \Pr(AandB) \le \min(\Pr(A), \Pr(B))$$
$$\max(\Pr(A), \Pr(B)) \le \Pr(AorB) \le \Pr(A) + \Pr(B) - \Pr(A)\Pr(B) \quad (2)$$

Some additional considerations are necessary before these bounds can be used in the types of safety analyses we are considering, however. For example, the events represented in the upper bounds above include any dependence that may exist. In contrast, the input data available for the events in a safety analysis ordinarily address the events independently. Furthermore, some situations are Markov-dependent in time so that event A occurring independently before event B causes a different event (say B^*) because of the dependence of B^* on the previous A, and on the other hand, event B occurring independently before event A can cause a different event (say A^*) because of the dependence of A^* on the previous B. For positive dependence, $P(B^*)>P(B)$ and $P(A^*)>P(A)$, but how much greater is unknown. If we are restricted to use only $P(A)$ and $P(B)$ as inputs (dependence effects are unknown), the classical Frechet bounds do not directly apply. Where only one (either one) of the Markov-dependent situations occurs, the upper bound becomes the maximum of the two:

$$\Pr(A)\Pr(B) \le \Pr(AandB) \le \max(\Pr(A), \Pr(B)) \quad . \quad (3)$$

This inequality is implemented in PHASER. For the more general case of an inclusive-or of the two Markov-dependent situations:

$$\Pr(A)\Pr(B) \le \Pr(AandB) \le \Pr(A) + \Pr(B) - \Pr(A)\Pr(B) \quad . \quad (4)$$

Eqn. 3 specifies a higher bound than would the direct (independent data) application of the Frechet upper bound as explained above. Eqn. 4 specifies an even higher bound. Although not specifying a strict upper bound, our judgment is that Eqn. 3 gives a more practically applicable model than Eqn. 4. As we, and others involved in this issue, become more experienced with this technique, we will continue to consider this issue.

Since PHASER uses a disjoint set algorithm [Ref. 1] for this application, the second Frechet bound can be modified to correspond to the form of the algorithm and Boolean result produced by PHASER. The resultant equality is:

[2] It is possible that information may later become available that would cause the positive dependence restriction to be removed.

$$\Pr(A or B\bar{A}) = \Pr(A) + \Pr(B and \bar{A}) \quad . \tag{5}$$

The second term of Eqn. 5 is accounted for by Eqn. 3. The forms of the Frechet bounds specified by Eqns. 3 and 5 have been used in the PHASER methodology under the specific conditions given, which apply to safety analysis modeled by Boolean-logic-based expressions (such as those developed for fault trees and event trees) where disjoint set algorithms are implemented.

The logic of inserting judgment-based dependence into the PHASER methodology follows the previously established precedent of allowing expert engineering judgment to determine values that cannot be precisely determined through principle-based analytical modeling or through definitive experiments. Similar to many other features in PHASER, this allows supplemental methodology where it is desired to transcend conventional methodology. The subjective dependence approach is modeled after the modified Frechet bounds results described above and on Dependency Bounds analysis [Ref. 5]. The latter portrays the bounds on variable parameters by specifying the limits of the cumulative distribution functions (CDFs) possible. We apply a subjective measure to estimate the CDF within the bounds and analogously apply the same measure to estimate the position within the upper and lower bounds of the corresponding fuzzy variables. This is described below.

First, consider dependence between two conjuncted events under the conditions described above, which are specified by Eqn. 3. Since a result influenced by dependence can be anywhere within or including the bounds specified, we allow a user to specify a position within the bounds by a dependence measure, ranging from but not including zero[3] (independence) to one (complete dependence). The dependence measure specifies a linearly converted position between the two bounds. If the user-specified dependence measure is termed d, the resultant probability is:

$$\Pr(A and B) = d[\max(\Pr(A), \Pr(B)) - \Pr(A)\Pr(B)] + \Pr(A)\Pr(B) \quad . \tag{6}$$

Eqn. 6 is applied to all of the function abscissa values (to the entire fuzzy function and to the entire probabilistic function for both variables A and B). An example application of Eqn. 6 is illustrated in Fig. 1. The probabilities of variables A and B are illustrated by light-lined trapezoidal fuzzy numbers, as shown. A user-specified value of $d = 0.3$ results in the heavy lined trapezoidal function shown. The dashed line shows the result that would have been obtained if the operands were independent. Note that dependence increases the joint probability so that a derived top event probability may indicate increased safety concern.

