



Retrospective Exposure Assessment using Bayesian Methods

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This paper presents the application of a Bayesian framework for retrospective exposure assessment of workers in a nickel smelter. Using only sparsely available historical measurements will result in exposure estimates with large uncertainties. However, additional information, in the form of expert judgments informed by knowledge of historical plant conditions, can be brought to bear on this process. The experts are provided with an information packet that contains historical process information, process throughput levels for each year, the dimensions of the workplace, ventilation records, and task descriptions for each job category. Based on this information, the experts provide subjective prior probability distributions for input parameters to a general ventilation model that predicts building concentrations. These priors can be synthesized with the historical measurements using Bayes theorem. The prior distributions of exposures are updated using the average measured exposures (historical measurements) and their associated variances to obtain the posterior probability distributions for building concentrations as well as concentrations at specific locations in the building. Expert input was also obtained from a plant industrial hygienist, in the form of probability distributions, regarding the amounts of time spent by each job category in different locations in the building. Monte Carlo sampling, from the posterior probability distributions of concentrations in different micro-environments and the probability distributions of time spent by each job category in those micro-environments, was used to obtain worker exposures using a time-weighted averaging model. © 2001 British Occupational Hygiene Society. Published by Elsevier Science Ltd. All rights reserved

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INTRODUCTION

Quantitative retrospective exposure assessment for occupational epidemiology comprises estimating the exposure levels for different worker categories as a function of time over the time period of interest. However, historic occupational exposure measurements are often only sporadically available, and subject to a number of uncertainties and biases. Exposure assessment strategies, measurement criteria, instruments, and analysis methods change over a time scale of decades. There can be enormous uncertainties in estimates of exposures assessed retrospectively using only such measurements, emphasizing the long-recognized need for additional information that can

refine these estimates. This leads to the use of estimation techniques such as employee interviews, work histories, mathematical and statistical modeling and extrapolation from a few existing exposure values to all exposures (e.g., Verma *et al.*, 1989; Plato *et al.*, 1997; Hornung *et al.*, 1994; Lewis *et al.*, 1997; Hallock *et al.*, 1994). A number of researchers have proposed using physical modeling with subjectively determined adjustments to project historical exposures from more recent measurements (Esmen, 1979; Schneider *et al.*, 1991). More recently, Cherie and Schneider (1999) have described using structured subjective assessments for reconstructing exposures.

Ramachandran and Vincent (1999) proposed a Bayesian framework for synthesizing objective but incomplete measurements with subjective expert input based on historical information about workplace conditions. Expert input, in conjunction with physical models, is obtained in the form of a probability distri-

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bution, and this constitutes the 'prior' estimate of exposure. The prior distribution of exposure is updated using the average measured exposure (from historical measurements) and its associated variance to obtain the posterior probability distribution. This paper describes an application of the proposed Bayesian framework to estimate the probability distribution of personal exposures to inhalable nickel aerosol for the worker population in one building in a nickel smelter in Ontario, Canada as a function of time. The methodology can be used in an occupational epidemiology study to construct a job exposure matrix, where each cell in the matrix contains a probability distribution of the personal exposure for a particular job code for a particular time period.

BAYESIAN METHODOLOGY

A Bayesian view of a measurement is that the process serves to refine previous knowledge of physical parameters by narrowing their probability distributions. This process of refining previous knowledge of the parameters is also called *updating*. If the physical quantity of interest (e.g., the exposure of a worker to inhalable nickel aerosol in a particular workplace) is represented by e , and the measurement process furnishes a number represented by M , then the Bayesian expression for the updated probability distribution of e is

$$P_{\text{post}}(e/M) = \frac{P_0(e)P_L(M/e)}{P(M)} \quad (1)$$

where $P_0(e)$ is the probability distribution of e prior to making the measurement, $P_L(M/e)$ is the likelihood that given the true value e , the measurement M is observed, $P(M)$ is the probability that the measurement M is observed, and $P_{\text{post}}(e/M)$ is the updated probability (or the posterior) that the exposure is e given that the measurement M is observed.

The Bayes formulation is combined with Monte Carlo simulations to provide the updated probability distribution of the exposure, given assumptions on the probability distribution of e prior to measurement (obtained from expert judgment elicitation), and the actual historical measurement M with its corresponding expected error. The updated probability density $P_{\text{post}}(e/M)$ is used to determine the best estimate for e . A physical model, which shall be described later, is used to predict the concentration of inhalable nickel aerosol in the workplace at various locations as well as personal exposures to it. The input parameters to this model include quantities such as the aerosol generation rate, the ventilation rate, and the time spent by a given worker category at different locations in the workplace. Estimates of input parameters and the uncertainties in these estimates are provided by experts in the form of probability distributions. Monte

