# Hazardous Materials Transport Risk Estimation under Conditions of Limited Data Availability

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**As public concern grows over the safety of hazardous materials transport, more policy emphasis is being placed on assessing the relative and absolute risks of various operations strategies. This is particularly apparent in the face of recent catastrophic events worldwide involving hazardous materials. At present, comprehensive hazardous materials transport risk assessments are difficult because of the paucity and poor quality of empirical data. These data problems are most acute for the rare, catastrophic event that is of primary concern to public safety officials. For these reasons, many approaches to risk estimation can be considered. This paper describes alternative approaches to hazardous materials transport risk estimation under conditions of limited data availability, including consideration of statistical inference, fault/event tree modeling, analytical and simulation techniques, subjective estimation, and Bayesian analysis. The hazardous materials transport problem is examined in terms of the feasibility of applying these techniques. Concern is raised over the likelihood of different approaches resulting in conflicting risk estimates, and a procedure for mediating these conflicts is discussed.**

As public concern grows over the safety of transporting hazardous materials, more policy emphasis is placed on assessing the relative and absolute risks of various operational strategies. At the heart of this problem is the subject of risk estimation. Traditional approaches to transportation systems analysis have focused on economic analysis and, consequently, much is known about operating costs and costing methodology; however, transport risk estimation is only now reaching adolescence.

A review of previous research efforts in this area reveals that, in the face of limited data availability, many studies have formulated risk estimation methodologies that lack a systematic structure, use subjective indices, neglect important risk components, and do not fully recognize the importance of both event likelihood and consequence. Moreover, several critical issues, such as the analysis of uncertainty and the accurate portrayal of low-probability/high-consequence events, have been largely ignored. This latter consideration is particularly important, because it is the rare, catastrophic event that is of utmost concern to public officials, industry, and the general population.

The objectives of this paper are to review previous work in this area, describe alternative approaches to transport risk estimation under conditions of limited data availability, and comment on the likelihood of conflicting estimates arising from implementing various approaches and how to mitigate these differences. Previous studies are cited to illustrate several of the issues raised in this discussion.

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## TRANSPORT RISK ESTIMATION

A crucial step in the risk assessment process involves estimating the frequency and consequences resulting from undesirable events, then evaluating the associated risk in quantitative terms (*1*). Risk is commonly expressed as a single number, known as the societal or expected risk. When adequate information is available, this number can be computed directly from historical data; otherwise, more theoretical approaches to risk estimation are required. The risk measure of interest can vary considerably, but typically, risk in hazardous materials transport is expressed in terms relating to expected property damage, injuries, or fatalities.

Expressing risk strictly in terms of a single number may simplify the tasks of estimation and evaluation, but it does not provide as much information as a risk profile, which is a probability distribution of incident likelihood and consequence (*2*). The shape of the risk profile particularly helps in distinguishing between the contribution to the expected risk of high-probability/low-consequence events and low-probability/high-consequence events.

Risk estimation itself is characterized by a sequential process, beginning with understanding the level of exposure (e.g., number of shipments, tons carried, distance moved), the frequency and type of incident occurrence (e.g., tank truck rollover, loose fitting, dropped in handling), and the consequence for a given incident (e.g., death, injury, property damage). The way these components are defined and measured depends on the data available, the purpose of the risk assessment, and the preferences of the risk analyst.

The most frequently studied mode has been trucking, reflecting the fact that trucks carry the largest share of hazardous materials and are responsible for the greatest number of reported incidents (*3*). Truck transport risk has been expressed in terms of community or population indices (*4–6*), total dollar cost (*7*), expected population and employment exposure-miles (*8*), expected fraction of shipment released (*9*), and the frequency of *N* or more fatalities (*10, 11*).

Risk estimation efforts focusing exclusively on the rail mode have measured annual expected fatalities (*12*) and risk profiles of fatalities (*13, 14*). Marine hazardous materials transport risk estimation has been more limited; a recent study on tanker and tanker barge transport illustrated the type of activity that

has been performed (e.g., risk was expressed in terms of expected release per shipment) (*15*). Multi-modal risk analyses have also been conducted, to support the development of a generic approach to risk estimation or the analysis of specific industries that would allow direct comparison between modes (*16–21*).

A detailed review of existing conceptual approaches to risk estimation reveals that most studies have relied heavily on whatever historical data were available, without concern for the quality of the data, its uncertainties, or its biases. There has also been a general lack of sophistication in the risk assessment process, with many studies resorting to the use of statistical inference for the sake of convenience. Furthermore, many of the applications are remiss in their representation of incident consequence, particularly with regard to the distribution of incident severity. Even the more sophisticated approaches have continued to rely exclusively on empirical data in the development of fault trees and Poisson models—using this information to establish event probabilities.

