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A Bayesian Approach to Retrospective Exposure Assessment

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A variety of health effects are caused by chronic, cumulative exposure over time to pollutants. In these cases, to establish dose-response relationships for epidemiological and risk assessment purposes, it is vital to determine the exposures of individuals or cohorts as functions of time. Most existing occupational exposure databases, however, do not contain continuous records of historical exposures to airborne contaminants. These gaps in the historical record may be filled by using the knowledge base that experts and professionals in the field possess.

In this article we present a new framework, based on Bayesian probabilistic reasoning, for obtaining estimates of exposure histories for airborne particulates from limited historical measurements, using subjective expert judgment. The framework has great potential applications in instances where there is sparse information or missing data on past exposures. Expert judgment, in the form of inputs to physical models, provides additional knowledge to retrospectively estimate exposure as a function of time from discrete and incomplete measurements. The expert judgments are informed by knowledge of historical plant conditions and work practices, and models describing process-dependent aerosol generation, ventilation, and worker activity patterns. The result will be probability distributions of the exposure of task-groups of workers as a function of time, in the form of a matrix.

There are many documented cases (e.g., asbestos, tobacco smoke, and radon daughters) of a causal relationship between the health risk for disease and long-term exposure to airborne environmental particulate contaminants. Strictly speaking, the health hazard in such instances is related to the temporal history of an individual's exposure, the kinetics of deposition and clearance of the inhaled material, and some measure of the harmfulness or potency of the contaminant. All of these are time-dependent quantities, and the integrated dose at time t since the start of the exposure may be expressed in a general form as

$$\text{Dose} = \int_0^T f\{E(t),\ R(t),\ G(t)\}\, dt \qquad [1]$$

Here, $E(t)$ is the exposure history derived from measurements of aerosol concentration, $R(t)$ is a function describing the retention of inhaled particles in the lung tissue that is well documented in lung deposition models[1] which are derived from toxicological data, and $G(t)$ describes the time-dependent potency of the contaminant to cause harm to the tissue.[2,3] For example, in the case of radioactive particulate matter, the potency to cause harm is related to the ionizing radiation of a well-defined type which derives from radioactive decay. Most exposure-based epidemiology assumes that cumulative exposure, i.e., $\int_0^T E(t)\,dt$, is a good measure of dose. It is important to realize that this is an approximation that is only valid when $R(t)$ and $G(t)$ are unity. Unlike simpler models that calculate dose as the cumulative exposure where each exposure is equally weighted, this model gives greater weight to the effect of earlier exposures through the parameter $G(t)$. Thus it is reasonable to expect that the deposited particles which stay a long time in the lung from earlier exposures have a greater impact on the health outcome than particles deposited more recently. In this manner, exposure histories can, in principle, be used in conjunction with pharmacokinetic and pharmacodynamic models to obtain better estimates of biologically relevant doses to organs or tissues.

The above model underscores the importance of having exposure data expressed as a function of time. While long-term prospective epidemiological studies can be very useful in determining the relationship between exposure and disease, this is not a luxury that can often be afforded by industries and standards-setting bodies, which have to act on information currently available. Therefore, to establish robust quantitative dose-response relationships for epidemiological purposes, it is vital to reconstruct past exposures of individuals or populations as functions of time over the periods of interest.

However, there is a paucity of historic exposure data for occupational air contaminants, with exceptions such as the coal mining industry.[4–6] In most cases, cumulative exposure surrogates (e.g., using duration of employment in an industry as a surrogate for cumulative exposure) or semi-quantitative estimates (e.g., describing exposures nominally as high, moderate, or low) have been used. These surrogates do not allow for the quantitative evaluation of health risks. The process of reconstructing exposure over long periods is fraught with a number of uncertainties and subjective biases: measurement criteria, instruments and analysis methods that change over time and changes in workplace practices, industrial processes, and plant-specific ventilation patterns that may modify exposures. Measurements of personal exposures to airborne particulates are, at best, temporally sporadic, and for the period prior to the 1970s, not even available. Due to these uncertainties and constraints, it is important to develop a systematic framework to estimate historical levels of exposure over a time span that has epidemiological significance and analyze various assumptions that are built into these estimates.

Esmen[7] recognized these limitations, and proposed a methodology for projecting historical exposures from current estimates by a series of adjustments to the current data. These adjustments are based on changes in the process, physical parameters of the agent, and use of personal protective devices. However, subjective judgments would strongly influence these adjustments. Schneider et al.[8] further explicated this approach by proposing the use of exposure modifiers as input parameters to a deterministic exposure model, and using historic exposure data to adjust the model parameters.

In this article, we present a scheme that requires additional inputs to estimate exposures as a function of time from relatively sparse discrete measurements. These additional inputs take the form of expert judgments from professionals with relevant experience and insights. A formal Bayesian probabilistic framework is presented for synthesizing expert judgment, historical information about workplace conditions, and incomplete measurements to determine exposure as a function of time and place. This will take the form of an exposure matrix by time and task-group, similar to that used by Stayner et al.,[9] except that exposures will be represented as probability distributions, instead of averages. Such an exposure matrix can then be used directly in epidemiological studies. This approach has the advantage of explicitly accounting for the relevant uncertainties and yields a probability distribution of the exposure history. That is, for each point in time in a given workplace, the exposure will be represented as a probability distribution. By way of illustration, the framework will be used for determining exposures to nickel aerosols for different task-groups of workers in a nickel smelting plant.