[3] Although allowed by the bounds, zero is excluded from the dependence routine since zero implies independence.

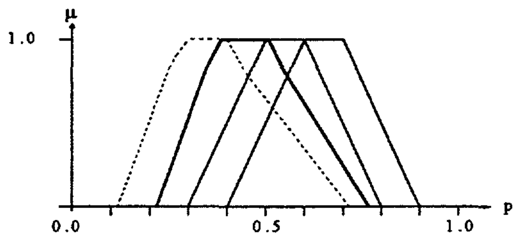

Figure 1. Illustration of Dependence

A group of three or more (n) conjuncted dependent events can have pairwise dependence between n(n-1)/2 pairs of events. Each can be specified by a d_i (i = 1,2, ... ,n(n-1)/2). Eqn. 7 generalizes Eqn. 3 to n variables.

$$\Pr(A_1)\Pr(A_2)\ldots\Pr(A_n) \leq \Pr(A_1 \text{and} A_2 \text{and} \ldots \text{and} A_n) \leq \max(\Pr(A_1),\Pr(A_2),\ldots,\Pr(A_n)) \quad (7)$$

Among various options, we have chosen to combine exhaustive specifications of pairwise dependence to obtain group dependence for conjuncted variables. We selected a weighted average of the pairwise dependencies to specify a position in the interval determined by Eqn. 7. The weighting was selected because pairwise dependencies with greater upper bounds were judged to have more influence in moving toward a greater interval position. Therefore, the weighting factor for each pair is the maximum value of the bounding interval for the dependence pair. The result, which is implemented in PHASER, is given in Eqn. 8.

$$\Pr(A_1 \mathit{and} A_2 \mathit{and} \ldots \mathit{and} A_n) = (w_1 d_1 + w_2 d_2 + \ldots + w_n(n-1)/2)[\mathit{max}(\Pr(A_1),\Pr(A_2),\ldots,\Pr(A_n)) - \Pr(A_1)\Pr(A_2)\ldots\Pr(A_n)] + \Pr(A_1)\Pr(A_2)\ldots\Pr(A_n) \quad (8)$$

where $w_i = \max(\Pr(A_j,\Pr(A_k))/ \sum_{i=1}^{n(n-1)/2} w_i$. For simplicity, we have made the notation of Eqn. 8 dual in nature. The i subscript (the weight subscript) varies from 1 to n(n-1)/2, while the j and k subscripts each vary independently from 1 to n. Where i happens to equal j or k or both, there is no association except notational coincidence.

PHASER has the optional capability to use a disjoint set algorithm to obtain the Boolean expressions used for computing top events. When computing with dependent variables, the disjoint set algorithm is unconditionally imposed. This allows the joining of disjuncted cutsets to be determined directly from Eqn. 5 with no additional dependence calculations.

III. Scale Factors and Confidence Factors

Scale factors are used in association with the inputs to PHASER in order to measure the relative amounts of probabilistic and subjective data available for any particular variable. The combination of hybrid scale factors to obtain confidence factors, as specified by Ref. 1, is repeated below (Eqns. 9 and 10), but is expressed more generally to account for n additive operands and m multiplicative operands, respectively. All of the probabilistic processing, the fuzzy processing, and the scale factor processing take place separately in PHASER. However, the probabilistic and fuzzy processing are related to each other through the confidence factor associated with each.