## RISK ESTIMATION METHODOLOGY

To accommodate the process of estimating incident likelihood, consequence, and (ultimately) risk in many engineering and science disciplines, several methodological approaches have been offered:

- Statistical inference,
- Fault and event trees,
- Analytical and simulation modeling,
- Subjective estimation,
- Bayesian analysis, and
- Some combination of these procedures (*22–25*).

These approaches may be applied to various elements of hazardous materials transport risk analysis, including estimation of incident occurrence probability, release likelihood, and associated consequence.

In several cases, the methodologies are fundamentally opposed to one another. For example, the use of statistical inference is based on the condition that sufficient data exist to perform an objective analysis. Whereas subjective estimation assumes this is not the case and, therefore, the opinion of an expert is the most appropriate surrogate. Bayesian analysis, where an expert's probability assessment may be combined with historical information, represents a point within this spectrum.

At another level, several uncertainties exist in each methodological process that are tied to the characterization of the transport problem. This is due, in part, to the stochastic nature of failures of engineered systems and the response of decision makers to an event when it occurs (*26*). There is additional difficulty associated with assessing low-probability/high-consequence incidents because of their rare occurrence and lack of opportunity to create experimental conditions to gain further knowledge (*27*). The common approach to addressing this problem is to aggregate to a broader problem focus where better information exists, at the expense of introducing biases that can pose problems with respect to representation and transferability (*28*). The following discussion examines the identified risk estimation methods in greater detail as they pertain to hazardous materials transport.

### Statistical Inference

Statistical inference is perhaps the most commonly used procedure for estimating risk. The premise here is that adequate statistical data exist from which to determine the likelihood and consequence of future events. The methodology assumes that a system's incidents occur independently and with constant probabilities. Therefore, past performance can be extrapolated to infer future expectation.

A number of considerations, however, make this technique somewhat troublesome (*2*). First, where accident records exist, information is often not available to estimate the level of exposure (e.g., miles traveled, tons carried); hence, exposure estimates must be made by using a data sample in which there is uncertainty about accuracy. Secondly, the size of the accident data base may be inadequate, as the historical accident data base may have been maintained for only a few years; furthermore, in many cases, reporting quality has been questioned (*3*).

Often, the response to this concern is to expand the problem definition to enlarge the sample to an adequate size for statistical purposes. This can be accomplished by expanding the vehicle class (e.g., the population of oil tankers is used as a proxy for liquid natural gas tankers), the geographic region (e.g., use of national accident statistics for a route-specific analysis), or any number of other parameters. However, care must be exercised to ensure that problem representation is not excessively compromised.

Finally, a problem exists with the assumption of stationarity in the process giving rise to the incidents. There are many reasons why this may not be the case. For example, a previous accident of a serious nature likely results in modifications to policy (e.g., the use of new container technologies), which threaten the stationarity assumption.

The use of statistical inference and its associated problems is well illustrated in a study conducted to develop incident rates for hazardous materials transport by mode and equipment type (*21*). The process included the use of a national data base of incident records involving vehicles transporting hazardous materials and several national data bases from which estimates of exposure could be derived (Table 1).

In this study, the incident data base represents a single year and is known to suffer from problems of underreporting and

TABLE 1 1982 INCIDENT RATE ESTIMATES (*21*)

| | Total | Significant Spills | Casualty-Related |
|---|---|---|---|
| All Types of Rail Cars and Trucks | | | |
| Rail | 1580 | 615 | 50.9 |
| Truck (for-hire) | 542 | 145 | 6.63 |
| Truck (private) | 55.6 | 36.3 | 1.71 |
| Tank Cars and Tank Trucks Only | | | |
| Rail | 1830 | 48.3 | 62.2 |
| Truck (for-hire) | 2524 | 1805 | 55.4 |
| Truck (private) | 37.6 | 24.8 | 0.243 |

NOTE: Incidents per billion vehicle-miles of hazardous materials.

misreporting. Furthermore, the exposure data suffer from consistency problems, in that truck and rail movements are tracked differently and cannot be compared directly. Several other methodological flaws also exist, which are quite common in studies conducted using statistical inference.

The major concern here is not the specific study in which these problems are identified, but rather the danger of widespread use of biased rates, as many policy makers are looking for such numbers to plug into their risk assessments without knowledge of the derivation of these estimates. Consequently, when a risk estimation methodology depends solely on statistical inference (or any other method), it is imperative to identify the uncertainties in the risk estimation process so that they can be incorporated into the decision process. It is also advisable to develop a risk estimation interval, rather than a point estimate, to reflect these uncertainties and to conduct subsequent sensitivity analyses that include the extremities of this range.