Such an approach necessarily draws on findings from a wide variety of fields: engineering knowledge of the factors affecting the generation and dispersion of combustion aerosols, ventilation theory, studies of aerosol sampler performance characteristics, uncertainty analysis, and psychology of expert judgment elicitation and decision making. The following sections will discuss these aspects.

THE BAYESIAN FRAMEWORK

In the Bayesian view, a measurement process serves to refine previous knowledge of physical parameters by adjusting their probability distributions. It is thus based on inductive reasoning. Most industrial hygienists are Bayesian practitioners (even if unknowingly and informally) when they make initial educated guesses about exposures in a workplace (even if they are crude estimates of high versus low exposures) which are subsequently refined by actual measurements of exposures. We present a framework that formalizes this common sense approach to exposure assessment. For more detailed treatments of Bayesian methods, the interested reader is referred to books by Little and Rubin[10] and Makridakis et al.[11] If the physical quantity of interest is represented by f, and the measured data are represented by m, then the Bayesian expression for the updated probability distribution of f is

$$P_{\text{post}}(f/m) = \frac{P_0(f)\,P_L(m/f)}{P(m)} \qquad [2]$$

where $P_0(f)$ is the probability distribution of f prior to making any measurements (“the prior”); $P_L(m/f)$ is the likelihood that given the true value f, the measurement m is observed; $P(m)$ is the probability that the measurement m is observed; and $P_{\text{post}}(f/m)$ is the updated probability that the physical quantity of interest is f, given that measurements m are observed (the “posterior”).

The above framework is applicable to a situation where subjective inputs such as expert judgments about the probability distribution of a particular parameter (such as aerosol concentration under specified plant operating conditions) are to be synthesized with objective measurements of the same parameter. The updated probability will provide a better estimate (i.e., narrower probability distribution) of the parameter of interest than either the subjective prior probability provided by the experts or the objective—but sporadic and incomplete—measurements with wide error bars.

A four-step procedure as described below will facilitate the use of the Bayesian framework:

1. Normalize all the available historical data to a common basis, so that the various exposure measurements are converted to a reference measure that is known to be directly relevant to human health.
2. Estimate the variance in exposures for the worker population due to environmental and analytical variability as well as systematic errors, essential for determining the likelihood function, $P_L(m/f)$.
3. Use expert judgment, coupled with analytical models, to obtain prior probability distributions, $P_0(f)$, of the parameter of interest (e.g., exposure of a worker cohort).
4. Refine the expert prior distributions using mean exposures from the data set and obtain posterior probability distributions of exposure modifiers, $P_{\text{post}}(f/m)$.

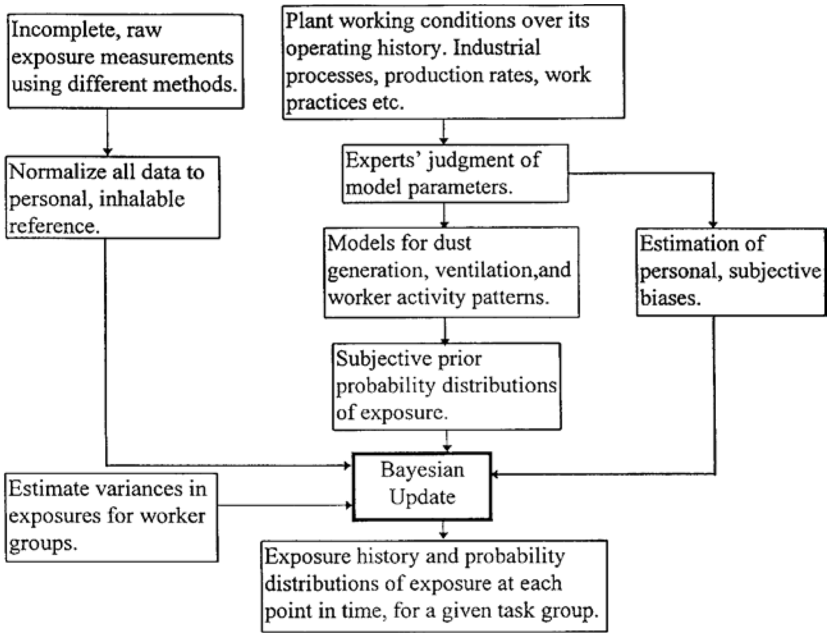

FIGURE 1
Bayesian methodology for retrospective exposure assessment.

Figure 1 gives an overview of the methodology. The following sections describe each of these four elements.

METHODOLOGY

Conversion of All Existing Data to a Common Basis

All available historical exposure measurements should be normalized to a common reference measure directly relevant to human health. Table I shows a historical data set for a particular task group of workers in a nickel smelter. Actual summary data sets similar to this are available to us. The data shown are the arithmetic mean exposures together with the number of samples (**bold**) and 95 percent confidence intervals (*italic*). It is important to note that the original raw measurements are no longer available and only such summary data are available.

