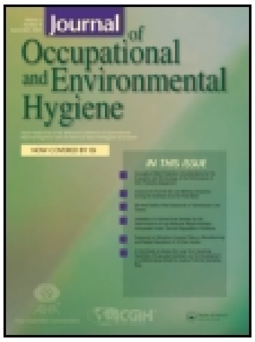

Journal of Occupational and Environmental Hygiene

ISSN: 1545-9624 (Print) 1545-9632 (Online) Journal homepage: http://www.tandfonline.com/loi/uoeh20

Exposure Modeling in Occupational Hygiene Decision Making

Monika Vadali , Gurumurthy Ramachandran & John Mulhausen

To cite this article: Monika Vadali , Gurumurthy Ramachandran & John Mulhausen (2009) Exposure Modeling in Occupational Hygiene Decision Making, Journal of Occupational and Environmental Hygiene, 6:6, 353-362, DOI: 10.1080/15459620902855161

To link to this article: https://doi.org/10.1080/15459620902855161

Journal of Occupational and Environmental Hygiene, 6: 353–362
ISSN: 1545-9624 print / 1545-9632 online

DOI: 10.1080/15459620902855161

Exposure Modeling in Occupational Hygiene Decision Making

Monika Vadali,[1] Gurumurthy Ramachandran,[1] and John Mulhausen[2]

[1]University of Minnesota, Division of Environmental Health Sciences, School of Public Health, Minneapolis, Minnesota
[2]3M Company, St. Paul, Minnesota

The primary objective was to develop a framework for using exposure models in conjunction with two-dimensional Monte Carlo methods for making exposure judgments in the context of Bayesian decision analysis. The AIHA exposure assessment strategy will be used for illustrative purposes, but the method has broader applications beyond these specific exposure assessment strategies. A two-dimensional Monte Carlo scheme by which the exposure model output can be represented in the form of a decision chart is presented. The chart shows the probabilities of the 95th percentile of the exposure distribution lying in one of the four exposure categories relative to the occupational exposure limit (OEL): (1) highly controlled (<10% of OEL), (2) well controlled (10–50% of OEL), (3) controlled (50–100% of OEL), and (4) poorly controlled (>100% of OEL). Such a decision chart can be used as a "prior" in the Bayesian statistical framework, which can be updated using monitoring data to arrive at a final decision chart. Hypothetical examples using commonly used exposure models are presented, along with a discussion of how this framework can be used given a hierarchy of exposure models.

Keywords Bayesian decision making, exposure models, two-dimensional Monte Carlo

Address correspondence to: Gurumurthy Ramachandran, University of Minnesota, Division of Environmental Health Sciences, School of Public Health, MMC 807, 420 Delaware St. SE, Minneapolis, MN 55455; e-mail: ramac002@umn.edu.

EXPOSURE ASSESSMENT AND BAYESIAN DECISION MAKING

Most exposure assessment strategies rely on the classification of workers into similarly exposed groups (SEGs), and several strategies for classification have been proposed.[(1−3)] Most commonly, the occupational hygienist (OH) uses a combination of professional judgment, personal experience with a given type of operation, review of exposures from similar operations, and/or exposure predictions developed using physical/chemical exposure modeling techniques to assign a subjective initial "exposure rating" and prioritize their SEGs. Similarly exposed groups that merit a high initial exposure rating or involve high toxicity substances are typically placed at the top of the priority list for quantitative studies.

Next, a baseline monitoring campaign is carried out. The measurement data collected are used to refine the initial rating and determine if the distribution of exposures for each SEG is well characterized and if the exposure distribution is acceptable. Acceptability is commonly evaluated by comparing an upper percentile, such as the true group 95th percentile, with the OEL. In the AIHA strategy, the 95th percentile of the exposure profile is estimated along with its upper confidence limit (UCL). Based on the magnitude of the group 95th percentile and its UCL relative to the OEL, the exposure is classified into one of four categories: (1) highly controlled, (2) well controlled, (3) [nominally] controlled, or (4) poorly controlled (Table I).

AIHA strategy suggests that 6 to 10 measurements be collected for most SEGs that are to be evaluated using exposure monitoring. In practice, since collecting even 6–10 measurements per SEG can be a challenge, exposure judgments are often made based on fewer measurements. In many situations, exposure assessment may be required for several chemical species simultaneously. Many plants have several thousand process, task, and substance combinations, making a complete quantitative exposure assessment for each all but impossible to accomplish. Anecdotally, it is estimated that greater than 90% of exposure ratings may be based on professional judgments without any monitoring data. Thus, there is a heavy reliance on the accuracy of professional judgments and the ability of occupational hygienists to correctly integrate them with monitoring data to reach an accurate exposure determination.

A recent strategy proposed a decision-making framework using Bayesian statistical analysis,[(4)] where a key conceptual advance was to determine the probability of the 95th percentile of the exposure distribution located in each of the four AIHA exposure categories. The framework is designed to explicitly take into account both monitoring data and professional judgment and other sources of information. The procedure

TABLE I. Exposure Category Rating Scheme

AIHA Exposure Rating	Proposed Control Zone Description	Qualitative Description	AIHA Recommended Statistical Interpretation
1	Highly controlled	Exposures infrequently exceed 10% of the limit[A]	$X_{0.95} \leq 0.10$ OEL
2	Well controlled	Exposures infrequently exceed 50% of the limit and rarely exceed the limit[A,B,C]	0.10 OEL $< X_{0.95} \leq$ 0.5 OEL
3	Controlled	Exposures infrequently exceed the limit[A,C]	0.5 OEL $< X_{0.95} \leq$ OEL
4	Poorly controlled	Exposures frequently exceed the limit[A]	OEL $< X_{0.95}$

Notes: A similar exposure group is assigned an exposure rating by comparing the 95th percentile exposure ($X_{0.95}$) of the exposure distribution with the full-shift, TWA OEL.
[A]"Infrequently" refers to an event that occurs no more than 5% of the time.
[B]"Rarely" refers to an event that occurs no more than 1% of the time.
[C]High concentrations are defined as concentrations that exceed the TWA limit or STEL.

results in a distribution of probabilities that can be graphed as a "decision chart" (Figure 1). The interpretation of such a decision chart is straightforward. For example, Figure 1 shows that there is a 30% probability that the SEG is highly controlled, 45% that it is well controlled, 20% that it is controlled, and a 5% probability that it is poorly controlled. By inspection of these decision probabilities, one can decide on a course of action that is consistent with the exposure profile most likely being well controlled (i.e., Category 2).