### Fault and Event Trees

Fault and event trees are so named because of the logic tree structures that each produces to describe the basis events that must occur to cause an incident and/or consequence (*23*).

A fault tree is formed of events often described by binary (Boolean) variables (the event occurs or not) and related by logical functions, essentially *or* and *and*. One constructs fault trees by identifying a top event—failure of all or part of the system—and sequentially identifying unions or intersections of preceding events that entirely describe each successive binary variable. Thus, the fault tree allows one to obtain a logical path between the top event and a set of basic events. Through this path, one can compute the probability of the top event as a function of the probabilities of the basic events. The application of fault trees requires significant events to have been tracked back through all possible sequences to their initiating events.

Figure 1 is an example of a fault tree. The event of ultimate concern is a potentially fatal hazardous materials transport failure. The logic structure suggests that this can only happen if an accident occurs *and* there is a resulting spill, fire, *or* explosion. The direct cause of an accident can be a result of one of many factors, as identified by the lowest level in Figure 1. Because of the logic structure of the fault tree, however, several initiating events are allowed to occur that do not necessarily result in a potentially fatal episode.

An event tree is formed of a sequence of event sets that can be associated with random variables and a probability distribution defined over them. Each branch on the tree forms a new variable, with its probability distribution conditional on values of previous random variables in the tree. Because the probability of each event is conditional on the occurrence of events that precede it in the tree, the joint probability of the intersection of events that constitute a sequence (scenario) is found by multiplication.

The event tree appearing in Figure 2 is based on an analysis of the same incident data base used in the statistical inference illustration referred to in Table 1. Note that there is an implied sequence with each major branch in the tree: a package failure occurs, which results in a spill, whose impact was property damage in excess of $10,000. The probability of each successive branch on the tree is conditional on the likelihood of the events that precede it. This illustration also demonstrates the importance of structuring a complete tree and a properly ordered one. Also, to maintain a handle on the size of a tree, events must often be aggregated. In Figure 2, death, injury, and property damage were each grouped into two severity categories, and a hierarchy of consequence was established, whereby an event resulting in death and injury or property damage was recorded as a death consequence, while an event resulting in injury and property damage was considered an injury consequence.

Fault trees and event trees have different structures and serve different purposes—although for some risk analysis problems it may be appropriate to use both techniques. For example, in Figure 3, fault trees are commonly used to represent a complex sequence of events, whereas event trees are often used to determine possible impacts of an event. For either methodology to be plausible, however, the probabilities of occurrence of the initiating and all subsequent events must be estimated with adequate precision, and the magnitude of the consequences accurately predicted. In actuality, this can result in the formulation of complex trees consisting of hundreds or thousands of sequences.

The primary advantages of fault and event trees lie in their more efficient use of available data. Data requirements become