As we can see in Table I, different measures of aerosol concentration have been used over the years. These include the index of concentration (particle number concentrations in particles per unit volume of air; mass concentration of overall dust, mg/m^3; and mass concentration of nickel), the strategy used (area and personal), and the samplers used (konimeters, Hi-Volume samplers, and personal samplers). Further, the samplers were used over different time scales. For example, konimeters were used for almost instantaneous "snap" samples by drawing 5 ml of air from the breathing zones of the workers and impacting the particles onto an adhesive-coated glass slide. By contrast,

TABLE I
Historical data of exposures for a homogeneous exposure group of workers in a nickel smelter

Period	Konimeter (ppcc)	Hi-Vol (mg dust/m^3)	Hi-Vol (mg Ni/m^3)	Personal (mg dust/m^3)	Personal (mg Ni/m^3)
1956–1963	959 (**24**) *(765–1153)*	—	—	—	—
1964–1966	561 (**15**) *(458–664)*	17 (**1**)	9.8 (**1**)	—	—
1967–1971	623 (**27**) *(530–716)*	16.5 (**2**) *(0–98)*	6.53 (**2**) *(0–55.8)*	—	—
1972–1975	529 (**18**) *(456–602)*	53.1 (**27**) *(6.9–99.3)*	37.2 (**11**) *(11.9–62.4)*	—	—
1976–1979	—	1.31 (**17**) *(0–79–1.83)*	—	1.31 (**11**) *(0–27.8)*	4.35 (**11**) *(0–10.4)*

Hi-Vol samplers drew between 1.4–3.5 m^3/min of air and measured a time-weighted, integrated aerosol mass concentration over much longer time intervals. In addition to these historical data, there is also a fairly current and comprehensive data set that contains measurements of personal inhalable aerosol mass concentration.[12,13]

The next step is to convert all these historical measurements to a single, truly health-related index. For nickel, the *inhalable* fraction, defining all particles that are capable of entering the body through the nose and/or mouth during breathing, is the most appropriate.[14] A simplistic approach might be to perform linear regressions between each of the different sets of measurements to obtain conversion factors so that all the data can be expressed as personal measurements. For the data set shown in Table I, suitable conversion factors can be achieved from the regions where the data overlap. The results of this procedure are shown in Figure 2.

Here the conversion from konimeter count to Hi-Volume dust mass and Hi-Volume nickel concentration was estimated from the arithmetic mean concentration from all the samples taken during 1964 to 1975 in the nickel smelter. The conversion to personal total nickel concentration was based on the average concentrations for the years 1976 to 1979. The next step is to convert the personal measurements to personal inhalable aerosol mass concentration measurements. Tsai et al.[12,13] and Werner et al.[15] have obtained conversion factors for this purpose from operation- and workplace-specific intersampler comparisons. The conversion factor for the case of this particular nickel smelter is 1.59. In this manner, all the data are expressed as inhalable aerosol.

Weaknesses in This Approach

Even though it is tempting to stop our analysis after obtaining the conversion factors, we should keep in mind that the data set that we have used is in a form that summarizes sporadic measurements being made every few years. This is reflected by some very unreasonable conclusions that can be drawn from a limited analysis such as this. For example, Figure 2 shows an approximately 100-fold difference in estimated exposures from 1956–1963 to 1976–1979. The exposure of more than 400 mg/m^3 for 1956–1963 is questionable, given that the most recent average given in Table I is 4.35 mg/m^3. This huge decline is driven very hard by the Hi-Vol nickel average in the 1972–1975 period, which was 40 times greater than the average in the 1976–1979 period. The 1972–1975 Hi-Vol average is also three to six times higher than the limited measurements prior to 1972, even though the average konimeter counts in earlier periods were the same as, or higher than the konimeter count average for 1972–1975. Such inconsistencies result from an extremely truncated data set, and point to the limitations of basing estimates of past exposures on such data. Therefore, it is advisable to improve our analysis by integrating other inputs such as expert judgment, and knowledge of the uncertainty and biases in the measurements.

Use of Current Data as Benchmark

In addition to historical data, current personal, inhalable aerosol concentration measurements are also available as shown in Table II. These data are the most representative of worker health-related exposure and are consistent with the latest particle size-selective criteria agreed to by the International Standards Organization (ISO),[16] the Comité Européan de Normalisation

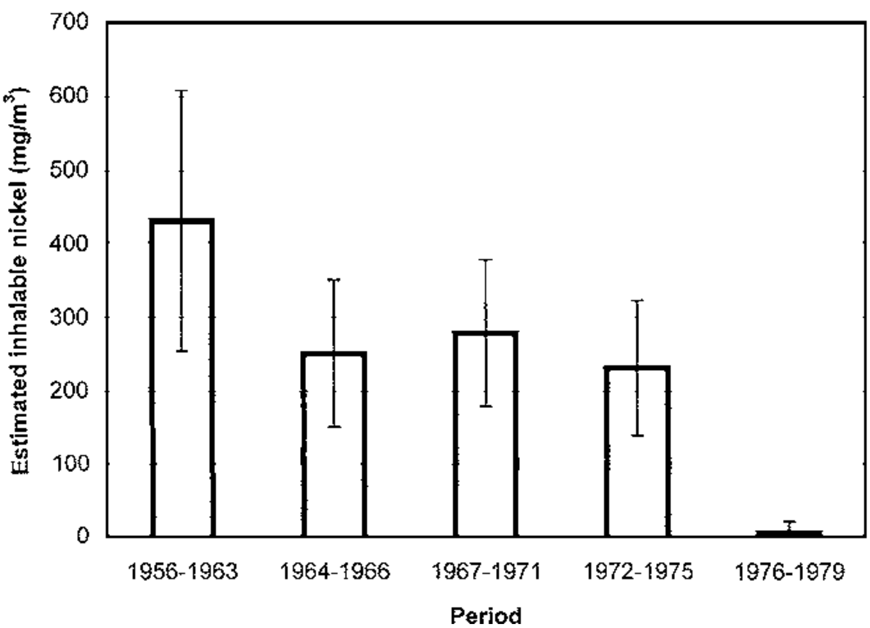

FIGURE 2
Results of obtaining historical inhalable exposures by linear conversions between different metrics of exposure.