Bayesian decision making is an inductive approach whereby a preliminary decision (the prior) arrived at by the OH using his/her professional judgment is modified by an analysis of current monitoring data (leading to a likelihood distribution) to yield the final decision (the posterior). The prior distribution represents the knowledge about the SEG possessed by the OH (i.e., professional judgment) that may derive from previous experience, training, historical or surrogate exposure data, or (of most relevance to this article) exposure models. The prior, likelihood, and posterior distributions take the form shown in Figure 2.

In the Bayesian context, an informative prior is one where different probabilities are assigned to different exposure categories, whereas a noninformative prior is one where all four categories are considered equally likely. It has been suggested that given an accurate informative prior; fewer monitoring data would be required to arrive at a decision with a high degree of confidence.[4] This is the promise of Bayesian decision making, i.e., strategies based on high

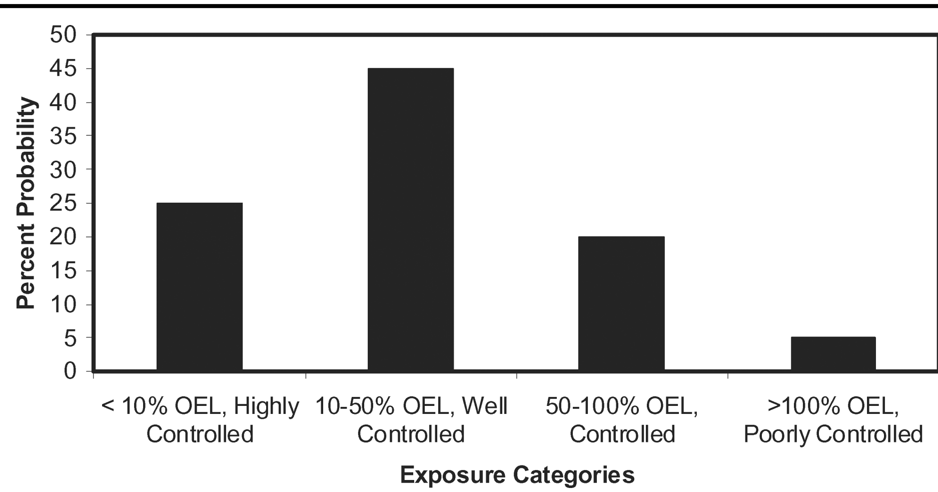

FIGURE 1. Example exposure judgment for a given task. The bar chart shows the probability that the 95th percentile of the exposure distribution lies in each of the four categories.

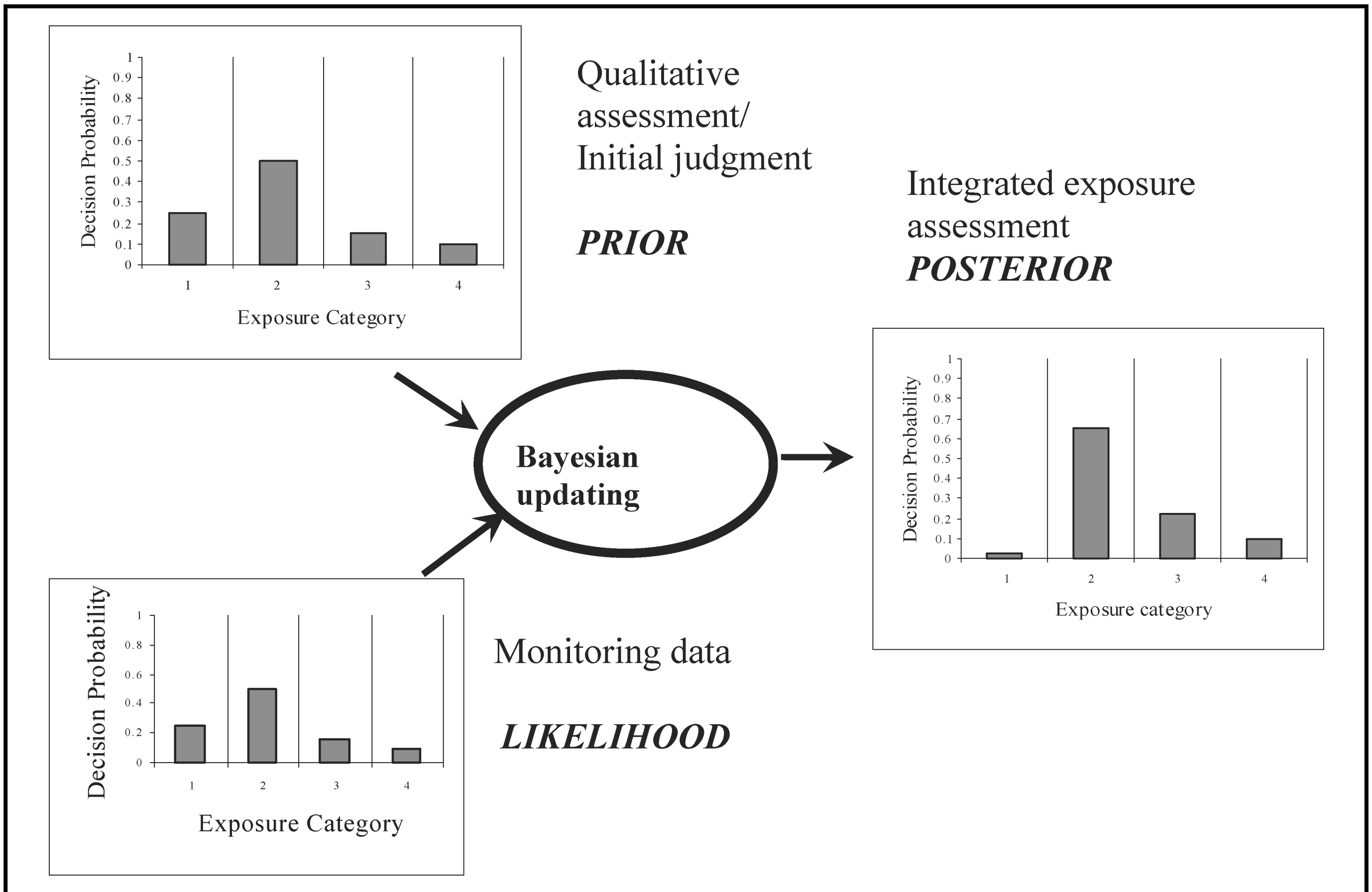

FIGURE 2. Schematic representation of the Bayesian model. The prior is the subjective judgment provided by the hygienist based on experience and knowledge of task or, as proposed here, on the output of an exposure model; the likelihood is the decision based on monitoring data alone and the posterior decision is the synthesis of prior and likelihood within the Bayesian framework.

quality priors will be highly effective and efficient. However, the converse is also true: inaccurate and overconfident priors will lead to incorrect decisions when monitoring data are sparse.