$$h_1+..h_n = \frac{a_1\hat{p}_1+\ldots a_n\hat{p}_n}{\hat{p}_1+\ldots\hat{p}_n}(p_1(x)+\ldots p_n(x)) + \frac{(1-a_1)\hat{f}_1+\ldots(1-a_n)\hat{f}_n}{\hat{f}_1+\ldots\hat{f}_n}(f_1(x)+\ldots f_n(x)) \quad (9)$$

$$h_1\times\ldots h_m = \frac{a_1+\ldots a_m}{m}(p_1(x)\times\ldots p_m(x)) + \frac{(1-a_1+..1-a_m)}{m}(f_1(x)\times\ldots f_m(x)) \quad (10)$$

Since scale factor processing (to obtain confidence factors) can become very complex for non-minimal (unsimplified) Boolean expressions, PHASER Boolean inputs are computed most efficiently if they are minimized. All scale factor processing is currently applied directly to the input, which is assumed to be minimized[4]. In contrast, the disjoint set expressions derived in the PHASER exact solution processing are non-minimal. This is because non-minimal expressions are required for accurate top event probability computations as well as for the PHASER dependence algorithm. PHASER Versions 1.00 and 1.10 tied the scale factor and top event processing together, allowing a user option on whether to compute the two with the disjoint set expression or the input expression. PHASER 2.10 allows a user option on whether or not the top-event expression is computed exactly, but enforces scale factor computation from the input expression. This change was especially important for maintaining processing efficiency, since confidence factors must also be recomputed for both the Importance and Sensitivity algorithms, which are new to Version 2.00.

An informative view of scale factors and confidence factors can be derived from an example problem, illustrated in Fig. 2. A simple fault tree is shown for which a "point estimate" of 2.86×10^{-8} has been derived from the basic events (described subsequently).

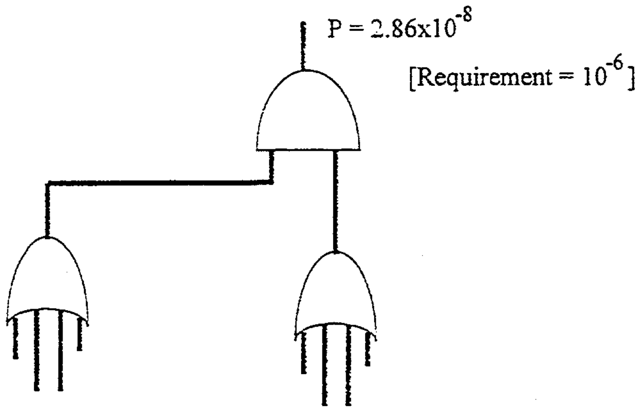

Figure 2. Example Fault Tree

[4] Most codes (e.g., SABLE, SETS) provide minimized output expressions, which are then appropriate PHASER input expressions.

Note that an example "requirement" is also indicated. The point estimate might suggest that the requirement would be easily met. This question will be examined as the example is pursued in more detail.

As shown in Fig. 3, the point estimate inputs used to compute the result 2.86×10^{-8} are all "order-of-magnitude" values. This illustrates one way in which more accuracy can be implied than is warranted. Also shown in Fig. 3 are indications of where the inputs came from. Some were data-based, some were subjectively derived from engineering judgment, and some involved portions of each. These represent the scale factor information (a = 1 for data-based inputs, a = 0 for engineering-judgment-based inputs, and a = ½ for the three "mixed" inputs. Note that PHASER lists the scale factor information and confidence factor information numerically rather than the graphical depiction used in Fig. 3.