Carlo sampling from these independent distributions is used to create the joint probability distributions. The model is evaluated for each sample (i.e., each set of input parameters), resulting in a simulated probability distribution for the model output (i.e., the exposure of a worker to inhalable nickel aerosol). This 'prior' distribution characterizes the uncertainty in model output, given the assumed uncertainty in the input parameters, and the model structure. The prior probability distribution is subjective and based on the prior expertise of the experts and knowledge of plant historical conditions. A 'real world' observation from the historical measurement dataset is used to update the model output from the Monte Carlo run using Bayes' rule, to provide a 'posterior' probability distribution. The likelihood function is empirically determined from the variability in the historical dataset. This synthesis is called the Bayesian Monte Carlo method, and has been used by Patwardhan and Small (1992) in predictions of sea level rise due to global climate change, Kandlikar (1994) to reconcile uncertainties in the global methane cycle, and Ramachandran and Kandlikar (1996) to obtain estimates of aerosol size distribution parameters from aerosol spectrometer data.

The algorithm proceeds as follows (Kandlikar, 1994):

1. A physical model is used to predict the measurements, based on the input parameters of the model. Prior joint probability distributions are defined to describe the uncertainty in the values of the input parameters.
2. A Monte Carlo or a stratified sampling scheme such as Latin Hypercube sampling is used to sample from this distribution.
3. The physical model is run with each set of sampled input parameters to calculate a prior distribution of model output (i.e., the exposure).
4. The likelihood function for model output is evaluated using the estimated variance in the historical measurements.
5. The model output and observed measurement are reconciled using Bayes' rule to yield posteriors for model output.

The procedure is mathematically formulated as below. Consider a model whose output e is a function of the input parameters $[x_1, x_2, \dots, x_n]$. The input parameters are known with some degree of uncertainty from historical plant records. Using these as anchoring information, the experts can provide their estimates of the input parameters. The input uncertainty is represented by a joint probability density function.¹

¹ The joint probability distribution of two discrete random variables X and Y is a function whose domain is the set of ordered pairs (x,y) , where x and y are possible values of X and Y , and whose range is the set of probability values

We randomly sample from this distribution, generating a probability mass function which is a discretized version of the probability density function. Let j ($j = 1$ to m) be the index for sample runs of the model, and k ($k = 1$ to n) be the index for model inputs. For any model run j , a probability mass function $P_j(x_k)$ is associated with each input model variable x_k . Similarly, a probability mass function $P(e_j)$ is associated with each output e_j . With a random or stratified sampling scheme such as Latin Hypercube, each sample contributes equally to the prior probability mass function. Therefore, with a sample size of m , the distribution for the model output is approximated by a discrete probability mass function with a probability of $1/m$ for each sample.

The likelihood function for the measurement M , given a model output e_j is evaluated. If the error (ϵ) on M is log-normally distributed (a justifiable assumption for occupational exposures) with a geometric standard deviation σ_M , then the likelihood function is given by

$$P_L(M/e_j) = \frac{\exp\left(\frac{-1}{2(\ln\sigma_M)^2}(\ln(M) - \ln(e_j))^2\right)}{\sqrt{2\pi e_j \ln(\sigma_M)}} \quad (2)$$

The posterior mass function for the sample model output e_j is determined by Bayes' rule as

$$P(e_j/M) = \frac{P(e_j)P_L(M/e_j)}{\sum_{j=1}^m P(e_j)P_L(M/e_j)} \quad (3)$$

Since the prior probability mass $P(e_j)$ for each sample run is $1/m$, Eq. (3) reduces to

$$P(e_j/M) = \frac{P_L(M/e_j)}{\sum_{j=1}^m P_L(M/e_j)} \quad (4)$$

In the Bayes–Monte Carlo approach, m sets of values for the input parameters are sampled and m values for the model output e_j are obtained. For each set, the distance $(\ln(M) - \ln(e_j))$ between the model output and the true value of the measurement is evaluated. These distances are assigned weights such that the smaller the distance the greater its weight. Additionally, since the measurements contain errors, the assigned weights have to reflect the magnitude of this error relative to the distance $(\ln(M) - \ln(e_j))$. The above procedure is described by the likelihood function given in Eq. (2). The weights described by the likelihood function are applied to ensembles of values of the priors, $P(e_j)$. Thus the values of $P(e_j)$ for which

the distances $(\ln(M) - \ln(e_j))$ are small are given more weight because the measurements are supporting the model output. Likewise, the values of $P(e_j)$ for which the distance $(\ln(M) - \ln(e_j))$ are larger are given less weight, because the measurements do not support the model output to the same extent.