TABLE II
Sample current personal measurements of inhalable dust and nickel concentrations in various areas in the smelter (from Tsai, 1994)

Workplace	Inhalable dust (mg dust/m^3)	Inhalable nickel (mg Ni/m^3)
Converter aisle	12.73	0.4357
Cottrell ESP	3.63	0.2811
Fluidized bed roaster	1.40	0.6748
Furnace	4.74	0.2687
Matte crushing	2.22	0.1521
Matte processing	0.72	0.2281

(CEN),[17] and the American Conference of Governmental Industrial Hygienists (ACGIH).[14] Assuming that there have been no changes in plant working conditions in the immediate past (i.e., five years), these exposure estimates may be considered reference measurements, E_{ref}, against which past historical measurements can be compared. The exposure at any past time can, therefore, be expressed as

$$E(t_{\text{past}}) = E_{\text{ref}} \times M(t_{\text{past}}) \qquad [3]$$

where $M(t_{\text{past}})$ is an *exposure modifier*. Thus, for the past five years, $M(t)$ is equal to unity and $E(t) = E_{\text{ref}}$.

Assessing Uncertainty in Historical Measurements

The second step is to estimate the variance in exposures for the worker population in the historical record. The 95 percent confidence intervals shown in Table I include the contributions due to random measurement errors, spatial variability within a workplace, and inter-worker and between-shift variability over a short period in time. In cases where only one measurement sample exists, the magnitudes of the error bars are probably underestimated by large and unknown amounts. Additionally, they do not include systematic biases and seasonal variability. It is quite complex to separate the individual contributions by these factors. For this purpose, we need the original raw data, information about the sampling strategy used (the siting of samplers, frequency of sampling, and so on), process information, environmental factors, and the sampling performances of the various instruments used (to estimate systematic measurement biases).

Accounting for Systematic Errors and Biases

The above analysis does not take into account systematic biases in the measurements. Systematic biases can arise from selection biases, e.g., selection of high-risk processes or tasks or high exposure periods for monitoring. Bias can also arise when there is a high day-to-day correlation or if there are cycles in the day-to-day measurements. Historical data were produced for various purposes, which resulted in different strategies, and have different biases embedded in them; for example, compliance monitoring may lead to different results than monitoring done to decide the appropriateness of engineering controls.

Accounting for these “unsuspected” errors is challenging. Morgan and Henrion[18] pointed out that there is a universal tendency to underestimate systemic errors in experiments. Shlyakhter[19] analyzed the trends in several historical data sets to quantify the overconfidence in uncertainty estimates and found a consistent pattern: values that were assigned low probabilities occurred more frequently due to unaccounted systemic biases.

Mathematically this means that the probability distribution of the deviations from true values does not follow the usual normal (or lognormal) distribution. Long tails in the distribution of deviations from true values are grossly underestimated by the normal distribution. These distributions are better described by an exponential distribution with a parameter u. Figure 3, based on Shlyakhter,[19] shows the cumulative probability of errors (in terms of $|x|$ standard deviations) for different values of u. This has important implications for the proposed research. The 95 percent confidence intervals in Table I are based on an assumed normal distribution and thus the number of standard deviations for this confidence interval is 1.96. However, to account for unsuspected errors, we need to use the exponential distribution with $u = 1$. This implies that the number of standard deviations for 95 percent confidence intervals is 3.8 (the point where the $u = 1$ curve intersects the 0.05 percentile in the cumulative distribution). Thus, the uncertainty is almost doubled when systematic errors are accounted for and the new 95 percent confidence intervals will be much wider than reported in the original historical records. As an example, the modified error bars are shown in Figure 2.

Using Expert Judgment along with Deterministic Models

In the third step of the research protocol, expert judgment is used, coupled with analytical models, to obtain prior probability distributions, $P_0(f)$, of the parameter of interest. The following subsections describe the analytical models, the hierarchical rationale behind decision-making, elicitation of expert judgment, their expression as probability distributions, and arrival at consensus among a panel of experts by mathematically aggregating these probability distributions. The resultant subjective probability distributions can then be reconciled with historical exposure measurements.

Exposure Modifiers

When there is a lack of available exposure data for short or long periods, other sources of information regarding the workplace may be called upon to aid the exposure reconstruction process. Schneider and colleagues identified “universal exposure modifiers” that mediate exposure in all workplaces.[8] These modifiers may be due to a number of factors such as changes in the industrial process (e.g., change in smelting temperature, ore feed composition), installation of pollution control equipment in

