Bayesian Hierarchical Framework for Occupational Hygiene Decision Making

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ABSTRACT

A hierarchical Bayesian framework has been developed for exposure assessment that makes use of statistical sampling-based techniques to estimate the posterior probability of the 95th percentile or arithmetic mean of the exposure distribution being located in one of several exposure categories. The framework can synthesize professional judgment and monitoring data to yield an updated posterior exposure assignment for routine exposure management. The framework is versatile enough that it can be modified for use in epidemiological studies for classifying the arithmetic mean instead of the 95th percentile into several exposure categories. Various physico-chemical exposure models have also been incorporated in the hierarchical framework.

The use of the framework in three settings has been illustrated. First, subjective judgments about exposure magnitude obtained from industrial hygienists for five tasks were treated as priors in the Bayesian framework. Monitoring data for each task were used to create a likelihood function in the hierarchical framework and the posterior was predicted in terms of the 95th percentile being located in each of the four AIHA exposure categories. The accuracy of the exposure judgments was then evaluated. Second, we illustrate the use of exposure models to develop priors in this framework and compare with monitoring data in an iron foundry. Finally, we illustrate the use of this approach for retrospective exposure assessment in a chemical manufacturing facility, to categorize exposures based on arithmetic mean instead of 95th percentile.

KEYWORDS: Bayesian; decision making; occupational exposure judgment; judgment accuracy; exposure model

INTRODUCTION

Two contexts in which occupational exposure assessment occur include managing workplace exposures and assessing compliance and assessing exposure-response relationships in epidemiological studies. Collecting monitoring data for every task and similar exposure group (SEG) can be time-consuming and expensive. Further, in many situations, exposure assessment may be required for several chemical species simultaneously. It is not uncommon for plants to have several thousand process, task, and substance combinations, making a complete quantitative exposure assessment...
for each all but impossible to accomplish. For epidemiological or retrospective exposure assessment studies, exposure characterization is often conducted using limited monitoring or even analogous data, as well as qualitative workplace or task descriptions available for the group of workers. Hence, for both exposure management and epidemiological studies, if sufficient monitoring data are not available, there is typically a heavy reliance on professional judgments and the ability of hygienists to correctly integrate these judgments with available monitoring data for accurate exposure categorizations.

Bayesian decision-making in industrial hygiene is an inductive approach whereby a preliminary decision (the ‘prior’) arrived at by the hygienist using professional judgment or mathematical modeling is updated using available monitoring data (via a ‘likelihood’ function) to yield the final decision (the ‘posterior’). Bayesian methods offer a rational framework to integrate subjective judgment and available monitoring data for decision making (Ramachandran and Vincent, 1999; Ramachandran, 2001; Wild et al., 2002; Ramachandran et al., 2003; Tielemans et al., 2007, 2008, 2011).

Hewett et al. (2006) developed a decision-making framework for occupational exposure assessment using Bayesian statistical analysis. Exposure management decisions need to be based on evaluation of the 95th percentile of the exposure distribution (Ignacio and Bullock, 2006). A key conceptual advance in their paper was the development of a strategy which focuses on determining the probability of the 95th percentile of the exposure distribution being located in each of the four AIHA exposure categories (that correspond to the 95th percentile being less than 10% of the OEL, 10–50% of the OEL, 50–100% of the OEL, and >100% of the OEL).

More recently, McNally et al. (2014) have used Bayesian methods for the assessment of inhalation exposures in an occupational setting using a web-based application for exposure assessment, the Advanced REACH Tool (ART). This tool combines various sources of information within a Bayesian statistical framework such as expert knowledge, data on inter- and intra-individual variability in exposures from the literature and context specific exposure measurements. The ART provides central estimates and confidence intervals for different percentiles of the exposure distribution, for full-shift and long-term average exposures.

This paper extends these ideas and illustrates the use of a hierarchical framework for routine industrial hygiene exposure monitoring, where the 95th percentile of the exposure distribution is analyzed. The 95th percentile is a useful estimate of the upper bound of a distribution of full-shift exposures and it is useful for exposure management decisions to be based on a statistic that includes almost all (95%) of the workers. For epidemiological or retrospective data analysis purposes, a similar chart can be arrived at using the arithmetic mean instead of the 95th percentile of exposure distribution. (e.g. Fig. 1). The AM is generally considered the most appropriate metric for calculating cumulative exposure (Seixas et al., 1988; Rappaport, 1991). In this case, the parameter space and thresholds will be different as will be shown later in the paper. The framework synthesizes monitoring data and professional judgment or other sources of information, such as mathematical exposure modeling results to arrive at an exposure decision. The result is a distribution of probabilities of different exposure categories that can be graphed as a “decision chart” in a manner similar to Hewett et al. (2006). Our approach is more akin to that presented by Hewett et al. (2006) than McNally et al. (2014) in the sense that the goal is to present the exposure in discrete categories rather than as point estimates with the associated uncertainties. However, our method can also be used to yield point estimates if needed. Additionally, the method presented here can be used for industrial hygiene decision-making as well as for epidemiological studies, and also seamlessly incorporates the outputs of physical exposure models for use in the decision-making.