METHODOLOGY FOR OBTAINING EXPERT PRIORS

The Bayesian framework is used to estimate personal exposures to nickel aerosol in a nickel smelter in the following manner:

1. Expert judgments of input parameters to a physical model for exposure are obtained in the form of probability distributions, and this is used to construct the 'prior', $P_0(e)$. The experts provide these judgments based on historical plant information.
2. All the available historical measurements are normalized to a common metric that is relevant to the known health effects of airborne nickel.
3. The total variability in exposures for the worker population is estimated, and used to calculate the likelihood function, $P_L(m/e)$.
4. The prior distribution is updated using the average measured exposure and its associated variance to obtain the posterior probability distribution, $P_{\text{post}}(e/m)$.

Using expert judgment with physical models to obtain prior probability distributions

Even subjective assessments of past exposures rest on a particular rationale and set of assumptions. It is better, therefore, to disaggregate the problem using a physical model, allowing expert judgment on its individual aspects (Morgan and Henrion, 1990). The experts used a conceptualization of the exposure process that comprises (a) an aerosol generation mechanism whose strength depends on the process throughput and an emission factor for the process, (b) a ventilation process that disperses the aerosol in the work area and is described by the flow rate of air and the mixing efficiency in the room, and (c) the fraction of time that the worker spends in each area within the workplace. A physical model that incorporates these elements was used to predict exposures. The experts were provided with an information packet that contains historical process information, process throughput levels for each year, the dimensions of the workplace, ventilation records, and task descriptions for each job category. Based on this anchoring information, the experts were asked to provide subjective probability distributions for each input parameter for the exposure model that is described in the next section. The experts were not aided by the interviewer in the selection of the form for the probability distri-

corresponding to the ordered pairs, given by $p(x,y) = P(X = x \text{ and } Y = y)$.

bution function to describe a particular input parameter. It is also important to note that the experts were not provided information on the actual historical concentration and exposure measurements.

The interviews of the experts were conducted by telephone and e-mail. The elicitation protocol included several elements — a description of the goals of the project, a review of the available information on plant processes, a discussion of how the experts were selected, a brief summary of the literature on scientific judgment and expert assessment, and finally the interview questions themselves. The experts were reminded, throughout the interview, of the findings from expert elicitation research literature that experts tend to be ‘overconfident’, i.e., they tend to underestimate uncertainty. Therefore, the interviewer challenged each judgment provided by the expert, requiring the expert to provide a rationale for the judgment, while simultaneously attempting to prevent an underestimate of the uncertainty in the judgment.

The exposure model. The general ventilation model was used to predict workplace air concentration under steady state conditions,

$$C_{\text{equil}} = \frac{G}{(V_s A + K Q_{\text{vent}} + R)} \quad (5)$$

where G is the aerosol mass generation rate, A is the horizontal cross-sectional area of the workarea (i.e., floor area), V_s is the settling velocity of the aerosol particles, Q_{vent} is the volumetric flow rate of air through the workplace, K is the dimensionless ventilation mixing efficiency, and R is the removal rate by other mechanisms. The K value selected, ranges from 1 to 10 (ACGIH, 1998). The generation rate G (mass of aerosol/time) is the product of the production rate of Bessemer matte PR (tons/yr) and the emission factor EF (kg of aerosol/ton of matte produced). The box model is a reasonable model to use in this case, despite the fact that the hot processes in the smelter create significant local updrafts. However, the large number of equally spaced converters in the aisle (19) make them akin to a uniform area source rather than a small point source. Therefore, it seems reasonable to use the equilibrium concentration to calculate exposures.

Time weighted average worker exposures for a particular job code were obtained using

$$E_i = \frac{\sum_{j=1}^N C_j t_{ij}}{\sum_{j=1}^N t_{ij}} \quad (6)$$

where E_i is the time-weighted integrated exposure for worker i over a time interval, C_j is the aerosol concen-

tration in the j th task microenvironment, and t_{ij} is the time spent by the i th worker in the j th task microenvironment.

The model uses a number of parameters that are determined or inferred from historical records with some degree of uncertainty. These uncertainties arise due to scientific uncertainties about how much each exposure modifier changes exposure. Based on the information about the plant conditions and processes, the experts provided estimates for all the variables in Eqs (5) and (6). While these estimates were in the form of probability distributions, the experts were free to choose the form of the probability distribution. Thus if the experts chose a uniform distribution, they would have to provide the upper and lower limits of the probability distribution, whereas if they chose a normal distribution, they would have to provide the mean and the standard deviation.

Historical plant information provided to the experts. While actual historical exposure measurements might be sparsely available, other types of information about the workplace are sometimes available in greater detail that are helpful in reconstructing exposures. The plant industrial hygienist for the nickel smelter provided access to a wide variety of internal company documents and records, that were then summarized and synthesized to create a more manageable information packet that was provided to the experts.