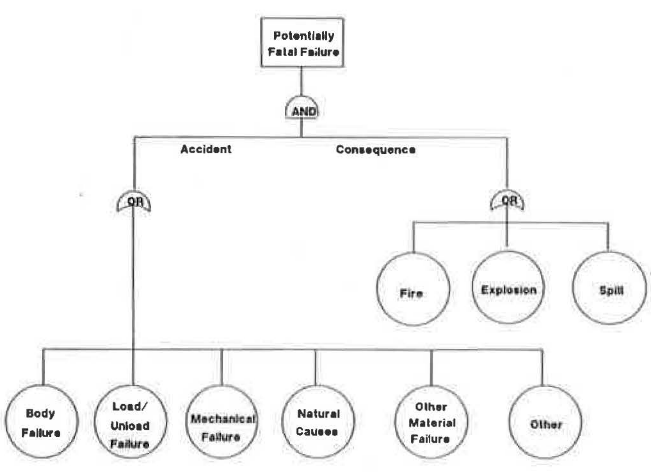


**FIGURE 1 Hazardous materials transport fault tree.**

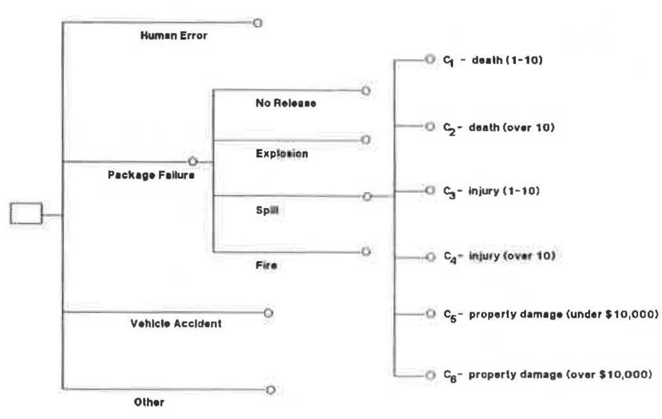


**FIGURE 2 Hazardous materials transport event tree.**

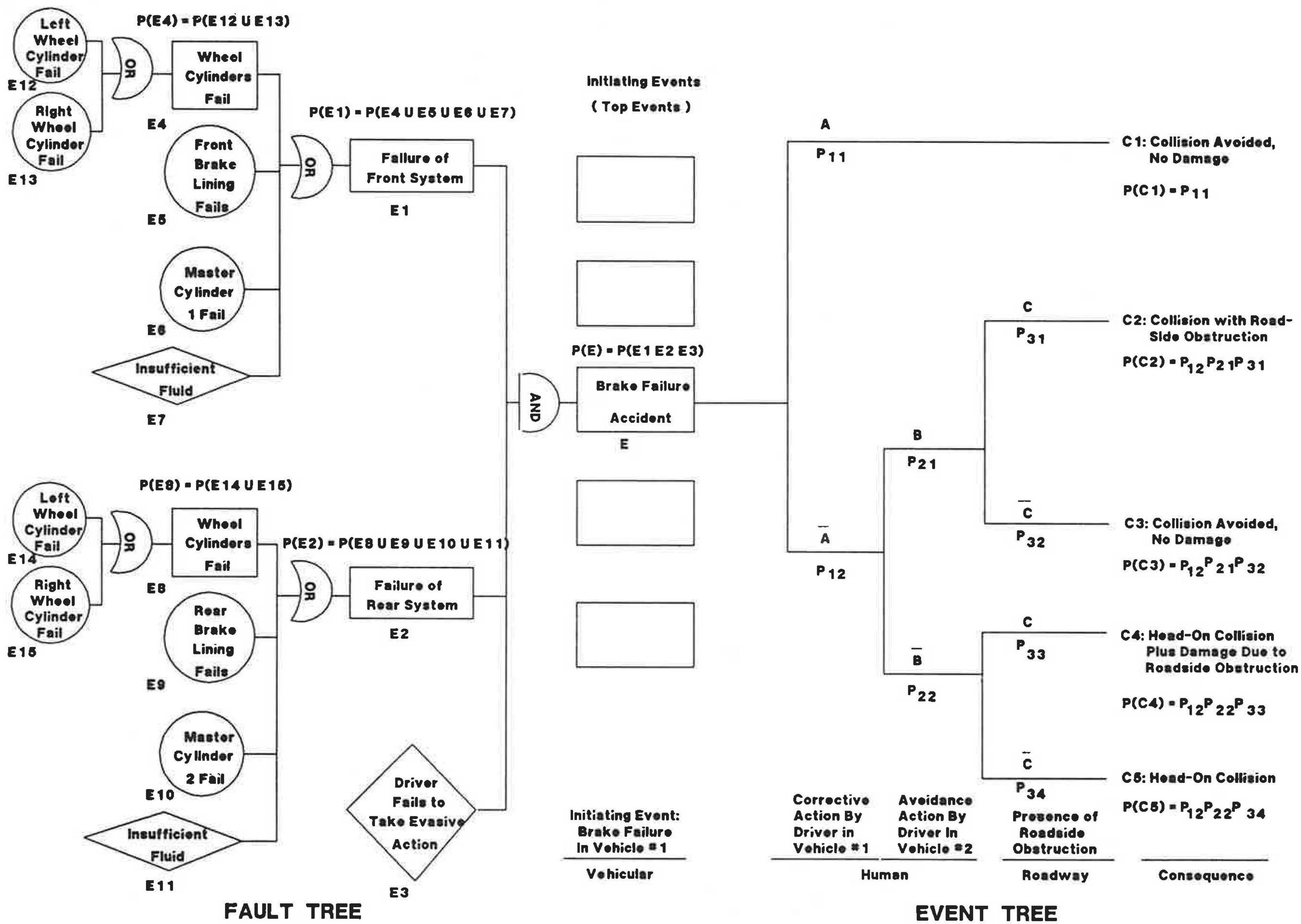


FIGURE 3 Combined tree structure for hazardous materials transport risk estimation.

an issue of obtaining meaningful samples of basic event data, such as the failure of a specific procedure. It is generally agreed that basic event data are easier to cull than data for disaggregate incident circumstances. Fault trees also lend themselves to the evaluation of the effectiveness of mitigating measures because measures under consideration can be represented through changes in the logic flow of the tree.