**METHODS**

**Bayesian hierarchical framework**

The fundamental concept of hierarchical analysis is to approach a complex problem by disaggregating it into smaller components or tiers. The advantage of the hierarchical model is to allow the components of a complex model to “learn” across different levels of the hierarchy. The tiers of the hierarchy include parameters such as monitoring data, experts’ judgments on exposure for similar exposure scenarios and process-specific information like room volume, chemical generation rates and room ventilation rates, and the uncertainties in...
each of these pieces of information. The analysis across all these tiers leads to the overall exposure judgment.

The uncertainties in our knowledge about each of these types of data can be expressed in the form of probability distributions that informs the overall analysis from a lower level of the hierarchy. Thus, the overall Bayesian framework is a combination of disaggregation and hierarchical modeling based on the available information for a given scenario. Thus, distributions for prior parameters can come from experts’ qualitative judgments or from exposure models. For expert judgments, the knowledge or analysis of an expert can be used to develop an appropriate prior distribution or distributions for parameters within the hierarchy. Exposure models can also be used for developing priors (Vadali et al., 2009) that can be integrated within the hierarchical framework to arrive at posteriors. When exposure models are used for defining priors, this is done by assigning distributions to the model parameters. In the case of uncertainty around a given parameter, a probability distribution can be assigned to describe it, thereby extending the hierarchy. For example, an exposure model may contain the chemical generation rate as a model parameter. However, this parameter itself may be the output of another model with its own parameters at a still lower level of the hierarchy. These hierarchies extend until all the components are sufficiently described.

The hierarchical model is built as follows using conventional Bayesian terminology (e.g. Lunn et al., 2000; Gelman et al., 2004). Since exposure data are most often adequately described by a log-normal distribution, the data likelihood comes from monitoring data points (log-concentrations) from an underlying log-normal density with geometric mean (GM) given by \( \exp(\mu) \) and geometric standard deviation (GSD) given by \( \exp(\sigma) \) where, \( \mu \) is the mean of the log transformed data, \( \sigma \) is the standard deviation of the log transformed data. More explicitly, the likelihood function, \( p(\text{data}|\mu, \sigma^2) \), can be defined as:

\[
\prod_{i=1}^{n} LN(y_i|\mu, \sigma^2) = \prod_{i=1}^{n} \frac{1}{y_i \sigma \sqrt{2\pi}} \exp\left\{ -\frac{1}{2} \left( \frac{\log y_i - \mu}{\sigma} \right)^2 \right\}.
\]  

(1)

where \( y_i \) denotes the \( i \)th log-concentration and \( n \) is the number of monitoring data.

Let \( N_{\text{cat}} \) be the number of categories (for example, with the AIHA categories described earlier, \( N_{\text{cat}} = 4 \)) and \( R \) be a random variable indicating the categories, i.e. \( R \in \{1, 2, ..., N_{\text{cat}}\} \). The proposed model is aimed at classifying the exposure into one of \( N_{\text{cat}} \) categories. Treating \( R \) as a random variable in the model directly produces its posterior distribution and is easily computed within a Bayesian hierarchical framework. Following Hewett et al. (2006), we set the boundaries for geometric mean and geometric standard deviation (i.e. the parameter space) with respect to the occupational exposure limit (OEL). The geometric mean is assumed to follow a uniform prior distribution on the log scale between \( GM_{\text{min}} \) and \( GM_{\text{max}} \).
where \( GM_{\text{min}} = 0.0005 \times \text{OEL} \) and \( GM_{\text{max}} = 5 \times \text{OEL} \), where OEL is the Occupational Exposure Limit specific to the chemical used. The five orders of magnitude relative to the OEL encompassed in this range cover the full range of exposures typically encountered for decision-making. The geometric standard deviation is also assumed to follow a uniform prior distribution on a log scale between \( \text{GSD}_{\text{min}} \) and \( \text{GSD}_{\text{max}} \) where \( \text{GSD}_{\text{min}} = 1.05 \) and \( \text{GSD}_{\text{max}} = 4 \). These values were selected as the range containing most of the values typically observed in occupational environments.