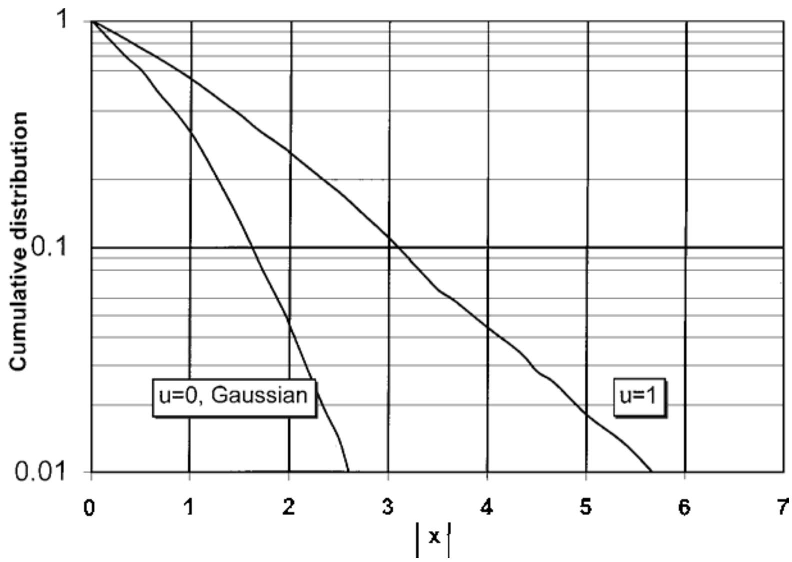

FIGURE 3
Cumulative probability of errors for different values of u (Shlyakhter, 1994).

the plant, changes in ventilation patterns, changes in work practices, and use of personal protective equipment. When used to represent a change in exposure preceding a period for which exposure measurements are available, exposure modifiers may be assigned numerical values which take the following form (which differs slightly from the formulation of Schneider et al.[8]):

$$\text{Modifier} = \left(\frac{\text{Exposure before modification}}{\text{Exposure after modification}}\right) \qquad [4]$$

These modifiers can be expressed in terms of explicit models available in the literature. The models will contain a number of parameters whose historical values are known with varying levels of uncertainty. Expert judgment will be used to estimate the parameter values and explicate the uncertainties.

Figure 4 shows the conceptual task at hand. Our starting point is the determination of E_{ref}, the reference measurement of current exposures. Then we determine the exposure modifier for each point of interest, $M(t_{\text{past}})$, that modifies the exposure with reference to current measurement.

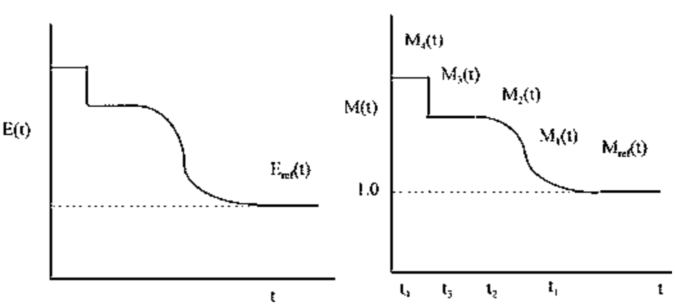

FIGURE 4
Obtaining exposure modifiers and actual exposures over past time periods.

Deterministic Models of Worker Exposure

It is preferable that the experts whose opinions are being elicited follow a common, clear, and well-defined rationale with explicit assumptions. In our case, this will be achieved by starting with a broad conceptualization of the worker exposure mechanism. The paradigm is as follows:

1. There is a source of the contaminant aerosol. The source output strength depends on the process and plant throughput.
2. There is a mechanism by which the aerosol is dispersed throughout the workplace. The parameters of interest are the rate of ventilation and recirculation.
3. Exposure for a given worker is related to the fraction of time that the worker spends in each location (microenvironment) within the workplace. This is related to work schedules and practices.

There are a number of models available in the literature for each element of this paradigm. Each model contains a number of input parameters. Changes in plant conditions (i.e., modifiers) will affect input parameters, thereby changing the outputs of these models. There can be sudden step changes in these modifiers (e.g., when a process is moved to a new plant location over a one-week period) or gradual changes (e.g., a change in feedstock quality over a two-year period). Other factors that may affect estimates of past exposures include changes in the use of respiratory protection equipment and occurrences of work stoppages.

Aerosol generation models. Nickel production involves mining and milling the ore, followed by smelting and refining it. Each of these contains a number of sub-processes. Smelting, where the ore is concentrated by removing rock, iron and sulfur, involves five steps: feed preparation, roasting, smelting, converting, and matte processing. In each process, aerosols are generated by different mechanisms. Bulk ore handling during milling may cause exposures to coarse dust while high temperature combustion during smelting may cause exposures to finer metal fume aerosols.

High concentrations of nanometer-sized particles are formed by nucleation in high-temperature processing units such as smelters. These particles then coagulate to form larger aggregates, which typically have dimensions of up to 1 μm. A number of factors determine the final aerosol particle size distribution and concentration, including chemical reactions, nucleation, condensation, coagulation, and the presence of seed aerosols. These phenomena are influenced by the temperature history and residence time in the smelter, and the vapor pressure of the species of interest, in this case nickel. Models that describe the basic formation and characteristics of such aggregates, in terms of combustion temperature and material properties have been developed.[20-23]

One might expect that particle size distributions in such workplaces would be bimodal with the fine mode formed by nucleation and subsequent coagulation and the coarse mode formed due to mechanical crushing and handling. A number of studies have looked at dust generation during the handling of bulk solid and aggregated material.[24-29] Plinke et al.[30-33] modeled dust generation as an interaction between external forces that separate particles and inter-particle binding forces. They empirically predicted the mass of dust generated as a function of mass of bulk material, material composition (described by its melting temperature, and particle density), moisture content, particle size distribution, and some parameter related to the power input into the system (such as the height from which bulk material is dropped and the impact area).