### Analytical and Simulation Modeling

Analytical and simulation approaches to risk estimation express the operations of the system in terms of functional parameters representing system components and external factors. The conditions under which incidents occur and consequences arise are associated with specific combinations of the values of these parameters. In the case of simulation, the parameters are stochastic and values are represented by probability distributions, often derived from empirical data. Simulation runs are made where parameter values are plucked from these distributions to form potential scenarios. Repeated runs must be made to create an adequate sample of simulated scenarios from which responsible evaluation can be conducted.

Analytical models are necessarily simpler because of their use of a deterministic, rather than stochastic, process. For this reason, analytical models have typically been applied to components of the overall risk estimation methodology, such as the development of an incident occurrence model, which is often represented as a Poisson model. Analytical models can also be used as inputs to the simulation process.

A typical analytical approach is to assume that spills are independent events that occur randomly with respect to distance over which material is transported (*29*). The number of spills, $n$, occurring over a distance, $L$, is a discrete random variable; if the independence assumption is met, then $n$ is Poisson distributed with parameter, $\nu L$:

$$P(n) = [(\nu L)^n/n!]e^{-\nu L} \tag{1}$$

where $\nu$ is the average number of spills per mile.

This is, in effect, a binomial distribution for a large number of independent events (trips) that result in only a few release occurrences and only two response classes (release or no release); $\nu$ can be (and often is) derived using empirical data. This approach can be carried one step further by rearranging terms to derive the average number of years between spills, based on the average number of miles traveled per year.

One class of analytical models with special application relates to cases when one is concerned with events having extreme consequences, but only events of lesser consequence have been observed. Thus, it becomes necessary to extrapolate from the less severe to the more severe by assuming the severe events are caused by the same physical mechanisms and processes that caused the less severe events. The only difference is that the catastrophic events are assumed to be more extreme realizations of the same process. The conditions associated with this process are known as extreme value theory (*30*).

A major problem with analytical models is that, in the process of accommodating mathematical simplicity, the model formulation can depart from direct physical significance. Although simulation is more representative, it is typically a cost-prohibitive technique due to the computational time and expense involved in executing a single run, and the need to conduct multiple simulations to accumulate a basis for risk assessment (*2*).

### Subjective Estimation

An approach often used in place of sparse data in developing risk estimates is subjective estimation by a so-called expert or panel of experts. These experts are assumed to be sufficiently familiar with the problem at hand that they can meaningfully extrapolate their experience and express it in quantitative and qualitative terms to accommodate the risk assessment process. Subjective estimation is perceived as an inherently low-confidence methodology (*2*). However, this perception may be a result of the general lack of appreciation of more subtle, but often as significant, subjective elements of transport safety.

Akin to subjective estimation is the use of subjective indices to represent risk factors (e.g., community population exposure on a scale of 1 to 10). While it may sometimes be appropriate to a methodology to represent qualitative effects that cannot be quantitatively measured, there is a real danger in developing risk estimation methods that are too dependent on this notion. First, the index scale can be somewhat arbitrary (e.g., How is the rank of "1" defined? In what way is a 1 different from a 2?). Second, various analysts may have different definitions for each classification (e.g., what is low to one may be moderate to another). Finally, it is difficult to translate policy options into this framework so as to evaluate their potential usefulness.

The use of subjective impact ratings by Yu and Judd (*20*) illustrates the application of subjective indices. A linear utility scale running from $-3$ (adverse impact) to $+3$ (positive impact) was used to classify projected fatalities, environmental impacts, economic impacts, and traffic impacts associated with potential routes serving a proposed nuclear waste repository site. Weights were subsequently assigned to each of these impacts for inclusion into a composite measure of effectiveness from which priorities for alternatives were established. It is interesting to note that the study was used to reach a formal conclusion based on this procedure—despite the appearance of all of the shortcomings raised in this discussion.

### Bayesian Analysis

A happy medium between some of the previously discussed approaches may be the use of Bayesian analysis. In essence, this approach permits the acceptance of both prior and posterior information in forming probabilities. Essentially, Bayes theorem states that

$$p(A/B) = p(A)[p(B/A)/p(B)] \tag{2}$$

where $A$ and $B$ represent information relating to the same event derived from different sources, and $p(A)$ represents the prior probability. $p(A/B)$ expresses the probability that Effect $B$ was caused by Event $A$.

The Bayesian approach can be designed to accommodate subjective estimation to form prior probabilities, and then use whatever empirical data exist to derive conditional posterior probabilities. This analysis design can, therefore, make full

use of available empirical observations (e.g., no catastrophic events in the last five years), without relying exclusively on the implications of this information (e.g., because no catastrophic event occurred in the last five years, there is zero probability of occurrence in the future).