We set \( N_{\text{cat}} \) action thresholds defined by \( \log (GM_{\text{min}}) < A_1 < A_2 < \cdots < A_{N_{\text{cat}}} = \log (GM_{\text{max}}) \). For example, with \( N_{\text{cat}} = 4 \) we set the action thresholds as follows: \( A_1 = \log (0.1 \times \text{OEL}) \), \( A_2 = \log (0.5 \times \text{OEL}) \), \( A_3 = \log (1.0 \times \text{OEL}) \) and \( A_4 = \log (G_{\text{max}}) \). These are used to set up prior distributions for our parameters as described in Hewett et al (2006). Figure 2 shows the boundaries we used for GM and GSD when the OEL is 100 ppm. We now define the geometric mean boundaries such that the 95th percentile lies in the different action intervals:

\[
\mu_{\text{min}} (R, \sigma) = \max \{ A_R - 1.645 \times \sigma, \log GM_{\text{min}} \}; \quad (2)
\]

\[
\mu_{\text{max}} (R, \sigma) = \min \{ A_R + 1.645 \times \sigma, \log GM_{\text{max}} \}; \quad (3)
\]

It should be noted that these do not specify where the data lie but where the geometric mean lies. Equations (2) and (3) represent the boundaries for \( R = 1, 2, \ldots, N_{\text{cat}} \). Figure 2 depicts a specific example with \( N_{\text{cat}} = 4 \). In that figure, any combination of GM and GSD represents an exposure profile whose 95th percentile resides in a category defined by the boundaries formulated in equations (2) and (3). We also point out that the Gibbs sampling approach we employ below for estimation allows the computation of the posterior for the 95th percentile of the data by drawing the histogram of the posterior distribution of \( \mu + 1.645 \times \sigma \).

Bayesian inference computes the posterior distribution for \( \theta = \{ \mu, \sigma, R \} \) given the data,

\[
P(\theta|y_1, \ldots, y_n) \propto d_{\text{cat}}(R|p) \times U(\sigma|\log \text{GSD}_{\text{min}}, \log \text{GSD}_{\text{max}}) \times U(\mu |\mu_{\text{min}}(R, \sigma), \mu_{\text{max}}(R, \sigma)) \times \prod_{i=1}^n \text{LN}(y_i|\mu, \sigma^2) \quad (4)
\]

Here, \( d_{\text{cat}} \) is the categorical mass probability function in each of the prior categories. Therefore, the prior distribution of \( R \) is specified by \( P(R = i) = p_i \) for each \( i = 1, 2, \ldots, N_{\text{cat}} \), so \( p_i \) is the prior probability for an observation to be in category \( i \). We let \( p = \{ p_1, p_2, \ldots, p_{N_{\text{cat}}} \} \). The log (GSD) or \( \sigma \) is assumed, ‘a priori’, to follow a uniform distribution \( (U) \) on the log-scale, i.e. over the interval \( (\log \text{GSD}_{\text{min}}, \log \text{GSD}_{\text{max}}) \). Similarly,
log(GM) or $\mu$ is assumed to follow a uniform distribution ($U$) on the log-scale, i.e. over the intervals defined in equations (2) and (3). We note that it is through the uniform distribution linking $\mu$ to $R$ and $\sigma$, that the data provide any information on the $R$. Figure 3 is a schematic representation of the Bayesian hierarchical model.

The expert will also need to provide values for the $p_i$s in equation (4). Precisely how the priors are formed falls under the realm of prior elicitation and numerous strategies, ranging from entirely subjective specifications based upon experience to numerical explorations, can be exploited. We follow the approach of Hewett et al. (2006), who interpret the prior probabilities in terms of the volume under the hypothesized likelihood surface in (equation 1), treated as a bivariate function of the log-transformed GM and GSD. The height $h_i$ for category $i$ can be used to formulate weights $w_j = h_i \times (\mu_{\text{max}}^j - \mu_{\text{min}}^j)$ as the volume of the likelihood surface. The prior probabilities are related to the weights in Hewett et al. (2006) as

$$p_i = \frac{w_i}{\sum_{j=1}^{N_{\text{cat}}} w_j}$$

3 Schematic representation of Bayesian hierarchical model
The posterior distribution in equation (4) corresponds to the hierarchical model:

\[ Y_i \mid \mu, \sigma^2 \sim \text{iid } \ln(\mu, \sigma^2), i=1, \ldots, n; \]
\[ \mu \mid R, \sigma \sim \text{Unif}(\mu_{\text{min}}, R, \mu_{\text{max}}), R; \]
\[ R \mid \mathbf{p} \sim \text{dcat}(p_1, \ldots, p_{NCAT}); \sigma \sim \text{Unif}(\log D_{\text{min}}, \log D_{\text{max}}) \]  
(6)

We programmed the model in equation (4) using the BUGS software (see [http://www.mrc-bsu.cam.ac.uk/bugs/](http://www.mrc-bsu.cam.ac.uk/bugs/) or [http://www.openbugs.info/w/](http://www.openbugs.info/w/)) to execute Markov chain Monte Carlo (MCMC) algorithms, such as the Gibbs sampler and Metropolis-Hastings algorithms (see e.g. Gelman et al. 2004; Marin and Robert, 2008, and Carlin and Louis, 2008). These algorithms have gained enormous popularity in Bayesian statistics. Their power lies in generating samples from the posterior distribution. We specifically used the WinBUGS ([http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml](http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml)) software package that automatically implements MCMC algorithms to draw posterior samples for \( \mu, \sigma, \) and \( R. \) The posterior distribution for \( R \) is discrete and the category with the highest posterior mass is chosen. The BUGS code is presented in the Appendix. The hierarchical model above subsumes the approach in Hewett et al. (2006) and is more convenient for implementation in BUGS.