The information packet contained the following pieces of information:

1. *Outline of nickel smelting operations.* This described the various physical and chemical transformations that the ore underwent in the smelter in general, and the converter aisle in particular. Bessemer converting, the operation that occurs in the converter aisle, is a process whose purpose is to oxidize iron and sulfur in the ore, eliminating all the iron sulfide. Nickel, copper, precious metals, and most or all of the sulfur that was combined with them remain in the matte. This is the finished or ‘Bessemer’ matte, the key intermediate in producing refined nickel products.
2. *Process flow sheets and layout of the converter area of the smelter.* These were summarized from more detailed diagrams of the workplace. Fig. 1 shows the general layout of the converter aisle building with the converters (numbered from 1 to 19) and the principal ventilators identified. The gray numbered rectangles show the locations where historical measurements were made (described in a later section).
3. *Ventilation data.* Large quantities of dust, fume and sulfur dioxide gas are produced in the converting process. The dust is recovered in the Cottrell electrostatic precipitators and returned to the process. A large proportion of the gas is discharged to the atmosphere through a 152 m high

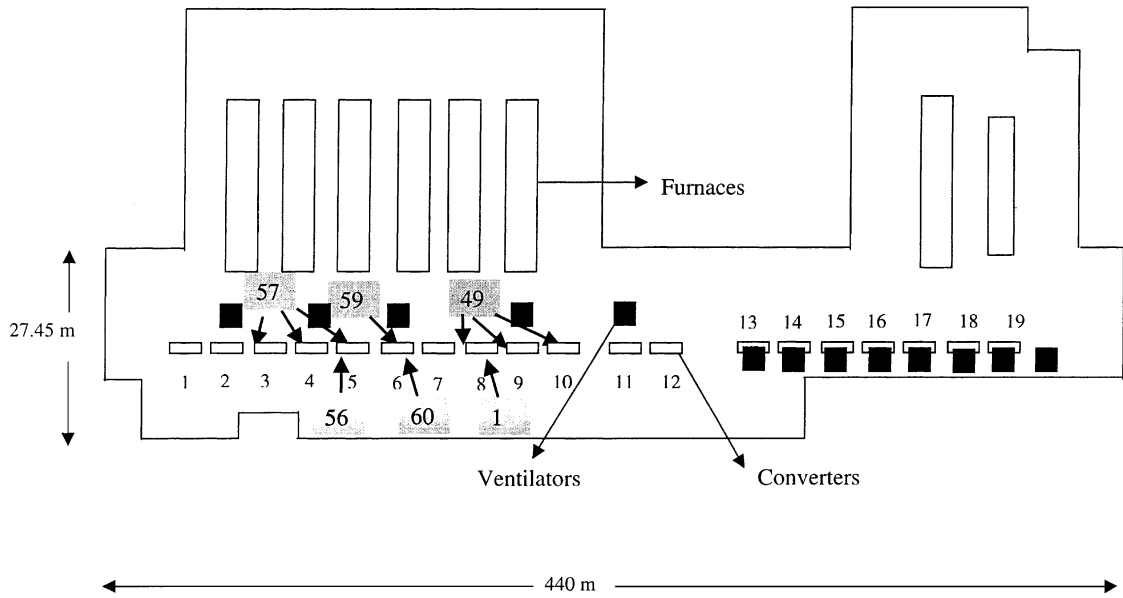


Fig. 1. Plan view of converter building showing the converter aisle with 19 converters and the ventilators. Stations 1, 49, 56, 57, 59, and 60 are some of the locations where historical measurements were made.

stack, or is vented through large roof ventilators. The hot processes are responsible for strong convection currents that create effective natural ventilation. Between 1956 and 1960, seven roof ventilators were installed to exhaust 99 000 m³/min from the converter building. Figure 2 shows a

view of the converter building showing the ventilators. Air is drawn through the lower sections of the building walls discharging through roof ventilators, at an estimated volume of 156 000 m³/min for the years 1960–1963. An additional 56 600 m³/min of air is drawn through the converter