The illustration cited here actually incorporates subjective estimation, analytical (Poisson) models, and empirical data (*31*). Suppose an expert provides an estimate of the frequency of release of spent fuel per transport shipment in the form of a probability distribution, as depicted in Figure 4. If we define $A_1, A_2, \ldots, A_6$ as corresponding to frequency rates of $10^{-3}$, $10^{-4}, \ldots, 10^{-8}$, respectively, then $P(A_1)$ would equal 0.01. Now suppose that the historical data base indicated 4,000 shipments of spent fuel without a release. Granted, this does not constitute a significantly large sample size (given the frequencies of release estimated by the expert), but it is valuable information that needs to be assimilated into the analysis framework. This information is used to derive $p(B/A)$ using a binomial (Poisson) distribution:

$$p(B/A_1) = (1 - 10^{-3})^{4000} = 0.0183 \quad (3)$$

$$p(B/A_2) = (1 - 10^{-4})^{4000} = 0.670 \quad (4)$$

Similarly, $p(B/A_3) = 0.961$, $p(B/A_4) = 0.996$, $p(B/A_5) = 0.9996$, and $p(B/A_6) = 0.99996$. Thus

$$p(B) = \sum_i p(A_i)p(B/A_i) = 0.907 \quad (5)$$

This leads to the final computation:

$p(A_1/B) = 0.0002$ $p(A_2/B) = 0.148$ $p(A_3/B) = 0.424$

$p(A_4/B) = 0.329$ $p(A_5/B) = 0.0882$ $p(A_6/B) = 0.01102$

In comparing $p(A_i)$ with $p(A_i/B)$, it can be seen that the presence of empirical information alters slightly the prior probability distribution, as it should. Given that no spills have occurred in the first 4,000 shipments, the likelihood that the true frequency rate is $10^{-3}$ or $10^{-4}$ is diminished, while the probabilities of lower frequency rates correspondingly increase.

## AGGREGATING VARYING RISK ESTIMATES

Only recently have researchers established the significant impact of risk definition and estimation on hazardous materials trans-