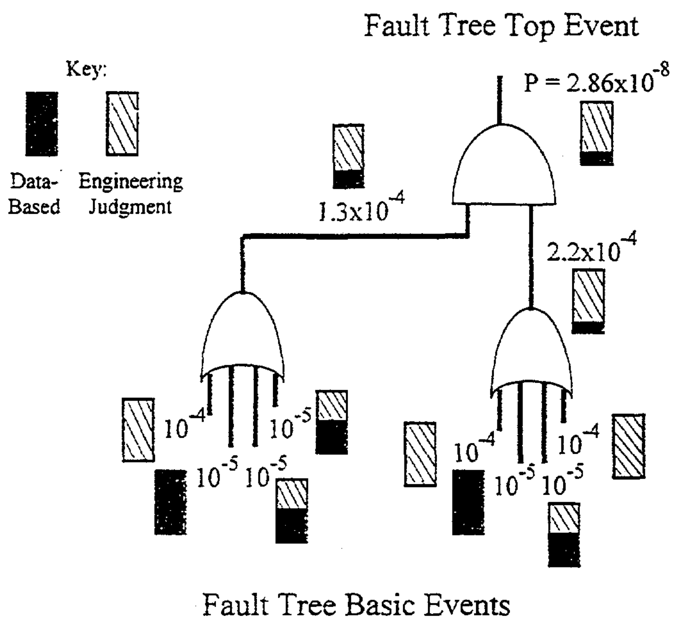

Figure 3. Fault Tree Indicating the Source of the Input Information

Also shown in the figure are the results of processing scale factor information up the tree to obtain confidence factor information. These computations used Eqns. 9 and 10. Variability will be added to this fault tree example in the next section.

IV. Safety Emphasis on the Extreme Concern

Fuzzy mathematics gives a different perspective on extremes than conventional PSA, because it incorporates subjectivity differently and because the mathematical operations involving each abscissa value are not constrained probabilistically by the corresponding ordinate values. One way of describing this difference is to consider three different possible values (mid-range, low-range, and high-range) for an input that is not precisely known, and one for which the process that causes the potential variation is not known. In conventional PSA processing, these might be members of a probability distribution, in which case multiple selections from the distribution are assumed to be independent,[5] so that no one value will be selected at a different frequency than that indicated by its probability function (PDF or CDF). For conventional probability functions (even "non-informative" probability functions) the most unsafe extreme value will not be selected repeatedly. However, a fuzzy description of the variation implies that there is no known frequency characteristic. The values that lie within the fuzzy intervals could have frequency characteristics across the spectrum, or they could all be located at the most unsafe extreme[6]. The allowance for the latter possibility is what distinguishes fuzzy analysis from probabilistic analysis and thereby leads to less suppression of indication of extreme values.

In Fig. 4, the previous example (begun in Figs. 2 and 3) shows the addition of variability to data-based inputs and uncertainty to engineering-judgment-based inputs. Also shown are the processing steps as the information is processed up the tree using the PHASER methodology. PHASER does not compress the ordinate when producing these types of plots. However, in Fig. 4 the ordinates of the plots are shown compressed proportionally to the scale factors and confidence factors for correspondence to the knowledge-source "bars."

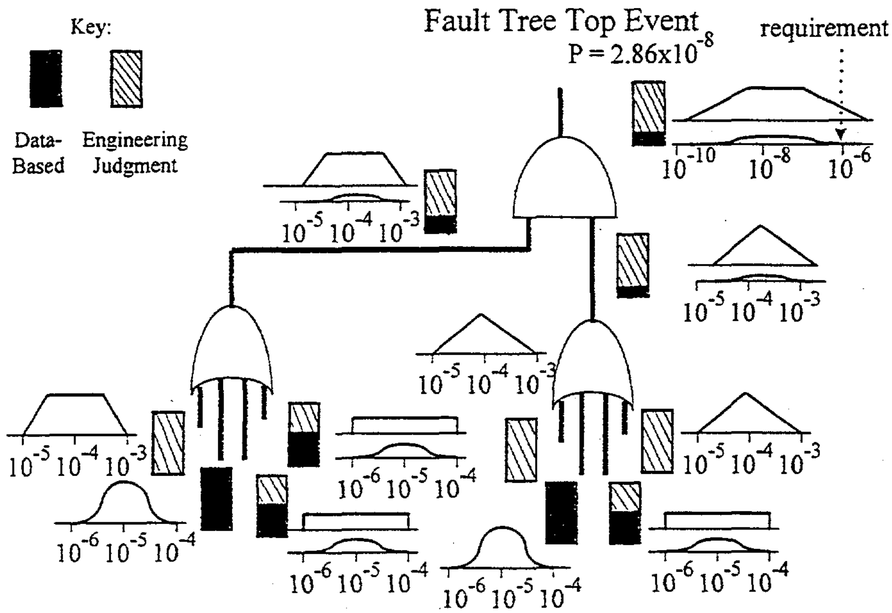

Figure 4. Previous Example with Variability and Uncertainty Added.