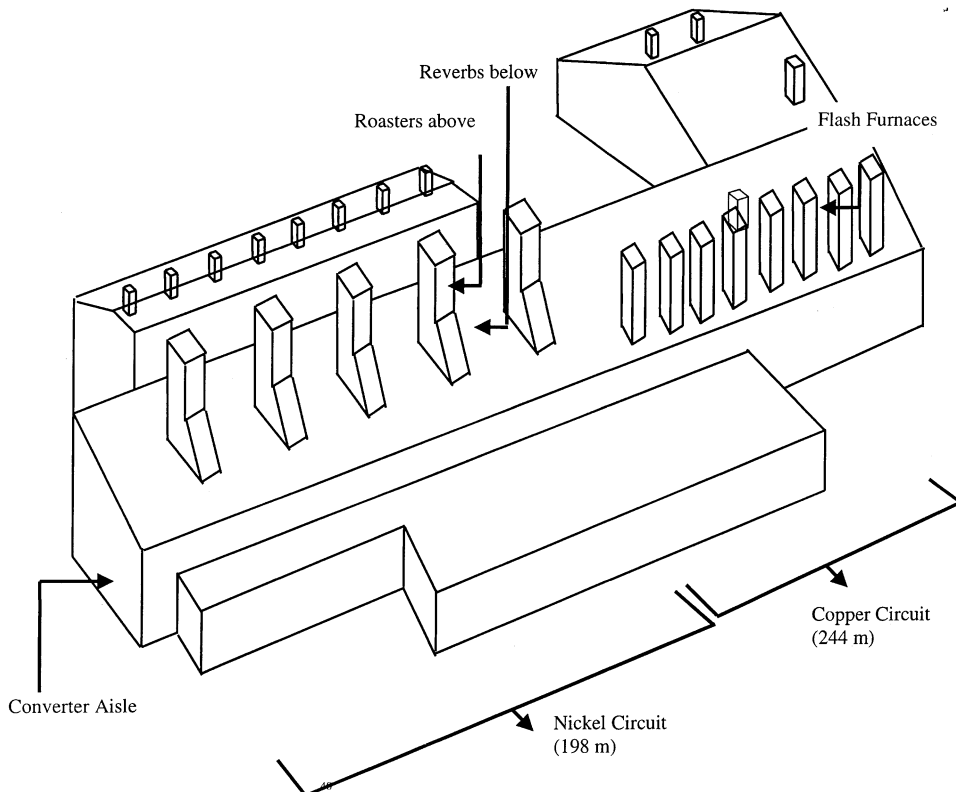


Fig. 2. Layout of converter building showing the nickel and copper converter sections and their ventilators.

hoods and flue openings, and then flows with the converter gas to the converter Cottrell plant and to the stack. For the years 1971–1979, another ventilation study provided flow rates for the Cottrells and gas temperatures.

4. *Particulate emissions.* In 1979, plant personnel conducted a series of experiments to determine the quantity of particulate emissions from the nickel converters. The rate of particulate emissions varied between 0.006 and 0.045 kg/min with an average of 0.019 kg/min. The average rate of particulate fugitive emissions was 0.19 kg/ton of Bessemer matte. This measurement, albeit just at one point in time, and with significant errors, provided a useful anchor point for the experts.
5. *Particle size distributions.* These were obtained using a Personal Inhalable Dust Spectrometer during the early 1990s (Tsai, 1995). The size distribution was approximated as bimodal lognormal, an assumption borne out by other studies (e.g., Ramachandran *et al.*, 1996). Particle size distributions in nickel smelters are typically bimodal with a fine mode due to combustion processes and a coarse mode due to various mechanical processes and agglomeration. For the converter aisle, the values of the size distribution parameters were: $\alpha_1 = 0.12$, $\alpha_2 = 0.88$; $MMAD_1 = 1.63 \mu\text{m}$, $MMAD_2 = 30 \mu\text{m}$; $GSD_1 = 1.31$, $GSD_2 = 2.25$, where α_1 and α_2 are the fraction of the total masses in each of the two modes, $MMAD_1$ and $MMAD_2$ are the mass median aerodynamic diameters of the two modes, and GSD_1 and GSD_2 are the geometric standard deviations of the two modes.
6. *Production levels of Bessemer matte:* Bessemer matte production data were obtained from company records. Table 1 gives the annual production of Bessemer matte.
7. *Development of a questionnaire for time activity patterns of workers:* A questionnaire–spreadsheet consisting of worker categories, standard tasks that each worker category performed and workstations each worker category spent time at was developed. This was filled out by an expert industrial hygienist, who was intimately familiar with the operations at the smelter. The expert provided uniform or flat probability distributions for the time spent by the worker at each workstation.

Expert selection. Inputs to models were elicited from three experts. Two experts provided probability distributions for the input parameters to the model given in Eq. (5), which predicted concentrations to airborne nickel. These two experts were selected on the strength of their contribution to the occupational hygiene literature, status in the scientific community (signified by membership on editorial committees of key journals and scientific committees), and their