**Figure 3** is a schematic representation of the hierarchical model. The goal of the model is to arrive at the final posterior. We can consider this as Stage 1 and build up the hierarchy from there. To arrive at the posterior we need to compute the likelihood function and the prior probability function. This is represented as a graphical model representation. The likelihood function is the probability of observing the monitoring data \( (Y) \) given all combinations of geometric mean (\( \mu \)) and geometric standard deviation (\( \sigma \)) for a particular data set. This is Stage 2 of the hierarchy. Since the values of \( \mu \) and \( \sigma \) can change based on further distributions assigned higher up in the hierarchy, they are represented as ovals in Fig. 3. The geometric mean is dependent on \( \sigma \), as shown in equations (2) and (3). The Stage 2 variables are further defined by assuming distributions on the minimum and maximum values of log (GM) and log (GSD). This is Stage 3 in the hierarchy. Stage 3 variables are fixed and hence represented by rectangles. The likelihood category is represented in terms of four categories each defined based on the OEL and \( \mu \) and \( \sigma \). Hence in the hierarchy, equations (2) and (3) define these four categories in Stage 4. The boundaries of these four categories are specified and therefore they are represented by a rectangle. \( R \) is a random variable that specifies the number of categories, in this case the four categories and hence represented in an oval.

The next step in the hierarchy is to specify the priors \((p_1, p_2, p_3, p_4)\). The priors can be derived through exposure modeling or elicited directly from an expert, in the form of probabilities. This is Stage 5 of the hierarchical model. Further hierarchy on the priors can be introduced in the model at Stage 6 by assigning distributions to the specific input parameters for the exposure models.

**Bayesian decision making in exposure management**

Probabilistically defined priors in exposure assessment can be obtained in several different ways: (i) the hygienist can directly provide the prior in the form of probabilities of the true 95th percentile \( (X_{95}) \) of the exposure distribution being located in each of the four exposure categories, (ii) the hygienist can specify the input parameters to an exposure model that, in turn, defines the prior of the exposure distribution, (iii) priors can also be based on available data published in literature, available from other companies or other factories within the same company. In this paper, we will illustrate methods using (i) and (ii).

**Subjective direct priors**

Monitoring data were collected for five tasks from a large scale company. For each task, company industrial hygienists were asked to provide their subjective judgments (priors) after reviewing all available information for that task, except monitoring data. The industrial hygienists evaluating a given task were also encouraged to personally view the actual facility and talk to the plant personnel regarding the specifics of the tasks. All of the information on workplace process, equipment, controls, and materials, such as the chemicals used, MSDS, PPE worn by the workers, duration of the task, and task environment specifics such as the general room ventilation for the tasks for which judgments were provided were made accessible to the hygienists. The priors were in the form of probabilities of the true 95th percentile \( (X_{95}) \) of the exposure.
distribution being located in each of the four exposure categories. This prior was used in the Bayesian framework along with the available monitoring data that were used to generate the likelihood to arrive at the posterior exposure judgment. For each of the examples shown in the Results section, a unique parameter space (i.e. boundaries for GM and GSD) was defined. We are not presenting the details of the tasks themselves but rather the process by which the Bayesian model operates.

Model-derived priors
In many situations it is not feasible to obtain monitoring data (e.g. retrospective exposure assessments or workplaces that are in the process of being designed). In such cases, an exposure modeling approach is very critical. The illustrative example described below shows how modeling inputs obtained using different means (from measurements and from subjective inputs can be combined). This method was used to assess a task at an iron foundry where the potential for exposure from respirable dust was investigated. Sand molds with iron parts were placed on a vibrating platform. The iron parts and sand get knocked out onto the platform where the sand is removed by a shakeout conveyor and the iron parts move to the shake-out back end. Two different ventilation models were used to generate the priors, the general ventilation (one well-mixed compartment) model and the near-field far-field (two well-mixed compartments) model. The one-compartment model assumes that a source is generating an airborne pollutant at a rate $G$ (mg h$^{-1}$) in a room of volume $V$ ($m^3$) with a ventilation rate $Q$ ($m^3$ h$^{-1}$). 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 in the compartment is $C = G/Q$.

