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# Application of a predictive Bayesian model to environmental accounting

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**Abstract**

Environmental accounting techniques are intended to capture important environmental costs and benefits that are often overlooked in standard accounting practices. Environmental accounting methods themselves often ignore or inadequately represent large but highly uncertain environmental costs and costs conditioned by specific prior events. Use of a predictive Bayesian model is demonstrated for the assessment of such highly uncertain environmental and contingent costs. The predictive Bayesian approach presented generates probability distributions for the quantity of interest (rather than parameters thereof). A spreadsheet implementation of a previously proposed predictive Bayesian model, extended to represent contingent costs, is described and used to evaluate whether a firm should undertake an accelerated phase-out of its PCB containing transformers. Variability and uncertainty (due to lack of information) in transformer accident frequency and severity are assessed simultaneously using a combination of historical accident data, engineering model-based cost estimates, and subjective judgement. Model results are compared using several different risk measures. Use of the model for incorporation of environmental risk management into a company's overall risk management strategy is discussed. © 2001 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

Business and environmental managers in industry are facing increasing demands for environmental performance from regulators, consumers, and their shareholders. At the same time, marketplace competition more and more frequently emphasizes the environmental

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performance of firms and products. Environmental and financial information required to meet such expectations while maximizing shareholder value is unavailable in many firms. This need for accurate and consistent cost information for environmental projects has generated an interest by business in what is known as "environmental" or "full cost" accounting [1]. Regulators and environmental activists are also supportive of environmental accounting because they believe that many environmental costs are hidden or under-valued and thus see full cost accounting as a way to "green" industry by appealing to the corporate profit motive.

This paper addresses two types of environmental cost that are often neglected even within full cost accounting programs: the highly uncertain costs associated with environmental accidents and secondary costs contingent upon the occurrence of accidents such as third party liability, disruption of production due to interruption of the supply chain, and increased insurance rates. Interest in characterizing certain contingent costs is certainly not new, for example, liability has been studied for decades. However, contingent environmental costs often represent an extreme example because the costs can be very large and uncertain, and their occurrence very infrequent. Because of their highly uncertain nature, many firms neglect or misrepresent contingent environmental costs when making business decisions, leading to capital investments, design choices, and production decisions that are not in the best interests of the firm or the environment [2].

The complicated physical processes that underlie environmental accidents and their infrequent occurrence make environmental risk difficult to assess quantitatively. Thus in most companies, environmental risk is managed through command-and-control measures, in the form of procedural manuals and rules, that are overseen by the department that deals with environmental, health, and safety issues, rather than the financial officers that oversee other financial risks. By organizationally segregating environmental risk management and relying too heavily on formulaic measures, firms reduce their flexibility and ability to make informed risk management decisions. For example, firms often buy insurance against environmental liability at the corporate level, but do not charge operating managers for their unit's portion of the premiums. The unit and line managers are thus poorly informed about the costs of environmental risks within their units, and are also limited in their ability to creatively manage those risks by inflexible risk management procedures.

This paper describes and demonstrates a new Monte Carlo spreadsheet implementation of a predictive Bayesian model of project net present value proposed previously [3]. The model has been recognized as general, not data intensive (inputs may include professional judgment as well as available data), and in need of computer implementation [4]. The implementation presented addresses this need, facilitating use of the model by technical professionals to assess variable and uncertain contingencies such as those due to environmental accidents. The approach allows characterization of environmental risks so that they can be better integrated into a company's overall risk management approaches.

Use of the spreadsheet model is demonstrated in this paper for the evaluation of the choice by a large industrial firm of whether or not to implement an accelerated PCB transformer phase-out. Variability in frequency and cost of PCB transformer accidents and their secondary effects are accounted for on the basis of historical, engineering model-based, and subjective information. The case study was abstracted from a series of site visits to a large electronics manufacturing firm located in Oklahoma City, OK. After developing the model for the PCB transformer replacement case, alternate methods of presenting the probabilistic net present value results to decision makers are discussed and compared.