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[5] Note that this is not the same as assuming all variables are independent.

[6] The bounds of fuzzy numbers do not imply accurate knowledge about the extremes, but merely allow incomplete knowledge to be described more accurately. This means that the potential for values at the extremes cannot be precluded unless sufficient knowledge about the process becomes available (which would result in higher confidence factors for probabilistic descriptions).

At this point, the example "requirement" of 10^{-6} is re-visited. The tail suppression shown in the probabilistic portion of the analysis might lead one to a different conclusion than the trapezoidal edge in the fuzzy analysis. The confidence factors give guidance about which of the two types of information is more appropriate for any particular safety assessment.

For safety analysis, the most important regime in a spectrum of uncertainty is the extreme that indicates maximum potential for loss of safety. This means that portrayal of extremes is of crucial importance in safety analysis. If knowledge about input characteristics is lacking, assumption of tail suppression due to asserted knowledge about the input characteristics could be misleading. The assertion could also turn out to be correct, but the point is that if one doesn't know, the potential safety assessment impact could be disastrous. There are many real-world examples of inputs to PSAs that are necessarily at least partly subjective. The concern is that modeling these based strictly on stochastic assumptions may lead to minimal expectation of extreme threats, whereas the minimal expectation may be merely an assertion, rather than a reflection of reality.

For this reason, we selected Importance and Sensitivity measures that directly reflected the behavior of the results at the "extreme" of most safety concern. This is described in detail in the next two sections.

V. Importance

If a safety analysis indicates a potential problem, one would like to know the most important contributors to the problem. The effects of individual events (variables) depend on the cutset(s) in which they appear. Since each cutset generally combines a number of contributory variables, each of which can be examined for contribution to the cutset, we use cutset Importance measures. Because of focus on the region of extreme concern, we arbitrarily choose our measure for the "extreme" value for safety concern (f_{gc}) on each fuzzy cutset as the largest abscissa value where the ordinate $\mu = 0.1$, and the "extreme" value (p_{gc}) on each stochastic cutset as the largest abscissa value where the probability density function $p = p_{max}/10$. The choice for the extreme was intended to indicate approximately where values of concern lie. Since each part of the result (fuzzy and stochastic) contributes to the total picture through the confidence factors, we combine the two through confidence factor weighting as shown in Eqn. 11 below.

$$I_c = a_c p_{gc} + (1-a_c) f_{gc} \qquad (11)$$

As a result, this extreme-oriented Importance measure identifies those cutsets that contribute most to the extreme of the range of values portrayed in the final result. Since the events that form the cutset are identified by PHASER, each of the events in each cutset of concern can be examined as potentially important contributors (especially those with multiple appearances). As a result, any effort required to improve safety can be prioritized on the most important events.

An example of the determination of Importance is shown in Fig. 5 for an example cutset for which a fuzzy variability function, a probabilistic variability function, and confidence factors have been determined. The Importance measure (a probability value) is indicated by the vertical line through the right-hand portion of the uncertainty range shown in the figure.