The two-zone model considers the region very near and around the source as one well-mixed box called the near field, while the rest of the room is another well-mixed box that completely encloses the near-field box. This box is called the far field and there is some amount of air exchange between the two boxes. This model requires knowledge of room ventilation ($Q$) and contaminant generation rates ($G$) in addition to a parameter known as the inter-zonal ventilation rate ($\beta$). The steady state concentrations in the compartments are given by $C_{\text{FF}} = G/Q$ and $C_{\text{NF}} = (G/Q) + (G/\beta)$. Both these models can be reasonably applied to this scenario, and the worker can be considered to be in the near-field of the two-zone model or in a well-mixed room. Dust generation rates and ventilation rates were obtained for this operation. For obtaining dust generation rates, multiple measurements were made for particle concentrations using Dust Trak (TSI Inc., Shoreview, MN) and air velocity (VelociCalc, TSI Inc., Shoreview, MN) was measured with velocimeter at four different locations around the shaker platform very near the dust generation sources. The generation rate was calculated as:

$$ G = C_{\text{near-source}} (mg m^{-3}) \times \beta (m^3 min^{-1}) $$

where $\beta$ is the ventilation rate through the near-source compartment, calculated as: $\beta = \text{Surface area of the volume around source} (m^2) \times \text{Air Velocity} (m s^{-1}) \times 60 (s min^{-1})$ and $C_{\text{near-source}}$ is the dust concentration measured very close to the source.

Bayesian decision making for exposure assessment in epidemiology
The Bayesian framework can also be used to analyze historical data for epidemiological purposes, where the arithmetic mean exposures are used to estimate cumulative exposures. The arithmetic mean is a function of GM and GSD. Equations (2) and (3) can be modified as follows:

$$ \mu_{\text{min}} = \max(A_R - 0.5 \times \sigma^2, GM_{\text{min}}); $$

$$ \mu_{\text{max}} = \min(A_R + 0.5 \times \sigma^2, GM_{\text{max}}); $$

Here the arithmetic mean is defined instead of the 95th percentile.

Data is presented from a chemical manufacturing company for two job titles involving benzene exposures for which historical personal benzene sampling data were available from 1974 to 1999. The data were divided up into three time periods according to key process changes that occurred at the facility over time and were believed to have an effect on benzene exposures at the facility. For the first job title, a compressor operator, there were 14 monitoring data points which measured the 8-h time-weighted average (TWA) for benzene for the task of interest from 1974–1983, 123
monitoring data points from the period 1984–1991 and 114 data points for the period 1992–1999. One hygienist who was extremely familiar with the facility and who had worked there for many years and collected all of the benzene monitoring data was asked to give exposure judgments for the two tasks for each of the three time periods. The hygienist was asked to classify the arithmetic mean benzene exposure concentration for each task into one of four exposure categories: (i) less than 0.1 ppm, (ii) 0.1 to 0.5 ppm, (iii) 0.5–less than 1 ppm, and (iv) greater than 1 ppm. He was also asked to provide a probability of the level of confidence in each judgment provided.

RESULTS AND DISCUSSION

Subjective direct priors

The priors, likelihood and posteriors for each task along with the OEL and actual data (extreme right column) are presented in Fig. 4. For all these examples, the monitoring data below the limit of detection (LOD) were replaced by LOD/2 while calculating the likelihood function. Two important comparisons can be made at this point. One is to see how well the prior judgment compares to the judgment based on the data alone (referred to as the likelihood in this context and as used by Hewett et al., 2006) and second to see how well the prior compares to the posterior. Ideally, if sufficient monitoring data were available for every task then hygienists would always be able to construct a likelihood judgment and can make control decisions based on that. But since monitoring data are often insufficient, we rely on professional judgment as an additional input to the final decision (the posterior). In Fig. 4, the hygienists’ priors refer to the professional judgments.

For Task 1 there were five individual monitoring or sampling results, for Task 2 there were six, for Task 3 there were seven, for task 4 there were nine and for Task 5 there were five monitoring data points. For Tasks 3 and 5, hygienists’ prior judgments were consistent with the exposure category predicted by the monitoring data. Since the prior and likelihood predicted the same exposure category for these tasks, the posterior also had the same exposure decision as the likelihood and prior. The true or reference exposure category is defined based on the full set of monitoring data. For tasks 3 and 5, the concordance of the prior and likelihood leads to the posterior decision category having a higher probability than either the prior or likelihood by itself. Thus, the final decision can be made with greater confidence.

For Task 1, the hygienist predicted a Category 2 ($0.03 < X_{95} < 0.15$ ppm) exposure whereas the monitoring data alone predicted a Category 4 ($X_{95} > 0.3$ ppm). For Task 2, the hygienist predicted a Category 2 ($1 < X_{95} < 5$ ppm) exposure whereas the monitoring data alone predicted a Category 4 ($X_{95} > 10$ ppm). Similarly for Task 4, the category was under-predicted relative to the data by the hygienist.