## 2. Spreadsheet model

Discrete, random accidents, such as PCB transformer spills and fires, can be represented by a predictive Bayesian compound Poisson model to assess cumulative damages over an assumed planning period [3]. In order to provide sophisticated but non-expert users uncomplicated and flexible access to the compound Poisson model, a Monte Carlo spreadsheet implementation of the model has been developed (referred to here as “NPVRISK”). The NPVRISK modeling tool is built around a Monte Carlo simulation module that the user connects with probabilistic models, such as the compound Poisson, selected from a library of available models. Input parameters for the probabilistic models are entered on NPVRISK worksheets provided for each model. The input worksheets contain graphical representations of the component probability distributions (e.g. distributions for accident size and frequency) along with tools and heuristic rules that facilitate estimation of distribution parameters from data and subjective judgment [3]. When the NPVRISK model is executed, the Monte Carlo simulation randomly samples the component distributions during each replication, and the samples are then combined resulting in a simulated distribution for the model output.

In the compound Poisson model for transformer spills, NPVRISK worksheets are used to develop probability distributions for the number of transformer spills occurring within a planning period, as well as for the direct damages per spill. In a similar manner, distributions for the number of transformer fires per period and damages per fire are obtained. Model worksheets are also prepared that develop distributions for the costs of contingent secondary impacts of transformer spills and fires. During Monte Carlo simulation these distributions are randomly sampled and each set of samples combined, resulting in a simulated distribution of the total damages over the analysis period due to transformer spills and fires, and their secondary impacts. The distribution of total costs in one period is then repeatedly discounted to represent distribution of total costs in each future year that the transformer will be in service. The cost distributions for all years are convolved numerically (along with cost distributions representing eventual replacement by a non-PCB transformer) to produce a distribution of total costs over one transformer’s expected lifetime.

The component distributions used to model the financial risk of PCB transformer spills and fires are developed in the following two sections.

### *2.1. Incident frequency distribution*

Assuming that the mean frequency of PCB transformer accidents over the period is constant, that the number of accidents is small, and that the numbers of accidents in all subintervals of time are independent, the Poisson distribution gives probabilities for the number of transformer accidents per period. However, transformer accidents are low probability events for which data are limited and available data may not reflect the conditions of the case to be evaluated. To alleviate these data requirements and incorporate expert knowledge such as the investigator’s degree of confidence that historical data reflect the system under investigation, Bayesian techniques can be used to form a predictive distribution with a Poisson sampling distribution and a gamma prior [3]. The result is a predictive Bayesian version of the negative binomial distribution expressed in terms of available information [5] as follows:

$$p(n|\alpha,\beta,\bar{n}_i,I)=\frac{(n+\alpha+I\bar{n}_i-1)!(\beta+I)^{\alpha+I\bar{n}_i}}{n!(\alpha+I\bar{n}_i-1)!(\beta+I+1)^{n+\alpha+I\bar{n}_i}} \tag{1}$$

where $n$ is the number of transformer accidents during the future period, $\alpha$ and $\beta$ are the parameters of the gamma prior distribution for the mean number of accidents, $\bar{n}_i$ is the average of available data, and $I$ is the number of available data points $(0 \leq I)$. This predictive negative binomial distribution will be broader than the underlying Poisson distribution, accounting for uncertainty in the parameters.

In the NPVRISK model, a Microsoft EXCEL® worksheet is provided that allows the user to estimate input parameters for the negative binomial incident frequency distribution using the guidelines suggested by Englehardt [3]. If multiple event frequencies are to be modeled using the negative binomial distribution, this worksheet can be copied as many times as needed. Negative binomial random variates are generated using the convolution algorithm suggested by Law and Kelton [6] implemented as an EXCEL® macro in Visual Basic for Applications (VBA) code. When called by the Monte Carlo simulation, the random variate generation code draws input parameter values directly from the negative binomial distribution worksheets.

### 2.2. *Incident size distribution*

Generally, incident size may be modeled with log-normal, Pareto I, and Pareto II distributions [7]. In analysis of transformer accidents, small PCB releases, such as the loss of a small amount of transformer oil during regular maintenance or inspection, may be decontaminated by on-site environmental, health and safety personnel at small cost. The frequency of such small incidents is unknown, but not important in the estimation of total cost of accidents. In such cases, the Pareto I distribution which models incidents greater than some minimum size of interest is appropriate. However, it may be difficult to specify the scale and location parameters of the Pareto I distribution based on limited available data that may not accurately reflect current circumstances. In this case incident size is modeled using a predictive Bayesian version of the Pareto I distribution [3] as follows:

$$f_Z(z|Z_0,\gamma,\theta,J,\overline{\ln(z_j)})=\frac{(J+\gamma)(\theta+J\,\overline{\ln(z_j)}-J\ln Z_0)^{J+\gamma}}{z(\ln(z)+\theta+J\,\overline{\ln(z_j)}-(J+1)\ln Z_0)^{J+\gamma+1}} \tag{2}$$

where $z$ is the size of transformer accident damage, $Z_0$ the assumed minimum accident size of interest, $\gamma$ and $\theta$ are the parameters of the prior distribution for the scale parameter, $\phi$, of the underlying Pareto I sampling distribution, $\overline{\ln(z_j)}$ the average of the natural log of the data, and $J$ is the number of available data points $(0 \leq J)$. $Z_0$ is the location parameter in the sense that varying $Z_0$ shifts the distribution along a logarithmic scale of incident size.

Small values of the scale parameter, $\phi$, produce Pareto distributions with long tails (increased probability of large events). However, for values of $\phi$ less than 1.0 the distribution mean is infinite. In practice, there are physical limits on maximum accident size and thus it is desirable to censor the predictive Bayesian Pareto distribution (Eq. (2)). Analytically, the censored distribution is $f_Z(z)/F_Z(Z_{\max})$, where $Z_{\max}$ is the maximum damage that could result from one accident, and $F_Z(Z_{\max})$ is the cumulative distribution function (CDF) evaluated at $Z_{\max}$. Within the Monte Carlo implementation, the Pareto distribution is censored by simply sampling the distribution until a variate less than $Z_{\max}$ is drawn, discarding those that exceed $Z_{\max}$.

Using the inverse transform method, an equation for a Bayesian Pareto random variate is derived as

$$Z = \exp\left[\frac{\theta + J\,\overline{\ln(z_j)} - J\ln Z_0}{(1-U)^{1/(J+\gamma)}} - \theta - J\,\overline{\ln(z_j)} + (J+1)\ln Z_0\right] \tag{3}$$

where $U$ is an IID $U(0,1)$ random variate, and other symbols are as previously defined. Eq. (3) is implemented as an EXCEL® macro in the NPVRISK model and used in the Monte Carlo simulation.

Formulation of the NPVRISK model as a Monte Carlo simulation, although adding computational burden, provides flexibility and allows the model to be quite general. Tasks that often complicate analytical modeling of extreme event probability, such as discounting, censoring, convolution of censored distributions and convolution of discrete distributions with different bin sizes, are greatly simplified in a Monte Carlo implementation. This flexibility allows the Monte Carlo-based NPVRISK model to address a wide range of benefit–risk analyses without the need for writing computer code or for analytical computation, thereby making analyses of the risk of extreme events more accessible.

## 3. Financial risk assessment of PCB transformers

The decision evaluated is whether to replace 5000 kV A PCB transformers with a silicon fluid model now, at an expected cost of US$ 25,000 each, or to wait until the end of transformers' expected lifetimes, on an average 15 years from now. Although the replacement cost for the transformer is substantial, the costs that *could* result from a transformer fire or spill, such as clean-up, lost production, and lawsuits brought by third parties, are uncertain but possibly very large. The financial risks of two types of acute PCB transformer accident, transformer fire and transformer spill, are assessed. With either type of event, in addition to the direct cost of damage and clean-up there are possible secondary effects such as increased insurance premiums, third party litigation, losses due to plant shutdown, and with extended shutdowns the costs associated with disruption of production at other facilities due interruption of the supply chain. To simplify the example considered here, the firm is taken to be self-insured and there are alternate suppliers available so the only secondary cost considered is that of third party litigation. Other contingent costs, such as lost production due to interruption of the supply chain, can be handled in the same manner that third party litigation is in the example presented.

The financial risk posed by the continued use of transformers containing PCBs is quantitatively assessed using the compound Poisson model described previously. Historical data

Table 1
Parameters of distributions of number of transformer spills and fires (Eq. (1))

| | Transformer spill | Transformer fire |
|---|---|---|
| $\alpha$ | 1.0 | 1.0 |
| $\beta$ | 404.6 | 4861.1 |
| $I$ | 0 | 0 |
| $\bar{n}_i$ | 0 | 0 |

used here are the industrial transformer accidents reported in the Emergency Response Notification System (ERNS) database between 1987 and 1994, as well as an internal database of transformer accident reports. The ERNS database contains 5034 transformer related entries for this period, of these a much smaller number were consistent with an industrial setting. There were 854 accidental transformer spills reported that were deemed consistent with this study. Similarly, there were 72 transformer fires reported that were applicable.