This article deals with the process of arriving at priors *using modeling.* We first argue that while industrial hygienists can directly provide a prior decision chart based on their professional judgment, the rationale behind it can be unclear, and human judgments are subject to cognitive biases that may affect such judgments. Therefore, the use of mathematical exposure models may offer a step in the direction of reducing such biases.

Mathematical models play an important role in any good comprehensive exposure assessment strategy.(5,6) Here, a two-dimensional Monte Carlo scheme by which the model output can be represented in the form of a decision chart is presented. Such a decision chart can be used as a prior in the Bayesian framework. We present a few hypothetical examples using commonly used exposure models. The article concludes with a discussion of how this framework can be used given a hierarchy of exposure models, i.e., how to choose between the decisions suggested by different models for a given scenario.

QUALITY OF PROFESSIONAL JUDGMENTS: RATIONALE FOR MODELING

Industrial hygienists have long relied on their expert professional judgments for efficient decision making. Although the term "expert" is often not clearly defined, studies have shown that working in a particular field over long periods can qualify a person as an expert. It has been suggested that the process of organizing knowledge in sophisticated patterns enables people to become experts.(7–9) These studies focused on understanding the performance differences between experts in a field and relative novices in the same field. Experts recognize larger patterns in problems when compared with novices—a novice's knowledge is much more fragmented and less integrated. Experts also use their knowledge on the subject to solve problems. It was also found that when faced with incomplete information, experts could rely more on their knowledge to make good decisions that could also be justified reasonably.(10)

Despite these advantages, a number of cognitive biases may influence these judgments. These arise because human beings typically use a limited number of simplifying heuristics to efficiently arrive at a judgment using available information.[11–13] These heuristics, or mental processes, do not typically utilize all of the available information and data in a formal algorithmic process but use "fast and frugal" rules of thumb to arrive at a judgment. Some of the more well-known heuristics such as anchoring and adjustment, availability, and representativeness[11] continue to be studied in a variety of fields. While they may be simple and efficient, they may, in some cases, be a source of inherent cognitive bias that is usually difficult to track or control.[14–16]

In the context of occupational hygiene, a few studies have reported on the quality of direct, subjective assessments of exposure, but their results *often reach conflicting results*. Kromhout et al.[17] studied the qualitative estimation of task exposures by occupational hygienists, supervisors, and workers at a number of plants and found a significant correlation between subjective ratings and the measured mean exposures at a given plant.

Hawkins and Evans[18] and Walker et al.[19] reported that experts were fairly adept at estimating upper percentiles. While factors such as experience, education, certification, type of available information, etc., were not evaluated systematically, there are sufficient indications in some studies that these factors might be significant determinants of rating decisions.[20,21]

Ramachandran and Vincent,[22] Ramachandran et al.[23] and Wild et al.[24] used Bayesian methods and modeling to combine expert judgments with exposure measurements. It was found that experts tended to agree with each other and that the Bayesian approach was an effective means for improving and refining the exposure estimates. It was noted that more studies were required to assess the correlation between the experts' backgrounds and their subjective judgments.

The above discussion illustrates the variety of factors and biases that can affect the accuracy of professional and expert judgments. Direct elicitation of a judgment may hide the rationale behind a decision and also be affected by subjective biases in a potentially unquantifiable manner. However, a disaggregation of the problem into several smaller parts (e.g., making a judgment about an input parameter to an exposure model) may reduce the level of uncertainty.[25]

Exposure modeling makes the rationale behind the judgment transparent and quantifiable. Models provide an explicit description of the mechanism of generation and dispersal of the contaminant and the subsequent exposures of the workers through various routes. The input parameters to the exposure models can be obtained through theoretical calculations, measurements, or subjective assessments and can be described in the form of a probability distribution. Even if the element of subjectivity is not eliminated, the use of models may reduce uncertainty and bias in exposure estimates.[26]

As shown in Figure 2, the decision charts are essentially probability distributions of the location of the true 95th percentile of the exposure distribution relative to the OEL. If the exposure distribution were known precisely, there would be only one true value of the 95th percentile. However, because the parameters of the distribution can only be estimated using limited measurements or using subjective professional judgment, there is uncertainty in the estimate of the true 95th percentile that can be represented as a probability distribution of its likely value.

Since there is uncertainty and variability in the inputs of any exposure model, there will be a corresponding uncertainty in the model output. Our goal, therefore, is to arrive at a prior decision chart (similar to that shown in Figure 2) based on the output of an exposure model rather than on the direct subjective judgment of an occupational hygienist.

Current Limitations in Treatment of Uncertainty in Model Parameters

A hypothetical example similar to that originally used by Jayjock[6] for a scenario using the steady-state solution of the general ventilation model will be used to illustrate different approaches to handling model uncertainty. A simple model was chosen to keep the focus on explaining the Bayesian construct, but this procedure can be applied to more complex models as well. A very simplistic approach is to consider only worst-case and best-case scenarios. A reasonable lowest and highest estimate can be assigned to the generation rate, G, and ventilation rate, Q. The steady state concentration, C, can be calculated as:

$$C(mg/m^3) = \frac{G(mg/hr)}{Q(m^3/hr)} \tag{1}$$

For example, consider the highest estimate for G to be 75 mg/hr and the lowest estimate to be 25 mg/hr. Similarly assume the highest and lowest estimates for Q to be 3.6 m^3/hr and 540 m^3/hr, respectively. The lowest and highest estimate for concentration can be calculated using the above formula to be 0.05 mg/m^3 and 20.8 mg/m^3, respectively. Since the estimates for both G and Q are extremes, the estimates for C are extremely unlikely values. While such an approach results in upper and lower bounds of concentration, it does not provide a probability distribution of exposures. Best- and worst-case estimates can be used as a quick guide by hygienists to check for extreme exposures, i.e., Category 1 or Category 4 exposures. However, in most instances, such easy decisions are not obtained and further analysis is required.