For Task 2, the hygienist predicted a Category 2 ($1 < X_{95} < 5$ ppm) exposure with ~75% probability, but the exposure predicted by the monitoring data alone was Category 4 ($X_{95} > 10$ ppm). The model combines the prior and likelihood probabilities and predicts a Category 2 exposure ($1 < X_{95} < 5$ ppm) with ~86% probability. When we look at the monitoring data available for this task, it can be seen that there is only one data point that is above detection limit and five of the other data points are below detection limit. The monitoring data for this task suggests that the task might have intermittent high exposures. Since one of the six monitoring data is above the OEL, it could very possibly be a Category 4 exposure. The monitoring data have a GSD of 16, indicating very high variability. This is also reflected in the likelihood chart which shows that the 95th percentile has 29%, 25%, and 45% probabilities of being in Categories 2, 3, and 4 respectively. Because of the high variability, the posterior decision for such a task has to be interpreted with caution. The high variability in the data is in contrast to the relative precision of the prior (75% in Category 2) which drives the posterior. Thus, an incorrect prior is driving the posterior decision. For this particular task, it can be concluded that further sampling must be conducted and the task must be reassessed for exposure categorization. Similar points can be made for Task 1 also.

These results are consistent with recent studies on the accuracy of subjective exposure judgments (Logan et al., 2009; 2011; Vadali et al., 2012a; 2012b). These studies suggest that in many situations, qualitative exposure assessments may result in such under-prediction (i.e. a tendency to assign a lower exposure category than the correct one) more often than expected. When no data are available, such under-predictions
can have drastic effects. Workers in SEGs whose exposure categories have been under-predicted would be at higher risk due to consequent inadequate risk management measures.

Human judgments and decisions are complex and are subject to a variety of biases. We rely on certain heuristics or rules of thumb, in order to make many judgments including probability assessments, typically when facing complex problems or incomplete information. These heuristics or mental processes do not typically utilize all of the available information and data in a formal algorithmic process but use more of “fast and frugal” rules of thumb to arrive at a judgment (Kahneman et al., 1982; Gigerenzer and Todd, 1999; Gilovich et al., 2002). Since heuristics are subjective in nature they may lead
to biases (Morgan and Henrion, 1990). Limitations and biases are specifically associated with the use of expert judgments (Alpert and Raiffa, 1982; Cooke, 1993; Kinney et al, 2007). Some commonly used heuristics include ‘availability, representativeness and anchoring heuristics’ (Tversky and Kahneman, 1974). The availability heuristic is a way of making a decision according to what is readily available in the mind depending on experience (Aronson, 1999) and not always based on factual data. This suggests that experience with similar exposure scenarios could be a significant determinant for exposure judgment accuracy. Using the representativeness heuristic, individuals judge scenarios based on how well they represent or match particular prototypes. It leads individuals to recognize patterns in information even when there are none. The anchoring heuristic involves people making estimates by starting from an initial value that is adjusted to yield the final answer. This effect is known as the ‘anchoring effect’, and many times the adjustments made are insufficient or too much (Jacowitz et al, 1995, Wilson et al, 1996, Hummel et al, 2001, Choplin et al, 2002 and Epley et al, 2005). All of these judgmental heuristics are sources of cognitive bias.

For example, a hygienist may use the ‘availability’ heuristic to recall from memory all past exposure assessments on a similar filter press using a different material containing xylene instead of methylene chloride. The hygienist may also utilize the ‘representativeness’ heuristic and may refer to the basic characterization information to identify the similarity of this new material, chemicals and process with the recalled exposure assessments. In addition the hygienist may use the ‘anchoring and adjustment’ heuristics to take information recalled from a representative process exposure assessment and adjust the upper tail judgment higher based on the higher vapor pressure of methylene chloride compared to xylene. The most likely case would be for the hygienist to utilize a combination of these and other heuristics to arrive at the final judgment.

Such biases have been reported in a variety of fields involving probability assessments, typically when facing complex problems or incomplete information (Alpert and Raiffa, 1982; Kahneman et al., 1982; Morgan and Henrion, 1990; Cooke, 1993; Gigerenzer and Todd, 1999; Gilovich et al., 2002; Kinney et al, 2007). Cognitive biases in data interpretation can be reduced by targeted data interpretation training (Logan et al., 2009; Vadali et al., 2012). Another way to do this is through the use of physical-chemical exposure models that might reduce bias (Vadali et al., 2009).