The ERNS data were used to choose the parameters of the gamma prior for the mean number of transformer accidents (both spills and fires) in Eq. (1). Using the number of transformer events in the 7-year period represented by the data and based on an assumed population of 50,000 transformers, the probability of transformer spill and fire per transformer year were estimated to be 0.00247 and 0.00021, respectively. These probabilities represent estimates of the means of the prior distributions for the Poisson distribution parameter $\lambda$. With estimates of only the means available the appropriate choice of $\alpha$ for both distributions is 1 (i.e. an exponential prior distribution). The resulting parameters of Eq. (1) for both transformer spills and fires are presented in Table 1. The values of $\beta$ have been found to yield gamma priors with the desired means. The number of data are taken to be zero in both cases.

The distributions for event size cannot be found directly from the ERNS data because these data include physical descriptions of the transformer events such as quantities of oil spilled and location, but do not contain cost information. Therefore, the ERNS data were combined with an engineering-based cost model to determine damages. The engineering cost model estimates costs of removal, transportation and disposal of PCB laden oil and oil laden soil and materials.

### *3.1. Engineering cost model*

The cost model consists of a set of cost functions derived from historical accident cost data and cost estimates obtained from local hazardous material response contractors. Cost functions are derived for three categories of transformer accident: spills with PCB concentrations below 500 ppm, spills with concentrations above 500 ppm PCB, and transformer fires. Spills of less than 454 g (1 lb) of PCB are assumed to be decontaminated by on-site environmental, health and safety personnel for less than US$ 1000 and are thus below the minimum size of interest.

Cost estimates were obtained for a typical transformer installed on a concrete pad, positioned on an asphalt apron that is underlain by soil. For each category of transformer accident, cost estimates were obtained from local hazardous material response contractors

Table 2
Cost assumptions and component costs used in accident cost estimates for cost model

| Cost category | Value |
|---|---|
| Labor (US$/h) | |
| Technician | 70 |
| Supervisor | 85 |
| Chemist | 100 |
| Safety equipment (US$ per man day) | |
| Suits, gloves, respirators, decontamination | 70 |
| Waste disposal (US$/t) | |
| Landfill | 100[a] |
| Incineration | 560[b] |
| Hazardous waste transport (US$ per loaded mile) | |
| Bulk waste | 3.00 |
| Containerized waste | 5.00 |

[a] Safety-Kleen, Grassy Mountain, Grayback Mountain Facility, Salt Lake City, UT.
[b] Safety-Kleen, Aragonite, Inc., Salt Lake City, UT.

for accidents involving 1, 10, 100, 500, and 1000 gal of PCB-laden oil. The amount of material removed is assumed to be a linear function of the quantity of PCB oil released, derived from empirical accident data. Cost assumptions used in forming the cost estimates are presented in Table 2. The cost estimates were combined with empirical cost data from accident reports collected by local agencies, and cost functions were formed by fitting piece-wise linear functions to the combined empirical and estimated cost data.

The cost model assumes that PCB spill and fire cleanup is performed according to US EPA PCB Spill Cleanup and Reporting standards (40 CFR 761.120-135). Spills with PCB concentrations less than 500 ppm and of less than 454 g (1 lb) of PCB do not require notification of the National Response Center and the spill boundary does not need to be verified by sampling and analysis. Within 48 h all soil in the spill area plus a one-lateral-foot buffer zone must be excavated and backfilled with clean soil. Solid surfaces must be double washed/rinsed. Decontamination can be performed by specially trained personnel within the firm.