The relationship between aerosol generation rate and process is known with varying levels of sophistication, ranging from crude emission factors to analytical models. Mechanical dust generation is the most well-understood, and is predictable by a number of models (cited above) with easy-to-use software available.[34] In contrast, models to describe the physical and chemical transformations that take place during smelting are more difficult to apply to real-life applications.

Using historical data on ore processing rates, composition of ore feed, and the type of process in vogue, experts can estimate the above model parameters and thus estimate the rate of aerosol generation at any period in the plant's history.

General and local exhaust ventilation models. After the dust becomes airborne, the room ventilation or local exhaust ventilation disperses the aerosol in the environment. The transport of particles by convection is influenced by a number of processes such as gravitational settling, inertia, Brownian and turbulent diffusion, and electrostatic forces. The "box" or general ventilation model assumes that aerosol entering a given box is perfectly and instantaneously mixed with the air in the box. Conserving aerosol mass, a general equation can be written for aerosol concentration:

$$VdC = Gdt - CV_s Adt - CQ_{\text{vent}}Kdt - CRdt \qquad [5]$$

The box has a horizontal cross-sectional area A and volume V. Particles settle down with a velocity V_s. G is the number of particles of a given diameter being generated within the box, C is the uniform particle concentration at time t, Q_{vent} is the volumetric ventilation flow rate, K is the dimensionless mixing efficiency of ventilation in the box, and R is the removal rate by other mechanisms such as filtration and has units of flow rate.

The equilibrium concentration of aerosol is

$$C_{\text{equil}} = \frac{G}{(V_s A + KQ_{\text{vent}} + R)} \qquad [6]$$

Depending on the assumptions made by the experts about ventilation rates, mixing efficiency, and inclusion of removal mechanisms other than sedimentation, a number of models can be folded into this framework.

Worker time activity models. One can use time-activity models of the general form:

$$E_i = \sum_{j=1}^{N} C_j t_{ij} \qquad [7]$$

where E_i is the time-weighted integrated exposure for worker i over the specified time period; C_j is the pollutant concentration in microenvironment (work area) j; t_{ij} is the total time spent by worker i in microenvironment j; and N is the total number of microenvironments that the worker moves through. Esmen[7] suggested a very useful method of using occupational titles (OT) to obtain the fractions of time spent in a particular microenvironment. Briefly, the idea is to express each OT as a vector function with time-dependent uniform tasks (UT). These tasks are uniformly defined across a particular industry and are independent of a specific plant. Then, X_i is the estimate of the fraction of time spent by a worker in a given OT performing a specific UT_i. Therefore,

$$OT = [X_1 X_2 \ldots X_N]$$

$$\text{and} \quad \sum_{j=1}^{N} X_j = 1, \quad \text{where } 0 \le X_j \le 1. \qquad [8]$$

Tsai[35] identified the limitations of this approach; poorly defined UTs, inaccurate X_js, and workers with similar OTs but different tasks, may lead to gross underestimates of exposure using the above approach.

If historical information on the time-fraction composition of OT classes exists, then it is straightforward to estimate exposures using equation (7), provided the exposure concentration associated with each uniform task (UT) is known. If the historical composition of each OT is unknown, then the X_js can be inferred from the current composition of the OT, and interviews of veterans and old-timers at the plant with additional expert judgment based on plant history.

Expert Judgment

Use of probability trees. As stated at the outset, the main task of retrospective exposure assessment is to determine $M(t_{past})$ for past periods of time, given knowledge of current exposure estimates. This is done using Bayes' theorem as described earlier. In our application, the aim is to obtain the probability distribution of the exposure modifiers $M(t_{past})$ at different points in time. First, expert judgment is used to determine prior probability distributions, $P_0(f)$, of the exposure modifiers.

One way to determine $P_0(f)$ is to directly elicit the subjective probabilities of different values of $M(t_{past})$. However, even a subjective assessment of $M(t_{past})$ is a complex decision, resting on a particular rationale and a hierarchy of assumptions. In view of this, it is better to disaggregate the problem, allowing expert judgment on its individual aspects. Morgan and Henrion[18] recommended that the decomposition of judgments into a series of conditional probability judgments later combined, tended to produce judgments that are closer to the truth than were direct assessments of overall probability.

This disaggregation is achieved by modeling each individual aspect of the problem. As described in previous sections, the determination of the exposure modifiers, $M(t_{past})$, is essentially the creation of models to estimate exposure history. Three broad classes of models have been identified: aerosol generation, ventilation, and time-activity models. Each of these models uses a number of parameters, which represent the next level of disaggregation. Some of these parameters may be products of a third tier of models, or are determined from historical records with some degree of uncertainty. Uncertainties in the model structure may arise due to scientific uncertainties about how each of the above mechanisms changes exposure. Characterization of this uncertainty must rely on subjective expert judgment.

These uncertainties can be dealt with by use of a *probability tree*, as shown in Figure 5, to visualize the analytic steps within the process.[36,37] Three categories of experts are needed: one for each branch of the probability tree—aerosol generation, ventilation, and worker activity patterns. This is because it is unreasonable to expect that an expert on one aspect, say aerosol generation, would be an expert on another aspect, say, plant-specific worker activities.