**Model-derived priors**

Generation rate was calculated by making three measurements of $C_{near-source}$ at each of the four locations near the source. These 12 measurements of $G$ could be described by a log normal distribution with a geometric mean of 51 mg min$^{-1}$ and a geometric standard deviation of 1.67. Likewise $\beta$ was described by a log-normal distribution with a geometric mean of 34 m$^3$ min$^{-1}$ and a geometric standard deviation of 1.50. The general ventilation $Q$ was described by a uniform distribution between 80 and 100 m$^3$ min$^{-1}$.

A two dimensional Monte Carlo approach described by Vadali et al. (2009) was used to generate the prior decisions. Eight monitoring data points (shown in Fig. 5) for respirable dust (OEL = 3 mg m$^{-3}$) were available for this task to generate the likelihood function. Within the Bayesian hierarchical framework, this was integrated with the likelihood from the monitoring data to develop the final posterior. Results are presented in Fig. 5. For both models, it can be seen that the model-generated priors agreed very well with the likelihoods and the posteriors predicted a Category 4 exposure.

In this example, we wanted to illustrate the use of mechanistic models where the input parameters include some for which we have measurements (i.e. $G$) while other parameters are subjectively estimated (i.e. $Q$). In many situations, it may not be possible to make any exposure measurements and modeling may be the only reasonable way forward. In the case of small numbers of exposure data, studies have shown that modeling provides as good if not better estimates than monitoring data (Nicas and Jayjock, 2002).

**Bayesian decision making for exposure assessment in epidemiology**

The hygienist made all qualitative task exposure judgments without reviewing the available company monitoring data or other information about each task beforehand, although he was very familiar with these tasks, having worked at this facility for more than
25 years, and having personally collected all airborne benzene samples. The expert judgments were used as priors in the Bayesian framework to incorporate this historical knowledge of facility operations into the final exposure category decision regarding mean exposures to benzene over time. For each time period, the available monitoring data were used to arrive at the likelihood. Since the likelihood provided the exposure category based on a large number of monitoring data, we considered it to represent the true exposure category for that time period. The likelihood was compared to the hygienist-specified exposure category (i.e. the prior).

For the time period prior to 1983, the hygienist predicted the mean exposures for this task to be in Category 3, whereas the data suggested that the true exposure was in Category 2. Similarly, for the next time period the hygienist predicted the exposure to be in Category 3 but the data predicted that the true exposure was in Category 1. For the third time period (1992–1999), the likelihood-based category and the hygienist-predicted category were the same, Category 1 (Fig. 6). The hygienist over-predicted the exposure category 2 out of 3 times. The tasks for which exposure was over-predicted were those that occurred over 15 to 30 years earlier. It is possible that the length of time that had passed since the operating conditions in question were present caused the hygienist to incorrectly recall the facility conditions and controls during the time periods of interest. It is also possible that the hygienist knew that controls had been put in place to reduce exposures but was unable to recall the quantitative effect of those control measures on airborne benzene concentrations. Interestingly, though, the hygienist expressed a very high probability or confidence level in the judgments provided for all three time periods of 95 percent.

For the second task, that of a laboratory analyst, there were fewer monitoring data available. There were 25 sample results for the first time period, six for the next time period and four for the last time period. In this case, it was observed that the hygienist under-predicted 2 out of 3 times. The hygienist predicted the highest category for all time periods to be 1, but for time periods one and three, the likelihood category predicted by the model was 2 (Fig. 7).

For this task, with limited data, the hygienist seemed to under predict the exposure. It is possible that the hygienist had less direct knowledge of this task in part because less exposure data had been measured.
collected (and as a result, less time had been spent by the hygienist observing the task). It may be that without training in making professional judgments, the hygienist is significantly affected by one or more personal experiences or recollections related to the task scenario, which in turn affects memory of the true exposure potential associated with each task. Overall, for all professional judgments that were provided by the hygienist for tasks conducted at the facility, the hygienist selected the correct exposure category 62 percent of the time. The hygienist over predicted by more than one exposure category 27% of the time and under predicted the correct exposure category 11% of the time.

Again, the Bayesian hierarchical framework offers a useful method by which insights into the accuracy
of the industrial hygienist judgments can be obtained. The results could also potentially be used to provide feedback to the hygienist and recalibrate his judgments.

CONCLUSIONS

Occupational exposures need to be categorized correctly. Improper classification can lead to non-compliance as well as improper controls being implemented. Misclassification of exposures can lead to directing of resources into inappropriate areas. Misclassification in epidemiological risk assessments can lead to incorrect dose-response relationships. The Bayesian hierarchical framework described in this paper is a promising tool that is not only flexible for industrial hygiene exposure decision making but also for epidemiological exposure characterization.