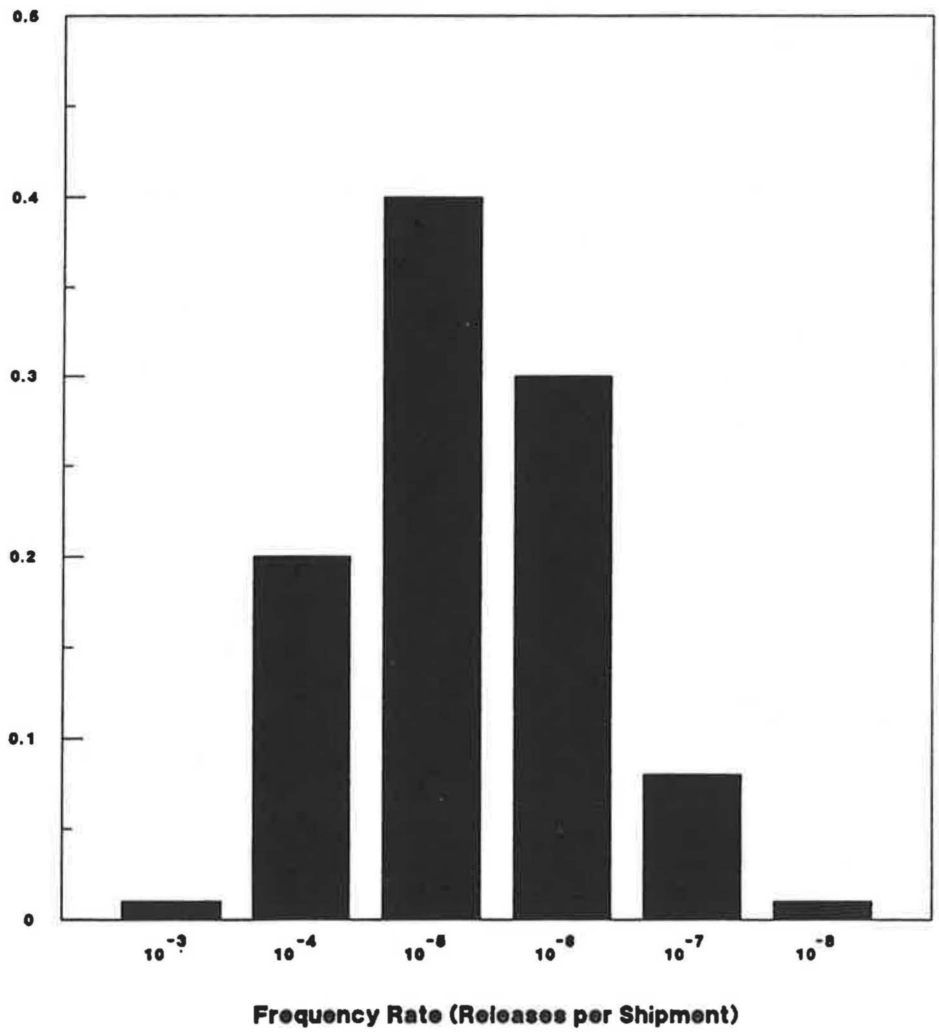


**FIGURE 4 Probability distribution of frequency of releases (*31*).**

port policy. In a study where multiple risk estimation procedures were examined, it was demonstrated that varying risk estimates based on population exposure alone yielded vastly different optimal routing strategies (*32*). Two independent studies of marine transportation of liquefied natural gas have also been conducted using the same information, which yielded risk estimates that differed by several orders of magnitude. From these efforts, the need for reaching consensus risk estimates has been formally recognized.

Prior attempts to find consensus estimates of transport risk have been virtually nonexistent. The exception being a study of subjective estimation in which a group of experts was convened to assess risks, and a consensus was reached using the Delphi technique (*2*). Fortunately, there exist, from other disciplines, fundamental approaches to judgment aggregation that may have partial or full transferability to the problem addressed herein.

For example, an information theoretic approach may be able to achieve this objective by identifying a solution space that satisfies the boundary conditions imposed (*33*). The decision maker initially holds to a fixed viewpoint, expressed by a probability vector $P$. However, the decision maker is given expert judgment that the true mean of random variable $X$ is $u$. The decision maker is then compelled to adjust his or her viewpoint to be consistent with the true parametric information that $E(X) = u$. It is reasonable to assume that this adjustment process will result in a new viewpoint as close as possible to the initial viewpoint of the decision maker and yet consistent with the expert (see Figure 5).

Considerable literature exists on this type of adjustment process as viewed in the context of generating prior probability distributions for Bayesian inference. Sampson and Smith proposed to use, as the measure of closeness, the widely employed Kullback-Leibler discriminator $I\ (Q,P)$. This represents the expected difference between viewpoint $P$ versus $Q$ if, in fact, the true probability distribution is $Q$. In the adjustment process, the expert judgment is given in the form of partial information concerning the parameters of an underlying, but unknown, probability distribution. In particular, it assumes knowledge of the mean of the distribution. This is

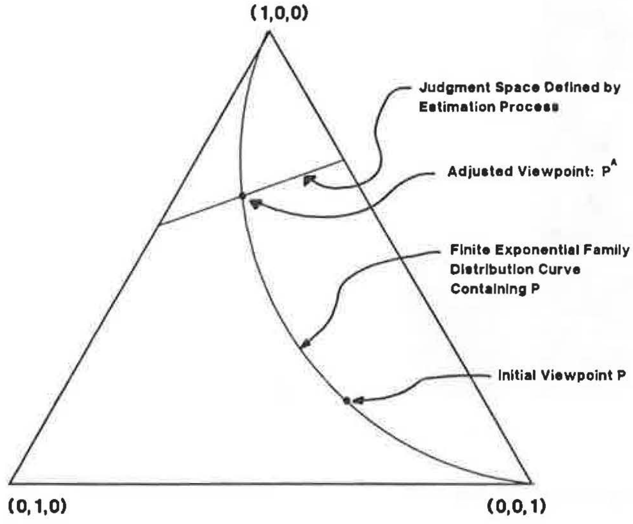


**FIGURE 5 Finding-adjusted viewpoints ($M$ = 2) (*33*).**

equivalent in the Bayesian construction to an observed average based on a large sample of observations.

Many situations also exist where the prior information would take the form of interval estimates of $P_i$. For example, in the case of rare events, it would be difficult to obtain precise estimates of $P_i$. If $S$ approaches produce probability ranges $a_{is} \leq P_i \leq b_{is}$, $1 \leq i \leq n$, then the $S$th estimate is consistent if and only if (*34*)

$$\sum_{i=1}^{n} a_{is} \leq 1 \leq \sum_{i=1}^{n} b_{is} \tag{6}$$

Otherwise, no probability vector satisfies the constraints given by the estimation process. The decision maker then pools, or aggregates, this data across the estimation approaches to obtain final interval estimates $a_i \leq P_i < b_i$, $1 \leq i \leq n$. The decision maker might compute $a_i$ and $b_i$ as the averages of the $a_{is}$ and $b_{is}$, respectively.