When spills of concentrations greater than 500 ppm or of more than 454 g (1 lb) of PCB occur, the National Response Center must be notified immediately. The cleanup of fluid from hard surfaces and the removal of contaminated soil and porous material must be initiated within 24 h. Materials such as soil, asphalt, wood, cement, and concrete are regarded as porous and are assumed to absorb PCBs and must be removed. The spill boundary must be verified by sampling and analysis. Solid, impenetrable surfaces such as metals may be decontaminated by a double wash/rinse. All decontamination must verified by sampling and analysis. All soils and impenetrable surfaces must be remediated to background levels (i.e. detection limits). All concentrated soils, solvents, rags, and other materials resulting from the cleanup must be properly stored, labeled, and disposed of as PCB or PCB-contaminated materials. All bulk and liquid waste materials with PCB concentrations greater than 500 ppm must be incinerated in an approved facility. Bulk materials with PCB concentrations less than 500 ppm may be disposed in an approved hazardous waste landfill.

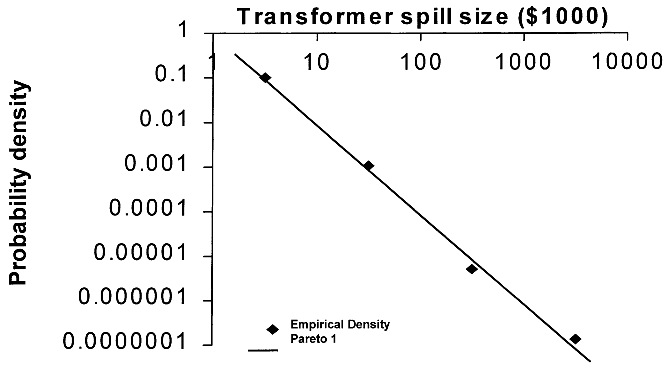


Fig. 1. Empirical and Pareto I probability densities for damage caused by individual industrial transformer spills between 1987 and 1994.

The cost functions were used to estimate the costs of site remediation and hazardous waste disposal for the transformer accidents in the ERNS database based on the quantities and concentrations of PCBs reported. If PCB concentration associated with an accident was not reported in the ERNS database, high PCB concentration (greater than 500 ppm) was assumed. All PCB waste from transformer fires were assumed to be greater than 500 ppm PCB.

The historical cost data derived from the ERNS database using the cost model were combined with empirical transformer accident cost data and this combined database was used to form the Pareto I priors for both transformer spills and fires. An example of the discrete transformer spill probability densities derived from cost data and the corresponding Pareto I distribution is shown in Fig. 1. The empirical density data in Fig. 1 were calculated from the spill cost data by dividing the number of spills in each cost bin (e.g. US$ 1000–10,000) by the total number spills and the bin width. In Fig. 1 these empirical probability densities are plotted (versus the geometric mean of bin size) on a log–log scale. The slope of the log–log plot of the Pareto I distribution shown in Fig. 1 provides an estimate of the mean of the prior distribution for the Pareto scale parameter, $\phi$, for transformer spills. A similar process is followed to estimate the parameters of the Pareto transformer fire cost distribution.

Having estimated the mean Pareto scale parameters for transformer spills and fires, gamma prior distributions are formed to represent the uncertainty associated with the Pareto scale parameters. As with event number, an exponential gamma prior is chosen to reflect limited information and confidence in the estimated Pareto scale parameters. Choosing a minimum event size of US$ 1000 (the minimum cost of response by a hazardous waste team) and a maximum event size of US$ 50 million, all of the parameters of the marginal predictive event size distributions (Eq. (2)) have been determined and appear in Table 3.

The cost distribution that remains to be estimated is that resulting from lawsuits by parties injured or harmed by transformer accidents. These costs are contingent upon event occurrence and severity and there is very limited information available regarding such third party liability in transformer accidents. However, some information about third party liability costs is available from legal service companies such as Jury Verdict Research,

Table 3
Parameters of distributions of transformer spill and fire event size (Eq. (2))

| | Transformer spill | Transformer fire |
|---|---|---|
| $Z_0$ | 1000 | 1000 |
| $\gamma$ | 1 | 1 |
| $\theta$ | 1 | 3.57 |
| $J$ | 1 | 1 |
| $\overline{\ln(z_j)}$ | 7.91 | 10.48 |

Inc. Insurance claims have been found to have distributions ranging from the Pareto to the somewhat thinner-tailed log-normal distribution [8,9]. Of these distributions the Pareto is the most conservative, having relatively higher probabilities of extremely large incidents. In that sense, the Pareto is the most objective (assumes the least) by the principle of maximum entropy [10]. Therefore, in the absence of information to the contrary, the Pareto is assumed.