For industrial hygiene data, the Bayesian framework can be used to validate expert judgments when data are available. Priors can be generated using purely subjective professional judgments. However, hygienists are not always accurate at predicting the correct exposure category. For such situations exposure models can be used to generate priors. If the model parameters are accurate, then reliable priors can be obtained. Even if limited data are available, they can be integrated within the framework to develop posteriors. The presentation of the decisions in the form of prior, likelihood, and posterior also offers the potential for feedback to the industrial hygienist. For example, if the prior decision and its corresponding probabilities are very different from what the data suggest through the likelihood probabilities, then the hygienist has the opportunity to reconsider the priors, and maybe decide to use a non-informative flat prior instead of a more informative but incorrect prior.

For epidemiological purposes, the statistic of interest can be changed very easily from the 95th percentile to the arithmetic mean. When we have priors and historical data this can be utilized to study exposures over periods of time.

The Bayesian hierarchical analysis offers a systematic framework to integrate information available on a task (be it monitoring data or information on exposure determinants such as generation and ventilation rates) and provide reasonable exposure estimates. Finally, an advantage of using this methodology for epidemiological studies is that it is useful for category assignment for a given SEG and helps with exposure assignments and uncertainty analysis.

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APPENDIX: BUGS CODE FOR THE COMPUTATION OF THE POSTERIOR OF THE 95TH PERCENTILE

```r
model {
  ## Specify the likelihood where N is the number of observations
  for (i in 1:N) {
    Y[i] ~ dlnorm(mu, tausq)
  }
  ## Specify the priors:
  ## Prior for sigma = log-GSD
  sigma ~ dunif(lDmin, lDmax)
  tausq <- 1/pow(sigma, 2)
  ## Prior for mu = log-GM
  ## First find the limits of integration mu.min and mu.max
  for (i in 1:NCAT) {
    mu.min[i] <- max(A[i] - 1.645*sigma, lGmin)
    mu.max[i] <- min(A[i+1] - 1.645*sigma, lGmax)
    wt[i] <- p[i]*(mu.max[i] - mu.min[i])
  }
  for (i in 1:NCAT) {
    probs[i] <- wt[i]/sum(wt)
  }
}
```

### Constants
- G.min <- 0.0005*OEL
- G.max <- 5*OEL
- D.min <- 1.05
- D.max <- 4.0
- lGmin <- log(G.min)
- lGmax <- log(G.max)
- lDmin <- log(D.min)
- lDmax <- log(D.max)

```r
for (i in 1:(NCAT+1)) {
  A[i] <- log(u[i]*OEL)
}
```

```r
## Specify the likelihood where N is the number of observations
for (i in 1:N) {
  Y[i] ~ dlnorm(mu, tausq)
}
```

```r
## Specify the priors:
## Prior for sigma = log-GSD
sigma ~ dunif(lDmin, lDmax)
```
R ~ dcat(probs[])  
theta ~ dunif(0,1)  
mu <- mu.min[R] + (mu.max[R] - mu.min[R])*theta  
## Compute GM and GSD  
GM <- exp(mu)  
GSD <- exp(sigma)  
## Compute Xpe (95th percentile)  
Xpe <- exp(mu + 1.645*sigma)  

## Data example from  
list(N = 5, Y = c(0.003, 0.006, 0.015, 0.039, 0.22), u = c(0.0005, 0.1, 0.5, 1.0, 5), OEL = 0.3, p=c(0.14,0.80,0.05,0.01), NCAT = 4)  
## Inits  
list(R = 2, sigma = 1.0, theta = 0.5)  

## Constants  
G.min <- 0.0005*OEL  
G.max <- 5*OEL  
D.min <- 1.05  
D.max <- 4.0  
lGmin <- log(G.min)  
lGmax <- log(G.max)  
lDmin <- log(D.min)  
lDmax <- log(D.max)  
for (i in 1:(NCAT+1))  
  A[i] <- log(u[i]*OEL)  
}  
## Specify the likelihood where N is the number of observations  
for (i in 1:N)  
  Y[i] ~ dlnorm(mu, tausq)  
}  
## Specify the priors:  
## Prior for sigma = log-GSD  
sigma ~ dunif(lDmin, lDmax)  
tausq <- 1/pow(sigma, 2)  
## Prior for mu = log-GM  
## First find the limits of integration mu.min and mu.max  
mu.min[i] <- max(A[i] + 0.5*pow(sigma,2), lGmin)  
mu.max[i] <- min(A[i+1] + 0.5*pow(sigma,2), lGmax)  
wt[i] <- p[i]*(mu.max[i] - mu.min[i])  
for (i in 1:NCAT)  
  probs[i] <- wt[i]/sum(wt[])  
R ~ dcat(probs[])  
theta ~ dunif(0,1)  
mu <- mu.min[R] + (mu.max[R] - mu.min[R])*theta  
## Compute GM and GSD  
GM <- exp(mu)  
GSD <- exp(sigma)  
## Compute AM (Arithmetic Mean)  
AM <- exp(mu + 0.5*pow(sigma,2))

REFERENCES