The experts are provided with relevant plant records that include process information and production reports, ore throughput, physical dimensions of workplace, ventilation records, task descriptions of each occupational title (OT), personnel and safety records that contain historical lists of standard operating procedures, and results of interviews with veteran plant workers who possess historical knowledge of plant conditions. They will also be provided information about current estimates of

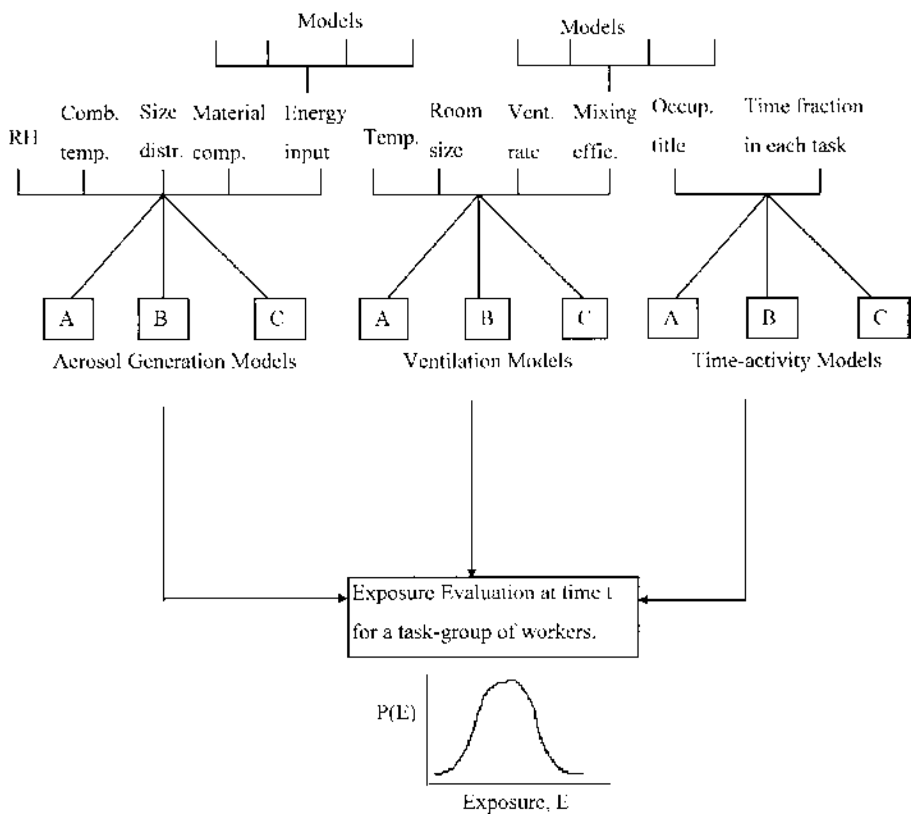

FIGURE 5
Example probability tree for exposure evaluation.

exposure based on the personal inhalable measurements. Based on this information, the experts are asked to provide subjective probability distributions for each parameter in each time period of interest. The parameters and their associated uncertainties will then be propagated through the models described above, along with expert-specified models, if any, to obtain probability distributions for exposures and exposure modifiers. Thus, the result would be a distribution of exposure estimates for each point in time, weighted by their likelihood of being correct, as judged by experts.

Morgan and Henrion[18] and Evans et al.[38] described protocols for elicitation of subjective probability distributions. Each expert is shown a preliminary probability tree (e.g., as in Figure 5), constructed using the exposure paradigm described in earlier sections. The experts can add or subtract parameters, models, or even layers from this probability tree. The probability tree thus identifies the scientific rationale for judgments and the conditional nature of decision making. In this manner, a comprehensive probability tree is constructed.

The result of each interview with an expert is a set of expert judgments on the relative plausibility of each level of the tree. Where there are contending models for the same mechanism, the expert assigns probability weights to each alternative that add to 1.00. These weights reflect the confidence of the expert in a particular model, according to his or her scientific judgment. For example, in the above tree, if an expert has a lot of confidence in the validity of model A for ventilation, some confidence in model B, and none at all in model C, this might result in an assignment of weights of 0.8, 0.2, and 0.0 for the three models, respectively. For each parameter of interest, a continuous subjective probability distribution is obtained that reflects the expert's state of belief. A series of questions is asked to establish several points (percentiles) on the distribution. The expert is asked to give reasons for his or her answers, and the interviewer questions the expert's judgment at every step. This procedure is normally adopted to combat overconfidence, a common trait observed in experts.[18]

Expert selection. Recruitment of qualified professionals and researchers to interpret the data is crucial. Previous studies have used a number of approaches ranging from substantive contributions to the scientific literature;[39] status in the scientific community, for example, membership on editorial committees of key journals, membership on national or international scientific committees and advisory boards;[38,40] and peer nomination.[41] Another factor to be considered in assembling the team is to provide for a variety and balance of institutional perspectives, by including experts both from industry and academia.

Quality of expert judgment. The quality of expert judgment depends on (a) substantive expertise, referring to the knowledge that the expert has about the quantity of interest, and (b) normative expertise, referring to the skill in expressing beliefs in probabilistic terms, also known as calibration.

Substantive expertise is assured in this project by the expert selection process, as described previously. This is quantified by eliciting the opinions of the experts (as probability judgments) about which of the participating scientists is most knowledgeable at each level of the probability tree. They are also asked to assign weights to their own perception of their level of expertise at each level.