Monte Carlo (MC) methods overcome the limitations of the above approach by being versatile enough to represent G and Q as distributions. One-dimensional (1-D) Monte Carlo methods have been applied earlier to study worker exposure to halogen gases[27] and for retrospective exposure assessment of nickel aerosol exposures.[23] Monte Carlo simulations allow for distributions to be imposed on each of the model variables.

For the example previously discussed, instead of calculating highest and lowest estimates, uniform distributions can be imposed on G and C. Uniform distributions are being assumed for illustrative purposes only. Consider the upper and lower bounds for G and Q to be 25 mg/hr and 75 mg/hr and 3.6 m^3/hr and 540 m^3/hr, respectively. MC simulations can be carried out using these distributions.

In MC simulation, a single value of G and Q is selected randomly from their respective distributions and the corresponding concentration, C, calculated as C = G/Q. This process is repeated a sufficient number of times to yield a large number of values of C that approximates the exposure distribution of C. This can then be used to determine a point estimate of the 95th percentile for the exposure distribution. In this example it happens to be 1.63 mg/m.[3] This method has an advantage in that a distribution for C can be obtained instead of point estimates of highest and lowest values.

However, the limitation is that it provides only a point estimate of the 95th percentile value (or any percentile). It does not provide a probability distribution of the 95th percentile value from which a decision chart can be constructed.

Two-Dimensional Monte Carlo—Uncertainty and Variability

The two-dimensional (2-D) MC method can be considered as a simple nesting of two one-dimensional MC simulations. The inner simulation represents the variability in model parameters and the outer simulation represents the uncertainty (i.e., lack of knowledge) surrounding them. Two-dimensional methods have been successfully used in the field of geophysics to study mineral structures,(28) radiative transfers in sea ice,(29) and, increasingly, in risk assessment and exposure assessment.(30)

The variability of a model parameter occurs naturally due to the underlying physical and chemical processes. For the general ventilation model, these can be described by distributional parameters for G and Q (e.g., the lower and upper bounds in the case of a uniform distribution or the mean and standard deviation for a normal distribution). Since there will be variability in the generation and ventilation rates, these can be represented in the inner loop of 1-D MC simulation, but the distributional parameters are not known with certainty. This is analogous to the uncertainty in the estimates of the mean and standard deviation obtained from a finite number of monitoring data.

However, since this uncertainty cannot be measured in this case, the value of the uncertainty will be assumed. By introducing the second layer of simulation, the uncertainty in the distributional parameters of G and Q can be accounted for. These are represented by the outer loop of 1-D MC simulation imposed on the distributional parameters of G and Q.

Using the previous example, distributions can be imposed on G and Q, for example, a uniform distribution with upper and lower limits. We assume a uniform distribution for illustrative purposes only. Any distributional form, e.g., lognormal, normal, triangular, beta, that is appropriate to the variable can be selected.

An additional layer of distributions can then be imposed on the lower and upper limits for both G and Q to reflect the uncertainty in those limits. The distributions for the lower and upper limits of G are called G_{min} and G_{max}, the corresponding distributions for the lower and upper limits of Q are called Q_{min} and Q_{max}, respectively. G_{min} and G_{max} are represented as uniform distributions with lower and upper limits with G_{min1} = 10 mg/hr and G_{min2} = 40 mg/hr, and G_{max1} = 60 mg/hr and G_{max2} = 90 mg/hr, respectively. Similarly for Q, Q_{min1} = 1 m^3/hr, Q_{min2} = 5 m^3/hr, Q_{max1} = 350 m^3/hr, and Q_{max2} = 650 m^3/hr. A single value is picked randomly from the distributions of G_{min} and G_{max} respectively, to define one distribution for G. Similarly, a random pick from Q_{min} and Q_{max} defines one Q distribution (outer loop). Using the G and Q distributions thus obtained, the inner loop of the MC simulation is run to produce a distribution of concentration C.

This entire process is simulated a sufficient number of times (for this particular case 1000 simulations were run) to obtain a large number of C distributions. Each concentration distribution yields one point estimate of the 95th percentile and, thus, a distribution of the 95th percentile is obtained that can be displayed as a histogram. This 95th percentile histogram can be expressed in terms of the AIHA exposure categories as a decision chart, when compared with the OEL (Figure 3). As before, the category with the highest probability would most likely drive further actions. Decision categories arrived at using different exposure models can be compared as part of the data analysis.

Decision Making with Competing Models

Keil(31) discusses the various options and the importance of selecting the most appropriate model. There is a wide variety of deterministic models that differ in their level of sophistication. Each level increases the cost of using the model due to the amount of information needed as inputs to the model. For example, the saturation vapor pressure model is a rather simple model because it requires only knowledge of the temperature and the saturation vapor pressure of the chemical.

The near field-far field model requires knowledge of room ventilation and contaminant generation rates in addition to a parameter known as the inter-zonal ventilation rate requiring a nontrivial investment in obtaining this information. An even more sophisticated model such as an eddy diffusion model, which takes into account concentration gradients that exist around pollution sources, requires even greater investments (Table II).

While costs increase as the level of sophistication increases, more complex models could also yield more refined exposure estimates. However, one has to be cautious about over-refining the model, which may lead to spurious results. Also, one may run into situations where different models provide significantly different exposure estimates that may lead to different decisions. In this section, we explore this idea with three models with different levels of complexity and that lead to different decisions. The three models used are:

Saturation vapor pressure model. This is a very simplistic and conservative model that assumes a volatile liquid contaminant is present in a closed room with no ventilation and reaches its saturation vapor pressure concentration at a given