Table 1. Production rates of Bessemer matte in the converter aisle

Year	Bessemer matte cast (dry tons)
1958	265 905
1959	332 806
1960	358 755
1961	384 408
1962	293 357
1963	269 916
1964	337 896
1965	330 808
1966	296 163
1967	371 340
1968	340 128
1969	221 135
1970	357 667
1971	334 631
1972	421 180
1973	418 161
1974	448 338
1975	456 549
1976	422 670
1977	170 872
1978	185 774
1979	145 749

familiarity with workplace environments. One of the experts was familiar with the workplace and the other was not. The third expert was an in-plant industrial hygienist with many years of employment at the smelter, and a thorough knowledge of the various activities at the smelter. This expert provided probability distributions for the time spent by each job category at various locations within the smelter complex, used in Eq. (6). While it would have been preferable to obtain expert inputs from many more experts to provide for a balance in institutional perspectives (Ramachandran and Vincent, 1999), this was not feasible for monetary reasons. However, the selection criteria assured that the individuals chosen had substantive expertise, referring to the knowledge the expert has about the quantity of interest. Calibration is a measure of the accuracy of the expert judgment. Some studies have shown that professional industrial hygienists are well calibrated for assessing exposures (Hawkins and Evans, 1989). However, in this study, the additional precaution of using anchoring information was used. Under this heuristic, for instance, a starting value of a parameter was provided to the experts in their information packet, which could then be adjusted by them to reflect their uncertainty about the parameter estimate.

Converting all measurements to a common metric

Over the period 1956–1979, measurements were collected using three methods that yielded different metrics of the airborne concentration of nickel: instantaneous particle number concentrations, mass concentrations from area samples, and mass concentrations from personal samples. The various types of

raw historical monitoring data from the converter aisle were converted to inhalable mass concentrations. The inhalable mass refers to particles that may enter the body through the nose or mouth during breathing, and is appropriate for the health effects related to nickel exposure. The conversion factors were obtained from side-by-side measurements using the various instruments that had been conducted by plant personnel over the years. The following subsections describe this in more detail.

Konimeter measurements. Measurements were taken from 1956 to 1975 in the converter area, using the Gathercole konimeter whose performance has been described by Verma *et al.* (1987). The sample is almost instantaneous and collected from the worker's breathing zone. Measurements were expressed in number of particles per cubic centimeter (ppcc). Data tended to be very noisy, with an analytical variability between 25 and 40% in the range 0–800 ppcc (estimated from data in Verma *et al.*, 1987).

Hi volume measurements. These area measurements of integrated mass concentration were made using a Hurricane air sampler (Model #16002, Gelman Instrument Company) with a sampling flow rate of up to 3539 LPM and a sampling time of ~3 h. The measurements (expressed as mg/m³) were taken from 1970 through 1977. Analytical errors for these gravimetric measurements were typically less than 5%.

Personal 37-mm filter measurements. Personal 37-mm filter samplers measured integrated mass concentrations over a full shift. Data from these measurements are available from 1976 to 1979.

Conversion of konimeter data to a personal inhalable values. The konimeter particle counts obtained in the breathing zone of the worker at a given workstation were first converted to a personal respirable mass concentration value. Respirable mass concentration values were then converted to a personal inhalable mass concentration value. The respirable fraction of an aerosol refers to the mass fraction that can penetrate to the alveolar region of the human respiratory tract. It is a subset of the inhalable mass fraction of the aerosol. Side-by-side comparisons of instantaneous konimeter measurements and real-time, 1-min average respirable aerosol concentrations measured by a GCA respirable dust monitor (Marple and Rubow, 1978) were performed at three different times in 12 separate locations in 1976–77. An average conversion factor of 0.0021 mg/m³/ppcc, with lower and upper bounds of 0.00059 and 0.0063 mg/m³/ppcc, was obtained from a linear regression fit to the data. This is comparable to conversion factors obtained by Verma *et al.* (1989) between 0.0002 and 0.003 mg/m³/ppcc for hardrock miners in Ontario.

Conversion factors for respirable dust to personal inhalable dust were obtained from measurements of particle size distributions using a personal cascade

impactor (Tsai, 1995). From these distributions the respirable and inhalable masses were determined, and a ratio of respirable to inhalable of 0.1 was obtained. Thus each value of konimeter particle count led to three inhalable values.

Conversion of Hi Volume total dust measurements and 37-mm filter measurements to personal inhalable mass concentrations. Personnel at the nickel smelter conducted side-by-side comparisons of Hi Volume measurements and personal 37-mm measurements in 1976. Conversion factors were obtained from these comparisons by dividing personal 37-mm values by Hi Volume values. Two conversion factors, respectively 0.1 and 0.4, were obtained from two separate side-by-side comparisons. Thirty nine side-by-side comparisons of measurements made with personal 37-mm filter samplers and inhalable IOM samplers were conducted in a study at the nickel smelter (Tsai *et al.*, 1995). A conversion factor of 1.97±0.23 with an $R^2 = 0.89$ was obtained. This value was used to convert 37-mm filter measurements into inhalable mass concentrations.