Normative expertise or "calibration" is a measure of the accuracy of the expert judgment. There are two components to evaluating calibration: (a) knowledge, that is, how accurate are the experts' estimates of the quantities of interest, and (b) self-knowledge, that is, how accurate are the experts' estimates of the uncertainty in their estimate of the quantities of interest. There is some evidence to suggest that calibration may not be a very significant problem. Hawkins and Evans[41] studied the ability of a group of 25 industrial hygienists to predict exposures based on experience and professional judgment. The experts reviewed information for a chemical batch process and then subjectively assessed the distribution of exposures. The study suggested that professional industrial hygienists are in fact well-calibrated and can indeed provide good estimates of exposures for retrospective epidemiological studies.

Aggregation of expert opinion. The derivation of consensus among qualified panel members has been approached from at least two angles: the behavioral and the mathematical. In general, behavioral approaches rely on psychological factors and interaction among experts, and mathematical schemes use a designated functional aggregation rule that accepts inputs from each expert and returns an arbitrated consensus.[42–44] Behaviorally derived agreements often suffer from problems of personality and group dynamics. Mathematical approaches avoid these problems, but introduce their own set; numerically dictated compromises may be universally unsatisfactory.

One approach is to synthesize a composite prior as a weighted combination of the priors of experts considered most knowledgeable at each level of the probability tree. These weights are based on the experts' assessments of their own expertise as well as that of their peers.

$$P_{0\text{composite}}(f) = \sum_{i=1}^{n} w_i P_{0i}(f) \quad \text{for } n \text{ experts} \qquad [9]$$

where the $P_{0i}(f)$ is the prior of the ith expert, and w_i are such that

$$\sum_{i=1}^{n} w_i = 1 \qquad [10]$$

Other approaches available in the literature are the logarithmic opinion pool and the conjugate method using beta-distributions.[45]

The last option is to not seek consensus at all, but to use each prior separately with the historical data and the likelihood function as described in the next section. This has the advantage of making explicit the differences in scientific judgment and their effect on quantitative exposure assessment.

Using Expert Judgment and Historical Data to Obtain Posterior Probability Distributions of Exposure Histories

This is the fourth step in the research protocol. The formalism of Bayes' Theorem, given in equation (2), is used to determine posterior probability distributions for exposure histories as follows:

- Expert judgment is used to obtain prior probability distributions of exposure estimates at every point in time in the period of interest. These would be input as $P_0(f)$ in equation (2).
- A likelihood function for the actual historical measurements is evaluated using an assumed variance in the measurements. This variance is obtained by the procedures described in the section "Assessing Uncertainty in Historical Measurements." Because exposures are usually distributed lognormally, the likelihood function is given by:

$$P_L(M/f) = \frac{\exp\left(\frac{-1}{2(ln\sigma_M)^2}(lnM - lnf)^2\right)}{\sqrt{2\pi}\,ln\sigma_M} \qquad [11]$$

  where $P_L(M/f)$ is the probability that a measured exposure, M, is observed when the true exposure is f.
- The expert priors and observed measurements are finally reconciled using Bayes' rule to yield posterior probability distributions for exposures.

VALIDATION OF METHODOLOGY

The purpose of the validation exercise is to ensure that the results of the synthesis of expert opinion and historical data are close to the true values. This obviously cannot be tested with actual historical data. However, a limited validation can be performed using a current data set that completely characterizes the exposures for a particular cohort. A small subset of this data set can be used as a surrogate for historical measurements at a point in time. This data set will be incomplete and will contain values of exposure as measured by various instruments. Models for aerosol generation, ventilation and control, and worker time-activity are used with values for input parameters being estimated by experts in the form of subjective probability distributions based on a knowledge of current plant conditions and work practices. The Bayesian framework is used to combine both expert judgment and the surrogate historical data set in providing a probability distribution of the exposure estimate at that point in time. A comparison of this estimate with the exposure levels as determined by the complete data set will provide the validation of the proposed methodology. The results of this comparison may also be used to tune some model parameters so that a better fit between prediction and actuality is attained before applying the models to historical data.

We will also reconstruct the exposure history with different assumptions regarding variances in worker exposures and a variety of expert priors. Thus the sensitivity of the posterior probability distribution to different assumed priors and to different assumptions about population variances can be evaluated. This exercise will aid in determining the effect of subjective biases in expert judgments on the final estimates of exposure.

CONCLUSION

We have articulated a new framework in this article, that allows us to estimate the exposure as a function of time for various groups of workers in a workplace. The framework has great potential applications in instances where there is sparse information or there are missing data on past exposures. Using the knowledge base that experts and professionals in the field possess may fill these gaps in the historical record. The expert judgments will be informed by knowledge of historical plant conditions and work practices, and models describing process-dependent aerosol generation, ventilation, and worker activity patterns.

Bayes' Theorem provides a way to synthesize these different inputs in a rational and scientific methodology that has not been tried before. The methodology is being applied to the case of worker exposures in a nickel smelter where some exposure measurements along with information on historical conditions is available, and the results will be reported in due course. The result will take the form of probability distributions of the exposure of task-groups of workers as a function of time, in the form of a matrix. Retrospective exposure assessment will continue to be of great importance in carrying out meaningful epidemiology which forms the basis for standards-setting, especially for substances where the time-course of the disease following exposure is so long (e.g., as in the case of nickel).

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