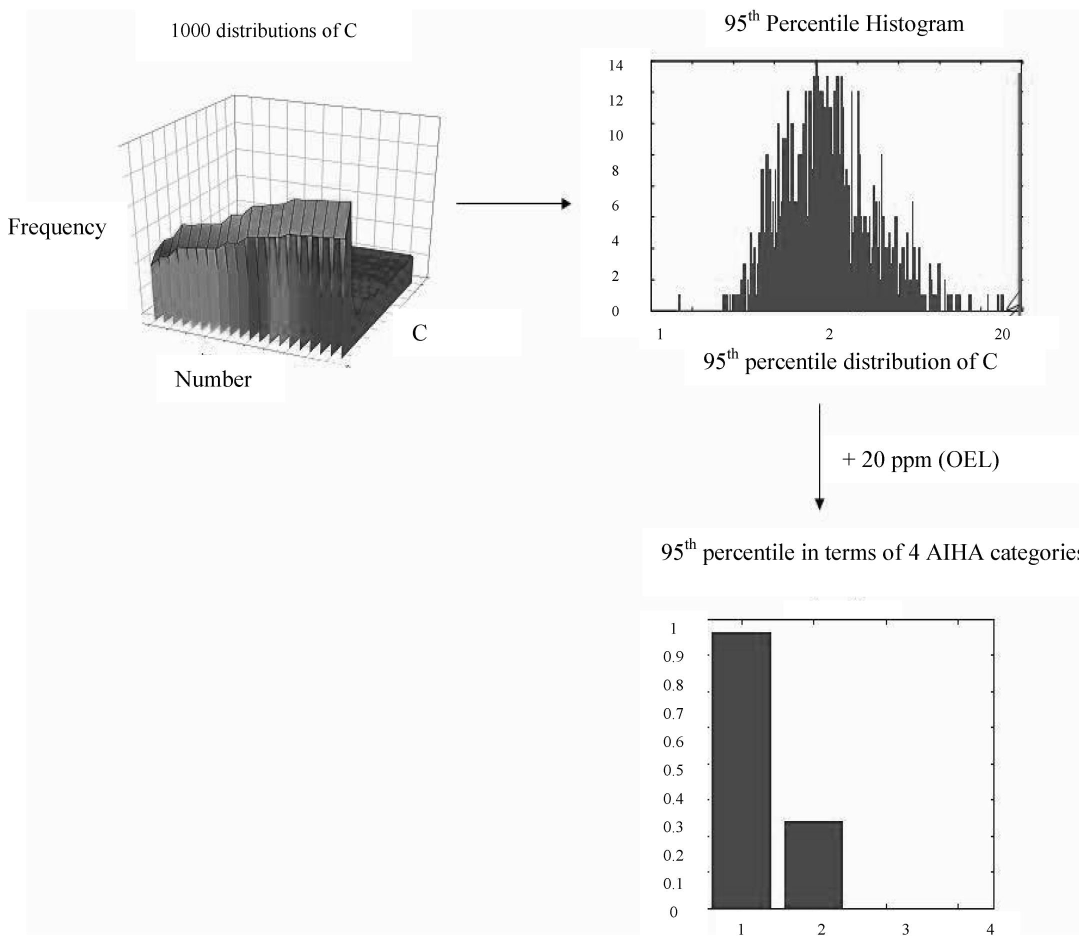

FIGURE 3. Schematic representation of process for obtaining a prior decision chart from the output of a two-dimensional Monte Carlo simulation. The large number of C distributions yields a distribution of the 95th percentile. By comparing this distribution with an OEL, a decision chart in terms of the AIHA categories is constructed. For this example, the OEL is assumed to be 20 ppm. The chart indicates that modeling predicts Category 1 to be the most likely exposure category.

temperature. The saturation concentration, C_{sat} is calculated as:

$$C_{sat}\ (ppm) = \frac{VP_{sat}}{P_{atm}} \times 10^6 \quad \textbf{(2)}$$

where VP_{sat} is the saturation vapor pressure at some temperature, and P_{atm} is the atmospheric pressure. The values for VP_{sat} can be determined from standard tables, and there is little uncertainty regarding them.

General ventilation model. This model assumes that a source is generating an airborne pollutant at a rate G (mg/hr) in a room with a ventilation rate Q (m^3/hr). The air in the room is assumed to be perfectly mixed, which creates a uniform contaminant concentration throughout the room irrespective of the distance from the source. The steady-state concentration for this scenario is given as:

$$C_{steadysstate}(mg/m^3) = \frac{G}{Q} \quad \textbf{(3)}$$

Therefore, the input parameters required for this model are the generation and ventilation rates.

Near Field-Far Field (NF-FF) model: The NF-FF model assumes that the entire workplace can be divided into two compartments, one within the other. The inner compartment encloses the generation source and is treated as the near field, and the outer compartment representing the rest of the room is treated as the far field. In addition to the parameters G and Q, this model also accounts for the airflow between the two compartments using a parameter for the inter-zonal ventilation rate called β.

The *steady-state far field concentration* is calculated as:

$$C_{far-field}(mg/m^3) = \frac{G}{Q} \quad \textbf{(4)}$$

and the *steady-state near field concentration* is calculated as:

$$C_{near-field}(mg/m^3) = \frac{G}{Q} + \frac{G}{\beta} \quad \textbf{(5)}$$

TABLE II. Comparison of Different Exposure Models

Exposure Models	Input Parameters Required for Model	Ease of Obtaining Parameter Information	Cost^A
Saturation vapor pressure	Saturation vapor pressure of chemical	* Easy (can be obtained from standard tables)	* Very Low
	Temperature of chemical	* Easy	
General ventilation	Generation rate of chemical	** Moderate (can be measured)	** Low
	Average ventilation rate through room	** Moderate (can be measured or obtained from room design specifications)	
Near field-Far field	Generation rate of chemical	** Moderate (can be measured)	*** Medium
	Average ventilation rate through room	** Moderate (can be measured or obtained from room design specifications)	
	Average inter-zonal ventilation rate	*** Difficult (could be difficult to measure accurately if the zones are not well defined)	
Eddy diffusion	Generation rate of chemical	** Moderate (can be measured)	**** Medium-High
	Eddy diffusion coefficient	*** Difficult because it depends on a several other parameters that are not known precisely	
	Average distance from source to worker	* Easy	

Note: Only the first three models are discussed in this article.
^{A}Relative cost for obtaining the required input parameter information.

Model choice has an important effect on the final decision and hence the required action regarding control measures. As the number of variables in the models increase, their behavior becomes increasingly complex, and decisions recommended by the model output may or may not be consistent with our expectations. With several competing models recommending different decisions, the choice of the prediction on which to base one's final decision and action becomes important.