Truncating the Pareto at a maximum settlement size of US$ 50 million produces a finite mean and adds realism, while affecting the probabilities minimally. The data available from Jury Verdict Research, Inc. are the mean costs of third party liability for both transformer spills and fires [11], which can be used to estimate the Pareto scale parameter, $\phi$, in the equation for the mean of a truncated Pareto distribution $[E(z) = \phi Z_0 Z_{\max}(Z_0^{\phi-1} - Z_{\max}^{\phi-1})]/[(1-\phi)(Z_{\max}^{\phi} - Z_0^{\phi})]$ [12]. Assuming a value of $\gamma = 3$ in Eq. (2), representing relatively low confidence, $\theta$ is then estimated as $3/\phi$. With mean third party liability costs of US$ 945,000 and 3,700,000 for spills and fires, respectively, and choosing a minimum liability of US$ 1000, the parameters of the marginal predictive liability cost distributions (Eq. (2)) are those shown in Table 4.

The compound Poisson distributions for damages resulting from transformer spills and fires and the distributions of third party lawsuit costs associated with a transformer accident are to be combined to produce distributions of total accident costs per transformer year. Although these distributions can be combined by numerical convolution, results are highly sensitive to model resolution due to the extreme skewness of the Pareto distribution and the contingent nature of third party liability. This difficulty can be avoided by combining the distributions through Monte Carlo simulation, as was done for the example presented here using the Bayesian benefit–risk model [13].

The resulting probability distribution represents the probability of different levels of total costs per transformer year due to transformer spill, fire, and third party liability resulting

Table 4
Parameters of distributions of third party liability resulting from transformer spills and fires (Eq. (2))

| | Transformer spill | Transformer fire |
|---|---|---|
| $Z_0$ | 1000 | 1000 |
| $\gamma$ | 3 | 3 |
| $\theta$ | 10.46 | 62.34 |
| $J$ | 0 | 0 |
| $\overline{\ln(z_j)}$ | 0 | 0 |

from transformer spills and fires. Evaluation of the distribution of total costs over time of not replacing the transformers requires computing the possible damages over the 15 years of remaining transformer life plus the perpetual cost of maintaining transformer service from then on. To do this the distribution of damages per transformer year for each of the 15 years is produced by discounting the current year distribution based on a real discount rate of 5%. The 15 resulting distributions are then convolved numerically to produce the probability distribution of total damages over the 15 years. This is then convolved with a distribution of the costs of maintaining non-PCB transformer service in perpetuity.

The delay-replacement option is to be compared with replacing the transformer immediately and then maintaining transformer service perpetually. The cost of replacement transformers is based on industry estimates provided by Westinghouse, Inc. The cost to purchase, install and maintain a 5000 kV A transformer with an assumed lifetime of 30 years is taken to be normally distributed with a mean of US$ 25,000 and a variance of US$ 2500. The distribution of the cost to provide transformer service perpetually is found by convolving a series of such normal distributions with proper discounting. The series may be terminated when discounting makes any future costs negligible (beyond 60 years in this case).

## 4. Results

The probability distributions for each alternative (to replace PCB transformers immediately and to not replace until end of service life) are shown on a linear scale in Fig. 2. The expected cost of the replacement option is US$ 28,554, while the expected cost of the delay-replacement option is US$ 58,251. These are the average costs a firm could expect to face if it were to make these choices a great many times. Although these simple expected cost values seem appealing, they are not the correct measures to use in comparing risky projects the impacts of which occur over many years [14]. The proper way to evaluate such projects depends on the risk associated with the project and the risk attitudes of the decision makers.

The risky nature of the delay-replacement option is more clearly seen in Fig. 3 where the probability distributions for each alternative are plotted on a log–log scale. The most prominent feature of Fig. 3 is the very long “tail” of the delay-replacement option. This reflects the improbable but possible occurrence of acute events with very large costs. How a firm will view this information will depend on how decision makers view the relative importance of small and large costs (i.e. their risk attitudes). A firm that is risk seeking and short of cash may wish to “take its chances” for a while because the chance of a large accident is very small. However, a firm that is less comfortable with risk and more concerned with ensuring the continuation of the firm, may be unwilling to take the same gamble.