Assessing variability in historical measurements

Uncertainties in measurements of airborne contaminants can be broadly classified as *random* and *systematic*. Random uncertainty arises from two sources: analytical variability and environmental variability. *Analytical variability* is normally distributed and stems from collection and analytical methods. For measurements based on gravimetry, such as those by the Hi Volume and the 37-mm personal cassettes, the coefficient of variance of the method is less than 5%. For konimeter measurements based on optical counting, the coefficient of variance is between 25 and 40%. Marple and Rubow (1978) estimated the analytical variability of the GCA respirable monitor to be ±20%. In general, *environmental variability* is more than analytical variability (Nicas *et al.*, 1991), and it includes between-worker and within-worker variability for personal exposures, and spatial and temporal variability for area measurements. In the data set available for this study, it is impossible to estimate between- and within-worker variability from the few personal exposure measurements. However, spatial and temporal variability (within each year) can be estimated.

Systematic bias in the measurement strategy is also very important, although rarely dealt with. One source of systematic bias in this study arises from the multiple conversion factors used to convert historical measurements made with different instruments to a common metric. This bias is accounted for, to some extent, by using ranges for the conversion factors rather than a single value. For instance, each raw konimeter measurement (itself an average of three samples) is converted into three inhalable values, each Hi Volume measurement is converted into two

inhalable values etc. There are other, equally important sources of systematic biases that are unquantifiable *post facto*. Monitoring may be used to evaluate employee exposure, assist in the design/evaluation of control measures or document compliance with government regulations. Biases result from selections that go into the monitoring process, e.g., selecting high-risk tasks or high exposure periods for monitoring, resulting in only workers who are highly exposed being monitored, or selecting the same time of day for each sampling period resulting in high correlation of day to day measurements. Such exposure estimates, obtained from a small subset of the workers (e.g., the most highly exposed ones), when used in epidemiological studies as being representative of the broader worker population, may produce biased dose-response relationships. In addition to biasing the average exposure estimates, they may also result in an underestimate of the total exposure variability. While it may be possible to guess the direction of the biases in some instances, there is no information permitting calculation of actual biases *post facto* (Olsen *et al.*, 1991). Some progress toward estimating uncertainties introduced by such biases can be made using the method proposed by Shlyakhter (1994).

Shlyakhter quantified unsuspected uncertainties by analyzing trends in several historical data sets. He found that empirical probability distributions of the normalized deviations of the measured quantities from the true values do not follow the usually implied normal (or lognormal) distribution. Long tails in the distribution of deviations from true values are grossly under-estimated by the normal distribution. Figure 3, based on Shlyakhter (1994), shows the cumulative probability of errors (in terms of $|x|$ standard deviations) for different values of an exponential parameter u . Shlyakhter's work suggests a wider distribution such as that in Fig. 3 describes the data bet-

ter than normal or lognormal distributions assumed in air concentration measurements.

The additional uncertainty can be interpreted as a safety factor accounting for past over-confidence in estimating errors (e.g., by neglecting to include systematic biases of the sort described above). Thus, by widening the distribution, the unquantified bias and the resulting uncertainty are accounted for. For example, in a normal distribution the 95% confidence interval contains data within 1.96 standard deviations from the mean. However, to account for unsuspected errors in environmental measurements, we need to use the exponential distribution with $u = 1$. This implies that the number of standard deviations for 95% confidence intervals is 3.8 (the point where the $u = 1$ curve intersects the 0.95 percentile in the cumulative distribution). To include the longer tails and a 95% confidence interval, the standard deviation must be doubled to 3.8. Thus, the uncertainty is almost doubled when systematic errors are accounted for. The distribution of errors for the various environmental data sets analyzed by Shlyakhter were similar, suggesting that a pattern of overconfidence may exist in a wide variety of environmental measurements. Shlyakhter's findings are thus assumed to be applicable to the data set analyzed in this project. We therefore calculated the 95% confidence intervals for the converted measurements for each year, and then multiplied this confidence interval by a factor of $3.8/1.96$ to account for systematic bias. The mean inhalable concentration is not changed at all; only the confidence interval around it is made wider by factor of ~ 2 . This wider confidence interval now accounts for analytical variability, environmental variability and systematic bias. While this approach of using a generic multiplication factor to incorporate the effects of systematic bias may be somewhat crude, we have no other recourse in the absence of any information which can allow us to estimate the direction and mag-

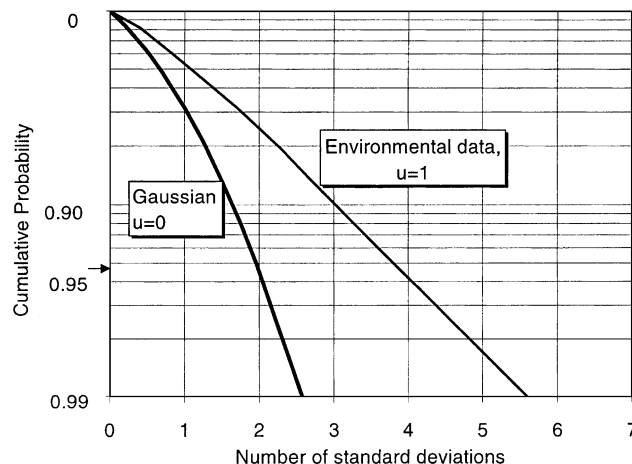


Fig. 3. Cumulative probability of errors (in terms of number of standard deviations) for a normal distribution and for most physical environmental data (Shlyakhter, 1994).

nitude of bias. Thus for each year, we can estimate the mean inhalable concentration (M) and the uncertainty (95% CI or σ_M) associated with this estimate. These data are used to construct a likelihood function for the actual historical measurements using Eq. (2).

