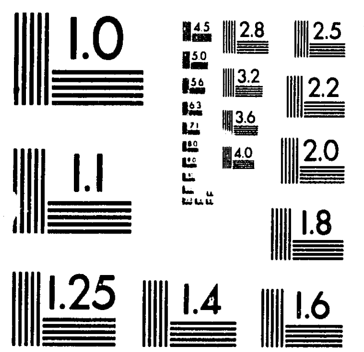
1.0
4.5
2.8
2.5
5.0
3.2
5.6
2.2
6.3
3.6
7.1
2.0
8.0
4.0
1.1
1.8
1.25
1.4
1.6

1 of 1

2

Conf-940312--33

SAND93-1236C

DEVELOPMENT OF SMART SEARCHING ALGORITHMS FOR VULNERABILITY AND UNCERTAINTY ANALYSES IN PROBABILISTIC RISK ASSESSMENTS*

Allan S. Benjamin
Special Projects Department 6411
Sandia National Laboratories
Albuquerque, NM 87150

In order to evaluate the risk inherent in a complex system, including a reasonable accounting of the many uncertainties that characterize both the environments to which the system is exposed and the responses of the system to these environments, risk analysts are forced to use statistical approaches. Some have chosen to assume that the variables have specialized distributions that lend themselves to rapid convolution. Others have resorted to Monte Carlo techniques or to similar sampling approaches. Such techniques have been used to determine the resultant distributions of various risk indices, such as the frequency of core melting in a nuclear power plant,[1] the probability of accidental nuclear detonation in a nuclear weapon system,[2] or the expectation of health effects from radioactive dispersal,[3] and to estimate the medians, means, and confidence intervals of these resultant distributions.

If the system is very well designed for safety, then simple convolution or sampling approaches may have to be augmented by intelligent searching schemes. An excellent example is the prediction of the probability of an accidental nuclear detonation for a nuclear weapon system. Under practically all situations, accidental nuclear detonation is virtually impossible because modern nuclear weapon systems are designed to preclude it. They have a series of strong links and weak links that are guaranteed to fail in a prescribed order when exposed to virtually all credible abnormal environments, such as fires, impacts, punctures, crushes, external pressures, lightning, or chemical attack. However, no engineered system is perfect, and under certain peculiar conditions involving combined environments that are spatially directed in the worst possible way, the strong links may fail before the weak links and an accidental nuclear detonation may be plausible. The challenge is to identify those conditions through an intelligent searching process and to determine whether their probability of occurrence is high enough to be of concern. (The current requirements for nuclear weapon systems stipulate that the probability of nuclear detonation must be less than one chance in a million for any credible abnormal environment or combination of abnormal environments.)

In the weapon system application, LHS generates millions of sample members, each consisting of a different set of parameter values, and we must employ intelligent searching techniques to reduce this set to a more workable number. We do this through a discriminator subprocess, which we will describe momentarily. The discriminator selects a fraction of the LHS sample members (i.e., several thousand) which are judged to possess the highest potential for producing the undesired outcome (i.e., nuclear detonation).

*This work was supported by the United States Department of Energy under Contract DE-AC04-76DP00789.

Benjamin - Page 1

MASTER

To evaluate the response of the system for the remaining sample members, we exercise a set of risk-compatible physical response codes such as TEMPRA-3D and STRESS-3D. These are fast-running thermal and structural analysis codes which are benchmarked to results obtained from more detailed finite-element codes. We describe the concepts employed in these codes in a companion paper.[6]

We combine results from TEMPRA-3D and STRESS-3D with a fault tree model which is produced by the codes SEATREE[7] and SETS/SABLE.[8] The fault tree for the weapon system application describes the pathways by which electrical energy may propagate from a source to the detonators in the nuclear explosives package. We use a cut set uncertainty analysis code, TEMAC,[9] to evaluate whether the undesired event occurs for each sample member and to analyze the principal contributing factors. For the sample members that produce the undesired outcome or come close to producing it, we perform further analysis using the more detailed finite-element physical response models together with the previously generated fault tree models. Thus we obtain a detailed analysis for those combinations of parameters that provide the highest potential for achieving the undesired outcome. The whole process, or a part of it, may be iterated as many times as necessary to assure that the accounting of potential pathways is reasonably complete.