These examples demonstrate the difficulty with using expected value (cost) in decision making. The expected cost measure reduces the cost and probability information down to a single number and makes it impossible for firms to distinguish the risk characteristics of a decision. (The expected cost is computed as the sum over all possible costs of the costs multiplied by their corresponding probabilities.) The expected cost approach thus ignores the amount of risk associated with an alternative and the risk attitudes of the decision maker

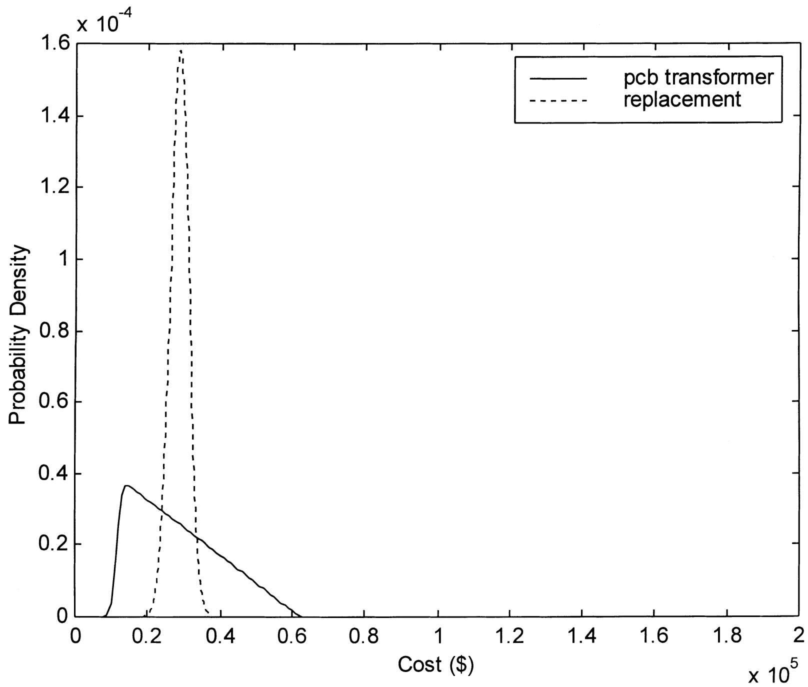


Fig. 2. Probability density functions for total cost of transformer replacement options.

Table 5
Comparison of the risk of the management options by several measures

| Risk measure | Management option | |
|---|---|---|
| | Replacement | Delay |
| Expected cost (US$) | 28554 | 58251 |
| Standard deviation (US$) | 2525 | 629030 |
| 5% exceedence cost (US$) | 32700 | 49000 |
| Conditional expected cost ($\alpha = 0.95$) (US$) | 33692 | 410710 |

by assuming that the value that a decision maker applies to a benefit (cost), as defined by his utility function, is linearly related to the magnitude of the benefit (cost). On the contrary, it is widely accepted that for most individuals the relationship between value and monetary worth is highly non-linear [15,16]. This is particularly true in the realm of losses [17].

One possible solution is to present decision makers with a probability distribution such as that in Fig. 3. However, few managers are likely to be prepared to use information in this form. Alternatively, there are summary measures other than expected (mean) cost that can be used to convey risk information. Table 5 presents several such measures. The traditional measure of variation from the mean is variance or standard deviation, but this measure is rather blunt and gives little information regarding the shape or length of the tail of a