Let us consider a very simple exposure scenario. Suppose there is 500 mL of a volatile chemical in an open container kept in a room at 20°C, evaporating at a constant mass rate into its immediate environment. The vapor pressure of the chemical at 20°C is 80 mm of Hg. Let us also assume that the ventilation rate for the room is described by a uniform distribution. The lower limit of the distribution is between 1 and 5 m^3/hr, and the upper limit of the uniform distribution is between 350 and 650 m^3/hr. Chemical vapors are generated at a rate that is also described by a uniform distribution. The lower limit of the distribution lies between 10 and 40 mg/hr, and the upper limit of the distribution lies between 60 and 90 mg/hr. The occupation exposure limit for this chemical is 20 ppm.

For this scenario let us consider three different models. *Model 1*: The saturation vapor pressure model assumes that the chemical is in a room with no ventilation and steady-state concentration is calculated when the room reaches saturation. *Model 2*: The general ventilation model assumes that the chemical is placed in a well-ventilated room with distributions of ventilation and generation rates as described above. *Model 3*: Near field-far field model, where in addition to the conditions in Model 2, a near field is assumed to be present around the pollutant generation source. This inner compartment has its own ventilation rate denoted as β, which will be assumed to have a triangular distribution[32] with min, mode, and max values that, in turn, assume uniform distributions. Min lies between 1 and 5 m^3/hr, mode lies between 6 and 11 m^3/hr, and max has a distribution between 12 and 17 m^3/hr.

Results comparing the three priors based on the three exposure models are presented in Figure 4. As expected, the highly conservative saturation vapor pressure model yields a Category 4 decision. The general ventilation model predicts that the highest exposure category is Category 1. The NF-FF model predicts near field and far field exposure concentrations. The far field concentration is consistent with a Category 1 exposure. Since this is the same as the general ventilation model, it is entirely expected.

The near field concentration, however, is more consistent with a Category 3 exposure. The near field exposure is the predicted exposure of the worker in the immediate vicinity of the source. Thus, we have three, model-based prior judgments that could potentially lead to three substantially different decisions regarding control.

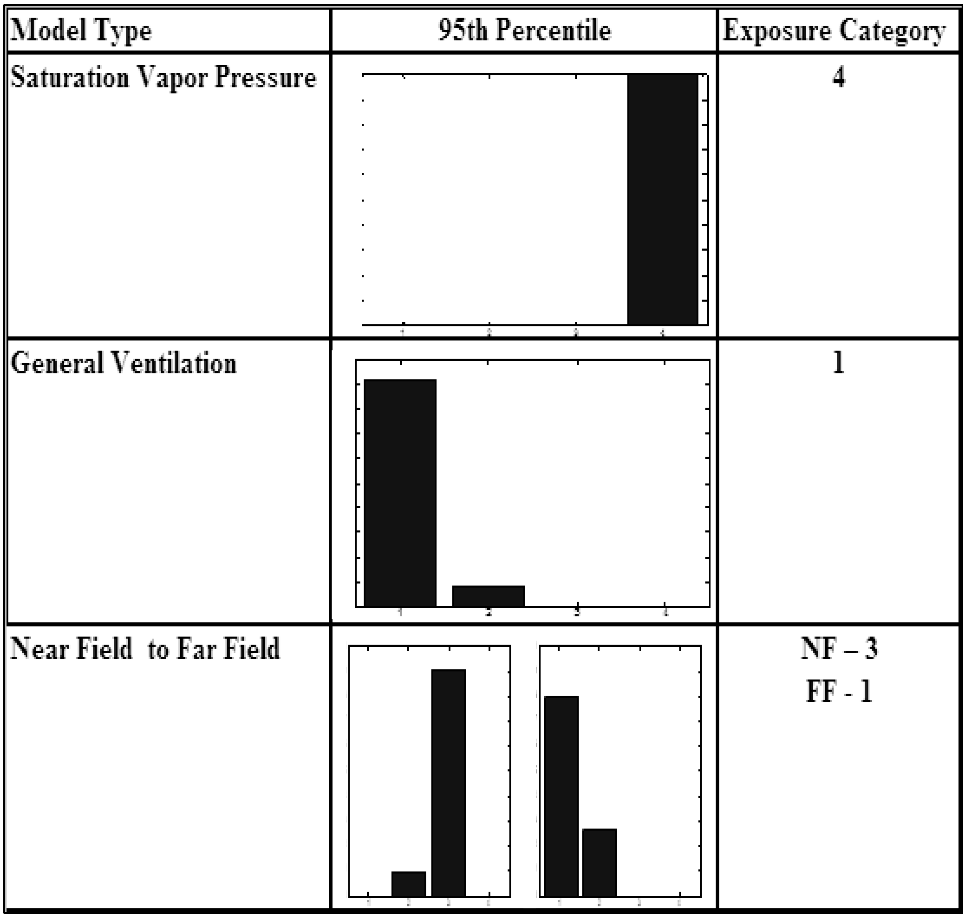

FIGURE 4. Comparison of the final prior exposure category obtained when using three different ventilation models. The saturation vapor pressure model is conservative and shows the exposure category is 4. The general ventilation model predicts the exposure category as 1 and this is consistent with the prediction of the far field model. The near field model shows the category as 3.

The choice of the "correct" model is obviously of great importance. There are at least two ways to make this choice. The first is to defer to professional judgment at this stage. Knowledge of the workplace environment would be the deciding factor for model choice. One could argue that the saturation vapor pressure model is excessively conservative and its assumptions do not reflect the exposure conditions; likewise, the general ventilation model is too lenient, since it does not account for proximity of the worker to the source. The near field model best represents the exposure scenario and therefore the most appropriate prior is a Category 3 decision.

The second approach to choosing the most appropriate model is to see which of the model predictions is most consistent with available monitoring data. This model would then be used in future assessments. This method for model selection can also be used as a feedback loop, where monitoring data for a particular task can be used to generate the likelihood, and this can be compared with the prior from each model. The model that best suits the likelihood can be picked as the most appropriate model for future use. Bayesian model comparison is a sophisticated version of this technique.[33]

For the above example with an OEL of 20 ppm, let us assume that we have five monitoring data points: 9.1 ppm, 7.9 ppm, 8.7 ppm, 10 ppm, and 8.6 ppm. These data can be used to construct a likelihood function that can be used to update the prior.[4] The likelihood decisions and the posteriors for each of the three ventilation models are shown in Figure 5. As can be seen, the likelihood decision (obtained based only on monitoring data) lies in Category 3 and is most consistent with the prior for the near field model. Thus, in future assessments of this hypothetical process, this model would be the best choice for generating the prior. Of course, for the current assessment this approach cannot be used, since we cannot select a prior based on its match to the likelihood function.