The discriminator subprocess provides the basis for intelligent searching. Two examples of discriminator subprocesses are illustrated in Figure 2. In the first example, we develop a much simpler representation of the system by employing only a few representative cut sets to describe the pathways to the undesired outcome and a few algebraic equations to describe the physical responses of the components. We select the representative cut sets and formulate the algebraic equations by analyzing results obtained with the more detailed fault tree and risk-compatible physical response models for a select number of cases. We then apply the simpler representation to determine, for each of the original millions of sample members, a figure of merit loosely interpreted as a "closeness to the undesired outcome". More specifically, the figure of merit records the margin by which the most critical race in each cut set is won or lost. Sample members having the highest figures of merit are retained for further analysis.

In the second discriminator example, we extract the first few thousand out of the original millions of sample members and use the complete fault tree and the complete risk-compatible physical response models to evaluate how close each comes to producing the undesired outcome. From this subsample, we identify a few tens of members which appear to have the highest potential for the undesired outcome. These few members are used as "seeds" for paring down the original sample. The sample members whose sampling parameters lie closest to the seeds are retained for further analysis.

To test these processes and their ability to speed the convergence to a solution, we devised a sample problem. This problem simulates, qualitatively, the key characteristics of a nuclear weapon system's response to fires, including the thermal races between strong links and weak links that determine the outcome. At the same time, it incorporates a set of simplifications that enable us to obtain an "exact" analytical solution for the mean probability of the simulated undesired outcome and the statistical parameters that characterize its uncertainty. In addition to providing a means for benchmarking the intelligent searching algorithm, the sample problem provides insights into the challenges involved in searching for small regions of vulnerability in a large parameter space.

At Sandia, we have been exploring intelligent searching processes that are based on the principles of importance sampling. Figure 1 illustrates one of these processes which is applicable to the nuclear weapon system application. In this example, we first derive an accident scenario (event tree) model using the EVNTRE code.[4] We exercise this model to provide environment parameter distributions for a Latin hypercube sampling analysis performed by the code LHS.[5] We also input distributions for weapon system orientations, material physical properties, and component physical thresholds.

The presentation will describe the modeling concepts, searching algorithms, and code interfaces that we have discussed above. It will also present the derivation of the sample problem, identify how it relates to risk applications such as the nuclear weapon system example, describe how it was used as a test bed for searching algorithms, and discuss the insights gained from these analyses. Finally, it will identify some of the potential uses of intelligent searching algorithms for a variety of risk-related problems.

Benjamin - Page 2

Benjamin - Page 3

Figure 1. Illustration of a Process for Evaluating Nuclear Detonation Pathways.

Benjamin - Page 4

Figure 2. Illustration of Two Discriminator Subprocesses.

REFERENCES

1. "Severe Accident Risks: An Assessment for Five U.S. Nuclear Power Plants," NUREG-1150, 1990.

2. D. D. Carlson, A. S. Benjamin, R. J. Breeding, and D. M. Kunsman, "Probabilistic Risk Assessment Methods for Nuclear Weapon System Applications, Volume 2 - Methods," SAND91-0323/2, August 1991.

3. D. C. Aldrich, et al., "Technical Guidance for Siting Criteria Development," NUREG/CR-2239, SAND81-1549, 1982.

4. J. M. Griesmeyer and L. N. Smith, "A Reference Manual for the Event Progression Analysis Code (EVNTRE)," NUREG/CR-5174, SAND88-1607, 1989.

5. R. L. Iman and M. J. Shortencarrier, "A FORTRAN 77 Program and Users Guide for the Generation of Latin Hypercube and Random Samples for Use with Computer Models," NUREG/CR-3624, SAND83-2365, 1984.

6. A. S. Benjamin, "Development of Fast-Running Thermal and Structural Response Models for Probabilistic Analyses of Complex Systems," SAND93-1235C, This Conference, 1994.

7. B. Bingham and S. Walker, "SEATree, A SETS Fault Tree Drawing Tool," Science and Engineering Associates, Inc., 90-258-20-A:3, 1989.