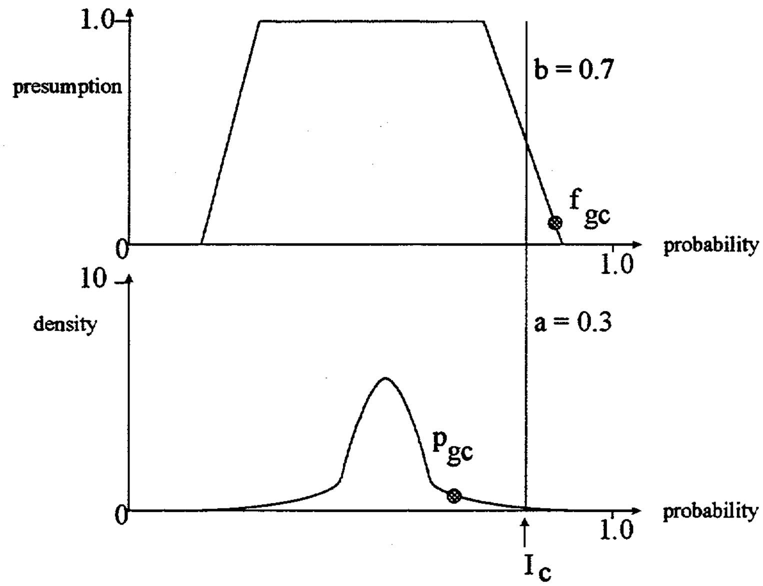

Figure 5. Illustration of Cutset Importance

Returning to the previous example of Figs. 2-4, an Importance plot is shown below in Figure 6. For illustration, this plot shows the Importance of the 16 cutsets, numbered as they were entered into the computation. In addition to indicating the Importance of the cutsets, these plots continue to follow the precedent of the previous figures by showing the knowledge source of the Importance.

PHASER displays Importance without the graphical depiction of knowledge source used in the example. An illustrative PHASER Importance plot is shown in Fig. 7.