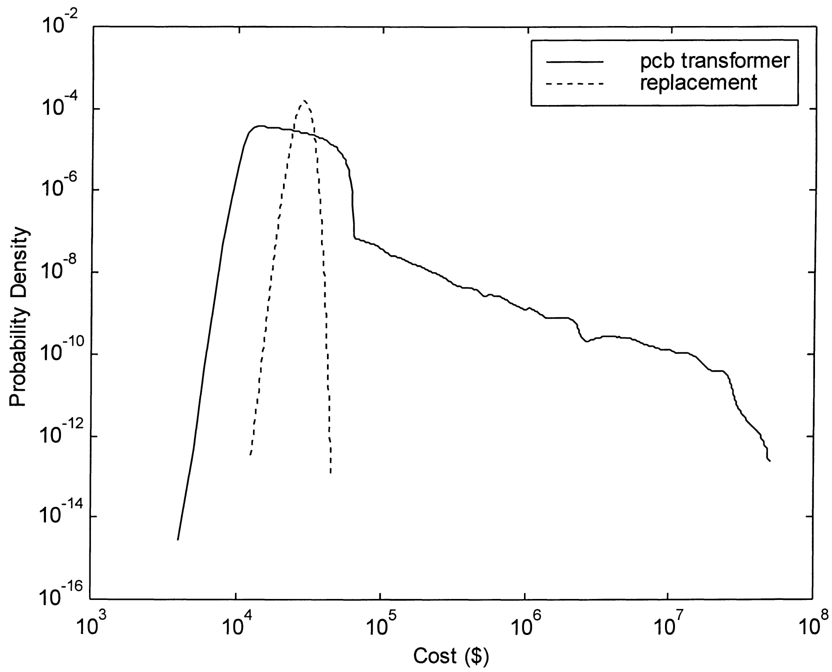


Fig. 3. Probability density functions for total cost of transformer replacement options (log–log scale).

distribution. Another measure is an "exceedence cost." The exceedence cost is the cost associated with a certain exceedence probability, where the exceedence probability of a cost value $x$ is defined as the probability that $X$ is observed to be greater than $x$ and is equal to one minus the CDF evaluated at $x$. The 5% exceedence costs shown in Table 5 illustrate that with 95% probability the cost of the replacement option will be less than US$ 32,700, while the similar measure for the delay option is US$ 49,000. The 5% exceedence cost for the delay option is less than the expected cost, indicating that this distribution has a long tail.

Although the exceedence cost measure reflects the length of the tail of a distribution, it gives little information regarding the shape of the tail. The conditional expected cost, gives more information about the shape of the tail of a distribution since it is the cost that is expected if cost is above some particular harm level $\beta$ [18]. In the example, the exceedence probability is taken to be 0.05, so $\beta$ is the 95th percentile. The conditional expected cost is the expected cost of $X$, given that $x$ is greater than $\beta$. As shown in Table 5, if the cost exceeds the 95th percentile (the 5% exceedence cost) the expected cost of the replacement option is US$ 33,692, while that of the delay option is US$ 410,710. These simple measures clearly indicate the high risk of the delay option relative to the replacement option and are generally understandable by decision makers such as corporate managers. A measure such as conditional expected cost allows a manager to take his organization's financial situation and risk attitudes into account, and make more informed decisions.

Although the methods described allow firms to make more informed decisions about highly uncertain environmental costs, there are several factors that discourage firms from using such methods. The first is that use of models such as the one presented here is not without cost. Although the time cost of using this model is not high, it requires an expertise that many firms do not have internally, particularly small- and medium-size firms. The second and perhaps more important deterrent to use is that disclosure requirements under Securities and Exchange Commission (SEC) rules require firms to report financial liability information to shareholders [19]. If not quantified, extreme events with very low probabilities, such as those addressed here can be considered negligible and thus not be incorporated in firms' financial reporting. Third and perhaps equally influential to a firm's use of risk assessment in planning is that documentation by the firm of knowledge of potential environmental and health risks can be used in court against the firm should an accident occur. This "ignorance is bliss" aspect of precedents in health litigation is a disincentive to economic analysis of health and environmental risks by industry.

## 5. Conclusion

Despite the barriers to use, the model presented in this paper provides analysts with a way to combine historical data, engineering model-based data, and subjective knowledge to derive quantitative risk assessment information about highly uncertain environmental liabilities. The model allows analysts to quantitatively describe environmental and contingent costs, even when information is severely limited. By quantifying all available information, the NPVRISK model allows firms to make informed decisions that accurately reflect their willingness to accept risk. The model also allows highly uncertain and contingent environmental costs to be included in full cost accounting programs, leading to capital investments, design choices, and production decisions that are in the best interests of the firm and the environment.

Use of the Monte Carlo simulation approach in a spreadsheet environment makes the model highly flexible and easy to use. Monte Carlo simulation greatly simplifies modeling of complicated real-world risk characteristics such as censored distributions and probabilistic contingent costs (e.g. lawsuits and production losses due to interruption of the supply-chain). The flexible and general nature of the model makes it accessible to a broader audience which should allow small- and medium-size firms to perform more sophisticated environmental risk–benefit analyses and more correctly represent environmental risks in their risk management and environmental accounting.

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