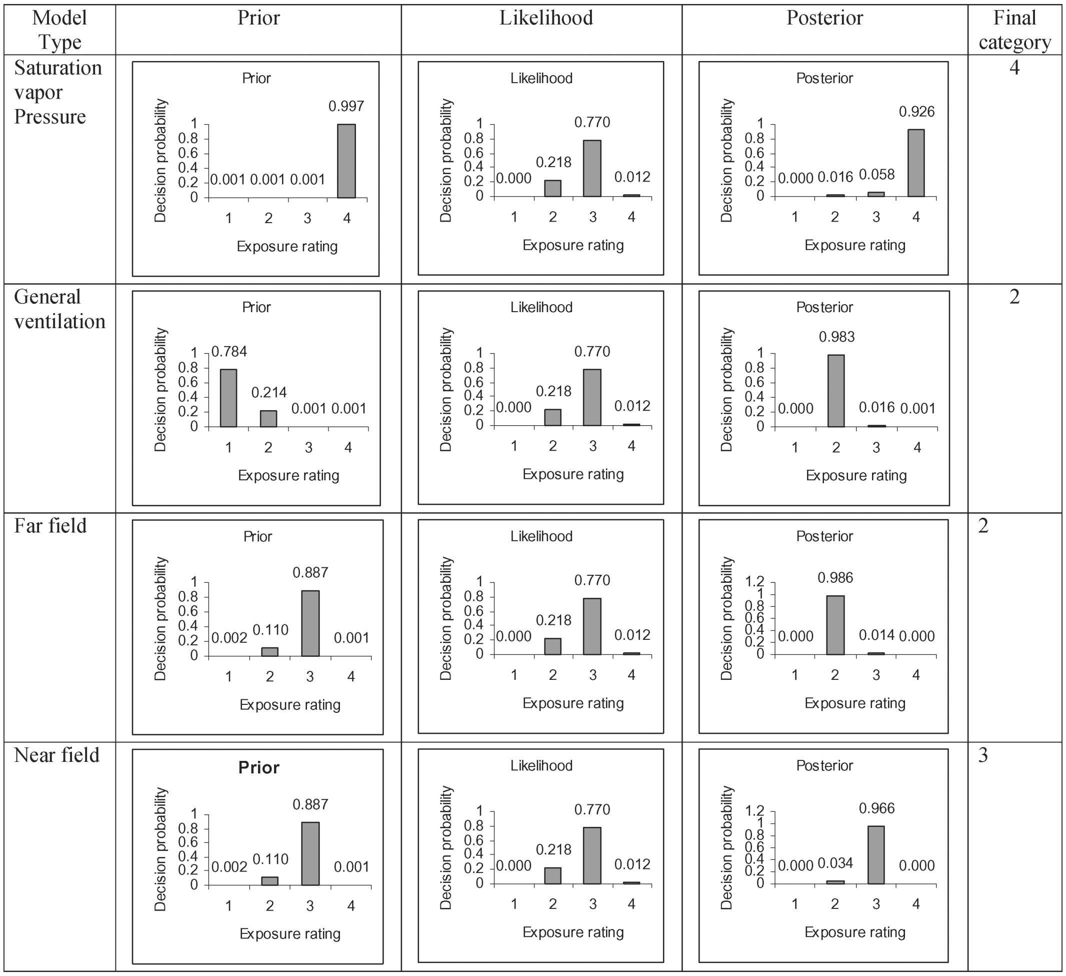

FIGURE 5. Likelihood function and posterior obtained from the Bayesian Decision Analysis software.[4] The data predicts that the exposure category is Category 3. The prior predicted from the 2D MC simulations predicted exposure Category 3 for the near field model.

CONCLUSION

The primary objective of this study was to demonstrate the applicability of exposure models in conjunction with two-dimensional Monte Carlo methods for making exposure judgments in the context of Bayesian decision analysis. One of the challenges that exposure modelers have faced is to show how the outputs of models can be used for occupational hygiene decision making. This is of particular benefit under the new REACH regulations in the European Union where producers and importers of chemicals have to demonstrate the safety of the use of chemicals under a range of exposure scenarios. The decision-chart format of output of the two-dimensional Monte Carlo method described here can be used as one of the approaches for this purpose. We chose several simple models for illustrative purposes and used steady-state solutions for the models for the sake of simplicity. However, the methodology is general and can be applied to more complex models and non-steady-state conditions. These model-based exposure judgments may improve upon direct, subjective judgments regarding exposure provided by the occupational hygienist, since they explicitly incorporate information about determinants of exposure in the form of model input parameters. Model input parameters may be obtained through theoretical calculations, actual measurements, or professional judgments. Thus, subjective professional judgments of exposure are not completely eliminated but replaced with professional judgments about exposure determinants.

Representing parameters as probability distributions allows a level of interaction between the hygienist and the model and also enables a better understanding of the overall system.[34] This allows for a detailed description of the system and, in the case of exposure judgments, may help provide focus on the actual workplace parameters that influence exposures. As with any modeling exercise, there is a certain level of uncertainty associated with model selection, selecting the model parameter values as well as Monte Carlo-imposed uncertainty. These may not always be tractable. Indeed, these are inherent limitations in using any model, and use of the two-dimensional Monte Carlo methodology does not remove these limitations. Users need to be cautious regarding these issues and to account for these inherent uncertainties where possible, as they should any time models are used.

The output in the form of decision charts makes it amenable for use as priors in Bayesian decision-making frameworks. The model-based priors can then be used in combination with exposure measurements to arrive at a more refined final decision category. The 2D MC method can be used to develop a multilevel screening or tiered model approach for these chemicals.

ACKNOWLEDGMENTS

This project was supported by grant 1RO1 OH008513 from the National Institute for Occupational Safety and Health of the Centers of Disease Control and Prevention.