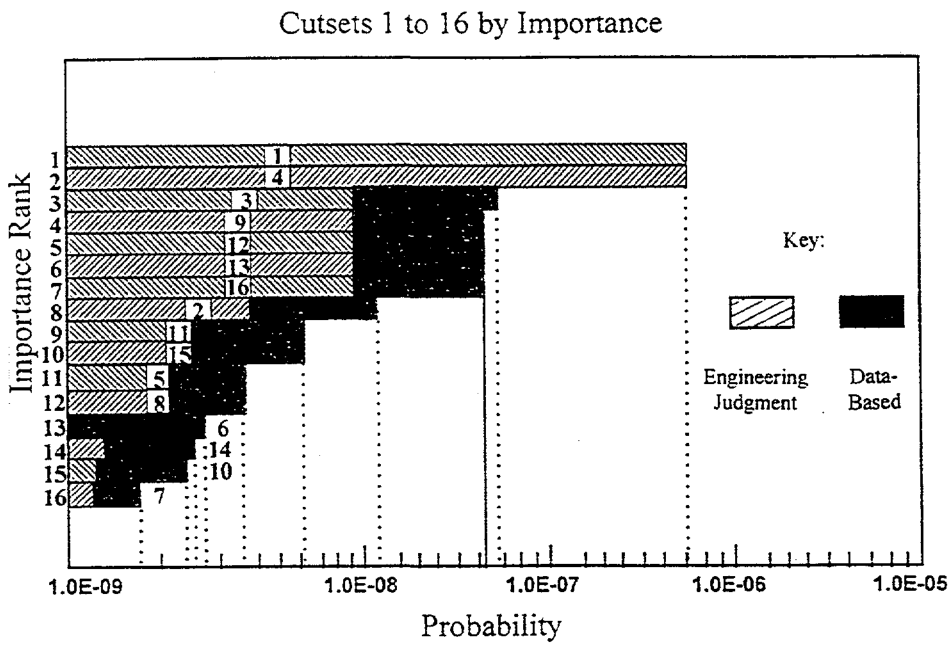

Figure 6. Importance Plots for Previous Example

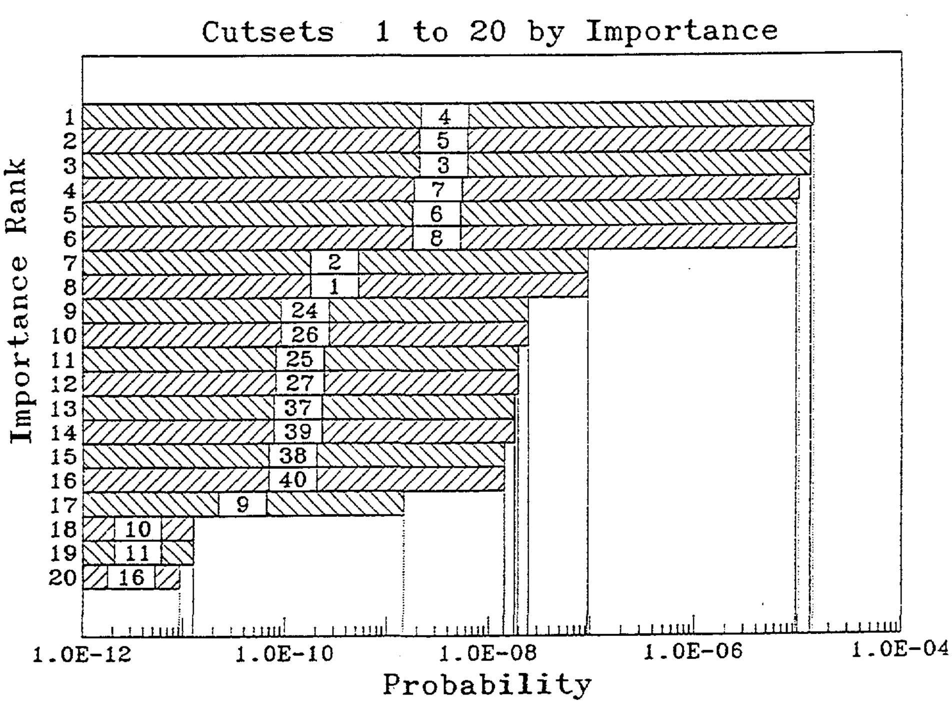

Figure 7. Illustrative PHASER Importance Plot

VI. Sensitivity

In evaluating variability or uncertainty, one would like to know which events have the most influence on the variability or uncertainty of the result. Because of safety assessment interest in the region of extreme safety concern, we obtain sensitivity for each individual contributory event by computing the top event composite result shown in Eqn. 12 for comparison with a reduced top event result obtained in the same way, but with a 10% reduction in the contributory event.

$$T = a_t p_{gt} + (1-a_t) f_{gt} \tag{12}$$

Terming the reduced top event composite result T^*, the comparison is done by computing the ratio between the top event composite reduction and 10%. This result, shown mathematically in Eqn. 13, is bounded by zero (no sensitivity) and one (maximum sensitivity).

$$S_e = \frac{T - T^*}{0.1 \times T} \tag{13}$$

The procedure is again based on identifying the upper extreme measure. We choose the greatest abscissa value (f_{gt}) for the top event composite fuzzy result where selection is made at the ordinate value $\mu = 0.1$, and the greatest value (p_{gt}) for the top event composite probabilistic result where the probability density function value, $p = p_{max}/10$. These are combined through the top event confidence factors to give an upper extreme indication of the final composite result as shown in Eqn. 12. A sensitivity plot for the example illustrated by Figs. 2-4 is shown in Fig. 8.