8. R. Worrell, "SETS Reference Manual," NUREG/CR-4213, SAND83-2675, 1985.

9. R. L. Iman and M. J. Shortencarrier, "A Users Guide for the Top Event Matrix Analysis Code (TEMAC)," NUREG/CR-4598, SAND86-0960, 1986.

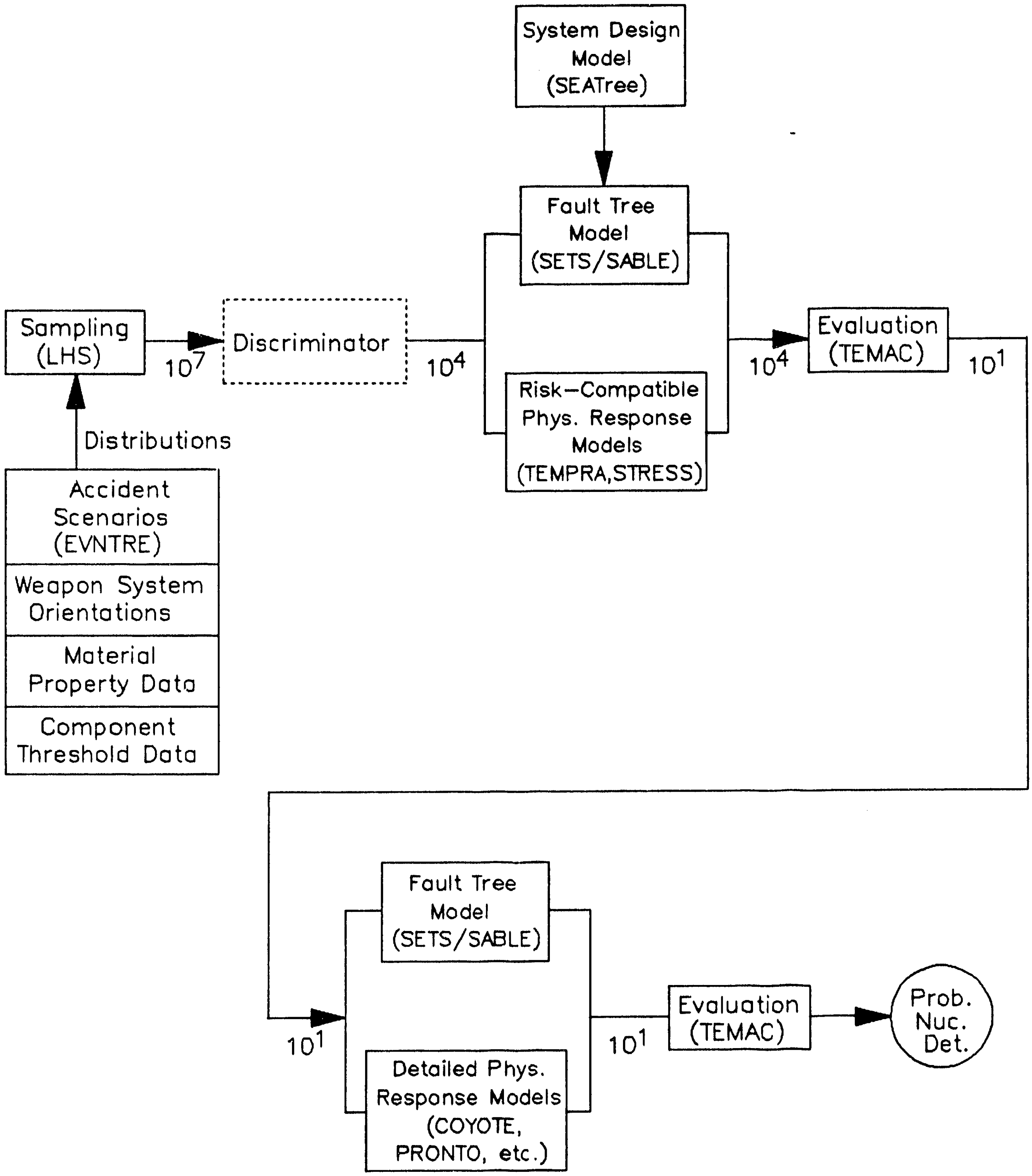

Figure 1. Illustration of a Process for Evaluating Nuclear Detonation Probabilities.