REFERENCES

1. **Corn, M., and N.E. Esmen:** Workplace exposure zones for classification of employee exposures to physical and chemical agents. *Am. Ind. Hyg. Assoc. J. 40*:47–57 (1979).
2. **Mulhausen, J.R., and J. Damiano:** *A Strategy for Assessing and Managing Occupational Exposures*, Second Edition. Fairfax, Va.: AIHA Press, 1998.
3. **Rappaport, S.M, S. Kromhout, and E. Symanski:** Variations of exposure between workers in homogeneous exposure groups. *Am. Ind. Hyg. Assoc. J. 54*:654–662 (1993).
4. **Hewett, P., P. Logan, J. Mulhausen, G. Ramachandran, and S. Banerjee:** Rating exposure control using Bayesian decision analysis. *J. Occup. Environ. Hyg. 3*:568–581 (2006).
5. **Jayjock, M.A., and N.C. Hawkins:** A proposal for improving the role of exposure modeling in risk assessment. *Am. Ind. Hyg. Assoc. J. 54*:733–741 (1993).
6. **M.A. Jayjock:** Uncertainty analysis in the estimation of exposures. *Am. Ind. Hyg. Assoc. J. 58*:380–382 (1997).
7. **Glaser, R.:** Thoughts on expertise. In *Cognitive Functioning and Social Structure Over the Life Course*, C. Schooler and W. Schaie (eds.). Norwood, N.J.: Ablex, 1987. pp. 81–94. Topic 13.
8. **Glaser, R.:** Expert knowledge and processes of thinking. In *Enhancing Thinking Skills in the Sciences and Mathematics*, D.F. Halpern (ed.). Hillsdale, N.J.: Erlbaum, 1992. pp. 63–75. Topics: 5c, 6, 13.
9. **Glaser, R.:** Changing the agency for learning: Acquiring expert performance. In *The Road to Excellence: The Acquisition of Expert Performance in the Arts and Sciences, Sports and Games*, A. Ericsson (ed.). Mahwah, N.J.: Erlbaum, 1996. pp. 303–311. Topics: 9, 10, 13, 19.
10. **Zeitz, C., and R. Glaser:** The expert level of understanding. In *The International Encyclopedia of Education*, 2nd ed., T. Husen and T. N. Postlethwaite (eds.). Oxford/Leuven: Pergamon Press, 1994. pp. 2194–2199. Topics 2, 6, 13.
11. **Kahneman, D., and A. Tversky:** The simulation heuristic. In *Judgment Under Uncertainty: Heuristics and Biases*, D. Kahneman, P. Slovic, and A. Tversky (eds.). New York: Cambridge University Press, 1982. pp. 201–208.
12. **Griffin, David, R.:** *Animal Minds*. Chicago: University of Chicago Press, 1992.
13. **Goldstein, D.G., and G. Gigerenzer:** The recognition heuristic: How ignorance makes us smart. In *Simple Heuristics That Make Us Smart*. New York: Oxford University Press, 1999.
14. **Kahneman, D., and A. Tversky:** Subjective probability: A judgment of representativeness. *Cognitive Psychology 3*:430–454 (1972).
15. **Kahneman, D., and A. Tversky:** Availability: A heuristic for judging relevancy and probability. *Cognitive Psychology 5*:207–232 (1973).
16. **Kahneman, D., and A. Tversky:** On the psychology of prediction. *Psychology Rev. 80*:237–251 (1973).
17. **Kromhout, H., Y. Oostendorp, D. Heederik, and J.S.M. Boleij:** Agreement between semiquantitative exposure estimates and quantitative exposure measurements. *Am. J. Ind. Med. 12*:551–62 (1987).
18. **Hawkins, N.C., and J.S. Evans:** Subjective estimation of toluene exposures: A calibration study of industrial hygienists. *Appl. Ind. Hyg. 4*:61–68 (1989).
19. **Walker, K.D, Catalano, P., Evans, J.S., Hammitt, J.K.:** Use of expert judgment in exposure assessment, part II: Calibration of expert judgments about personal exposures to benzene. *J. Expo. Anal. Environ. Epidemiol. 13*: 1–16 (2003).
20. **Macaluso, M., E. Delzell, V. Rose, J. Perkins, and K. Oestenstad:** Inter-rater agreement in the assessment of solvent exposure at a car assembly plant. *Am. Ind. Hyg. Assoc. J. 54*:351–359 (1993).
21. **de Cock, J., H. Kromhout, D. Heederik, and J. Burema:** Experts' subjective assessment of pesticide exposure in fruit growing. *Scand. J. Work Environ. Health 22(6)*:425–432 (1996).
22. **Ramachandran, G., and J.H. Vincent:** A Bayesian approach to retrospective exposure assessment. *Appl. Occup. Environ. Hyg. 14*:547–557 (1999).
23. **Ramachandran, G.:** Retrospective exposure assessment using Bayesian methods. *Ann. Occup. Hyg. 45*:651–667 (2001).
24. **Wild, P., E.A. Sauleau, E. Bourgkard, and J-J. Moulin:** Combining expert ratings and exposure measurements: A random effect paradigm. *Ann. Occup. Hyg. 46*:479–87 (2002).
25. **Morgan, M.G., and M. Henrion:** *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. New York: Cambridge University Press, 1990.
26. **Nicas, M., and M. Jayjock:** Uncertainty in exposure estimates made by modeling versus monitoring. *AIHA J. 63(3)*:275–83 (2002).
27. **Shade, W.D, and M.A. Jayjock:** Monte Carlo uncertainty analysis of a diffusion model for the assessment of halogen exposures during dosing of brominators. *Am. Ind. Hyg. Assoc. J. 58*:418–424(1997).
28. **Fukuma, K., and D.J. Dunlop:** Monte Carlo simulation of two-dimensional domain structures in magnetite. *J. Geophys. Res. 102(B3)*:5135–5144 (1997).
29. **Light, B., G.A. Maykut, and T.C. Grenfell:** A two-dimensional Monte Carlo model of radiative transfer in sea ice. *J. Geophys. Res. 108(C7)*:3219 (2003).
30. **R.E. Keenan, B.L. Finley, and P.S. Price:** Exposure assessment: Then, now and quantum leaps in the future. *Risk Anal. 14(3)*:225–230 (1994).
31. **Keil, C.B.:** A Tiered approach to deterministic models for indoor air exposures. *Appl. Occup. Environ. Hyg. 15*:145–151 (2000).
32. **Nicas, M., and J. Neuhaus:** Predicting benzene vapor concentrations with a near field/far field model. *J. Occup. Environ. Hyg. 5*:599–608 (2008).
33. **Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin:***Bayesian Data Analysis*, Second Edition. London: Chapman and Hall/CRC, 2004.
34. **Steven, C. Bankes:** Tools and techniques for developing policies for complex and uncertain systems. *Proc. Nat. Acad. Sci. USA 99(Suppl. 3)*:7263–7266 (2002).