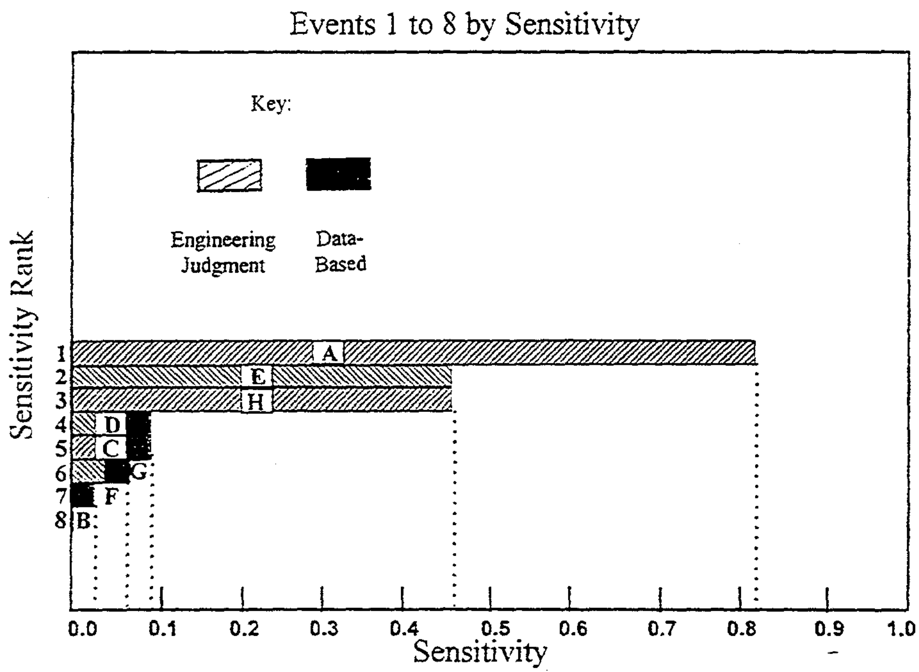

Figure 8. Sensitivity Plot for the Previous Example

As was shown in the Importance plots, this example graphically depicts the knowledge base, while PHASER does so numerically. An example PHASER sensitivity plot is illustrated below in Fig. 9.

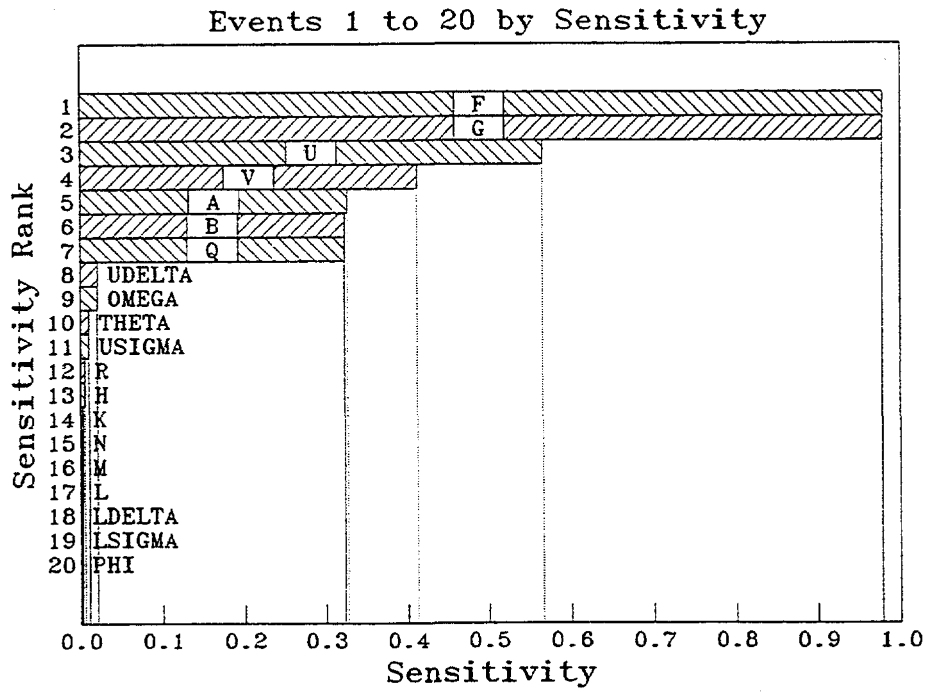

Figure 9. Illustrative PHASER Sensitivity Plot

Events having the greatest Sensitivity generally have the most influence on the uncertainty in the vicinity of the most extreme safety risk, and obtaining more information about these events has the greatest potential for reducing uncertainty about the safety assessment.

VII. Summary and Comments

The new features in PHASER 2.10 that were not available in PHASER 1.00 are the ability to address subjective judgment about dependence and the ability to obtain Importance and Sensitivity measures. The dependence capability obviates the common assumption of event independence, and the Importance and Sensitivity allow prioritization of any effort required to better understand and mitigate against input phenomena. At least one more version of PHASER is planned in order to add Windows 95 compatibility, and a few plotting enhancements are under consideration. The software can be made available to those interested in exploring these capabilities more thoroughly through a Research and Development Letter Agreement. Our "customers" will continue to receive new releases unless we are notified otherwise.

VIII. References

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