Benjamin - Figure 1

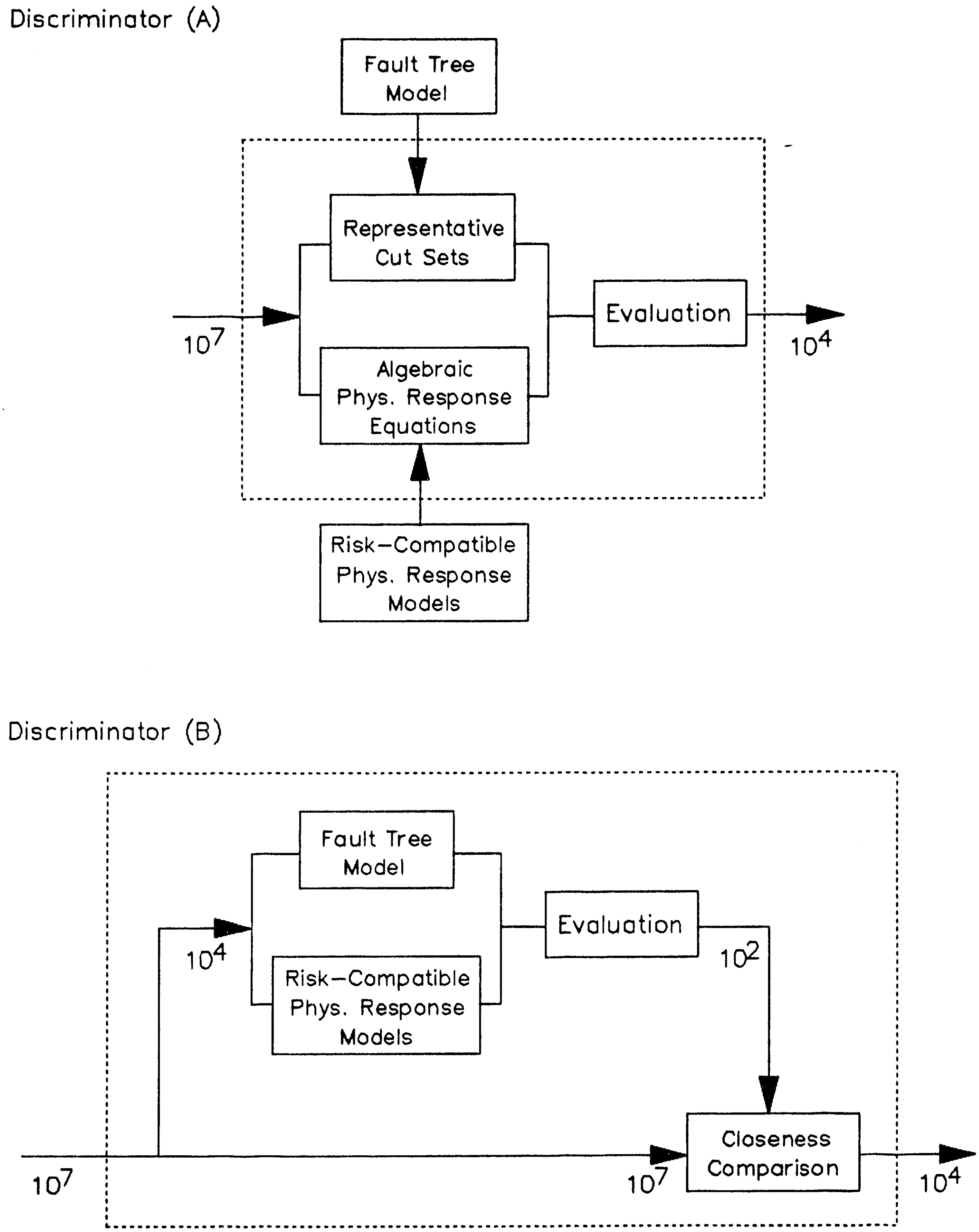

Figure 2. Illustration of Two Discriminator Subprocesses

Benjamin - Figure 2

DATE
FILMED
2 / 4 / 94
END