Adopting the maximum entropy principle (*35*), the decision maker computes $p^*$, a solution to

$$\max \left[ - \sum_{i=1}^{n} P_i \ln (P_i) \right] \tag{7}$$

subject to

$$\sum_{i=1}^{n} P_i = 1 \qquad P_i \geq 0 \qquad \forall\, i$$

$$a_i \leq P_i \leq b_i \qquad \forall\, i$$

Previous research has shown how to solve this problem with the addition of inequality constraints on the $P_i$ (*36*). Factors influencing this process include the number of estimates and the variation in their respective values (*37*).

This approach is illustrated in the following example. Suppose we are interested in the probability of a hazardous materials transport incident occurrence according to five classes of incident severity. Assume that several independent probability estimates were made, which yielded the following intervals:

| *Class* | *Portion of Shipment Volume Released (%)* | *Probability Interval* |
|---|---|---|
| 1 | 0 | 0.45–0.90 |
| 2 | 1–10 | 0.15–0.55 |
| 3 | 11–30 | 0.01–0.10 |
| 4 | 31–60 | 0.00–0.001 |
| 5 | 61–100 | 0.00–0.001 |

The index $i$ corresponds to the incident severity class. The $a_i$ and $b_i$ are $a_1 = 0.45$, $b_1 = 0.90$, etc. The following solution is based on an algorithm presented by Freund and Saxena (*35*). First, the function $V_i(x)$ is defined as follows:

$$\begin{aligned} V_i(x) &= a_i \qquad 0 \leq x \leq a_i \\ V_i(x) &= x \qquad a_i \leq x \leq b_i \\ V_i(x) &= b_i \qquad b_i \leq x \leq 1 \end{aligned} \tag{8}$$

where

$$V(x) = V_1(x) + V_2(x) + \ldots + V_5(x) \tag{9}$$

Next, an order set, $T$, is constructed of the $a_i$, $b_i$, 0, and 1:

$$T = (0, 0.001, 0.01, 0.1, 0.15, 0.45, 0.55, 0.9, 1.0)$$

The values of $V(x)$ are sequentially evaluated until a pair of consecutive elements of $T$ ($t_1$ and $t_2$) is found between which $V(x)$ assumes a value of 1.0. The values of $V(x)$ are computed as follows:

$V(0.0) = 0.610$ $V(0.001) = 0.612$ $V(0.01) = 0.612$

$V(0.1) = 0.702$ $V(0.15) = 0.702$ $V(0.45) = 1.102$

Therefore, $t_1 = 0.15$ and $t_2 = 0.45$. Defining $S_1 = \Sigma_{a_i \geq t_2} a_i = 0.45$, $S_2 = \Sigma_{b_i \leq t_1} b_i = 0.102$, and $m_1$ and $m_2$ as the number of $a_i \geq t_2$ and $b_i \leq t_1$, respectively, if $m_1 + m_2 = 5$, then $B = t_1$. Otherwise

$$B = (1 - S_1 - S_2)/(n - m_1 - m_2) \qquad (10)$$

In this instance, $m_1 = 1$, $m_2 = 3$, and $B = 0.448$. The maximum entropy distribution is obtained by setting $P_i^* = V_i(B)$. Therefore, the consensus probability estimates are

$P_1^* = 0.45$ $P_2^* = 0.448$ $P_3^* = 0.10$ $P_4^* = P_5^* = 0.001$

It is important to note that in mitigating conflict, the judgment aggregation approach must be applied with care. Situations can arise where the source of the conflict is quite real; that is, sufficient uncertainty exists so that convergence to a point estimate may be a damaging representation of the problem.

## CONCLUSIONS

Hazardous materials transport risk assessments are typically faced with the problem of selecting an appropriate risk estimation methodology under less-than-ideal conditions, often a result of the quality of available data. The approaches discussed in this paper show clearly that no methodology is preferred for all circumstances. Rather, good judgment must prevail in determining what is acceptable methodology given the problem at hand, and the strengths and weaknesses of each approach. Contemporary views of risk, particularly Bayesian thought processes, provide a refreshing opportunity to remove some of the dependence of risk estimation on adequate empirical data.

Uncertainties exist in all of the risk methodologies, and where increasing uncertainty exists, an increasing need for responsible risk estimation also exists. For these reasons, it is advisable to develop risk estimation intervals rather than point estimates, and to apply sensitivity analysis, particularly for low-probability/high-consequence events.

As more interest is directed at risk assessment in hazardous materials transport, situations will arise where conflicting risk estimates may emerge. To address this problem, a comprehensive approach to judgment aggregation must be formalized.

In summary, although significant progress has been made by hazardous materials transport researchers in understanding and refining risk estimation methodology, a formidable challenge remains to elevate this activity to a more respected level.

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