RESULTS AND DISCUSSION

Expert prior elicitation

Table 2 describes the judgments of the two experts regarding the values of the input parameters for the models. Expert 1 chose normal distributions to describe all parameter estimates, while Expert 2 used uniform distributions. For the production rates of Bessemer matte, PR , both experts were fairly confident of the values provided by the company, as evi-

denced by the small values of uncertainty around the mean values.

Expert 1 assumed the total flows measured in 1960–63 applied from 1958 until 1971. He apportioned this 212 795 m³/min between the nickel and copper converter areas, using the fraction of the converter aisle lengths used for nickel and copper converters (see Figs 1 and 2 for building dimensions). This yielded a flow of $Q_{\text{vent}} = 95\,706$ m³/min for the nickel converter area. For the years 1971–1979, he used the roof ventilation of 155 600 m³/min plus the Cottrell flow rates (corrected for temperature) to give a new total of 200 946 m³/min, which was apportioned as before to yield a flow of $Q_{\text{vent}} = 90\,377$ m³/min for the nickel converter area. The flows were assigned an RSD of 0.30 for both time

Table 2. Expert inputs for parameters to general ventilation model

Parameter/yr	Expert 1 Input			Parameter/yr	Expert 2 Input		
	Distribution	Mean value	Relative standard deviation		Distribution	Mean value	Lower and upper bound of distribution
Bessemer matte production for each year (dry tons/yr)	Normal	From Table 1	0.05	Bessemer matte production for each year (dry tons/yr)	Uniform	From Table 1	±5% of mean
Flow rate (m ³ /min) 1958–1963	Normal	95 706	0.30	Flow rate (m ³ /min) 1958–1960	Uniform	75 000	50 000–100 000
Flow rate (m ³ /min) 1964–1979	Normal	90 377	0.30	Flow rate (m ³ /min) 1961–1970	Uniform	140 000	100 000–200 000
Emission factor (kg/ton) 1958–1969	Normal	0.19	0.40	Flow rate (m ³ /min) 1971–1976	Uniform	156 221	100 000–200 000
Emission factor (kg/ton) 1970–1979	Normal	0.19	0.30	Flow rate (m ³ /min) 1976–1979	Uniform	156 221	120 000–220 000
Mass weighted average settling velocity for aerosol × floor area (m ³ /s) 1958–1969	Normal	67 838	0.40	Emission factor (kg/ton) 1958–1960	Uniform	0.41	0.20–0.60
				Emission factor (kg/ton) 1961–1970	Uniform	0.21	0.10–0.30
Mass weighted average settling velocity for aerosol × floor area (m ³ /s) 1958–1969	Normal	67 838	0.40	Emission factor (kg/ton) 1971–1976	Uniform	0.19	0.13–0.25
				Emission factor (kg/ton) 1977–1979	Uniform	0.19	0.15–0.23
Mixing factor, K (dimensionless)	Normal	5	0.05	Mixing Factor, K (dimensionless)	None	4.0	None

periods, reflecting the expert's degree of uncertainty in these estimates. Expert 2 estimated that 2/3 of the space in the converter aisle was occupied by nickel converters and 1/3 contained copper converters, and divided the flow rates through these two regions of the building in the same ratio. The flow rates for the years 1958–1960 were $Q_{\text{vent}} = 50\,000\text{--}100\,000$ m³/min, and for the years 1961–1970 were $Q_{\text{vent}} = 100\,000\text{--}200\,000$ m³/min. However, for the years 1971–1979, the ventilation rates through these two areas were assumed to be the same: $Q_{\text{vent}} = 120\,000\text{--}200\,000$ m³/min.

For the emission factors, *EF*, Expert 1 used the mean value of 0.19 kg/ton, obtained from the in-plant experiment described in a previous section, but assumed a relative standard deviation (RSD) of 0.30 for the period 1970–1979, with the RSD increasing to 0.40 for an earlier period 1958–1969. Expert 2 used the experimentally determined value for 1977–1979 with a range of 0.15–0.23. For the period 1971–1976, he slightly increased the uncertainty bounds around this value to 0.13–0.25. For the previous two time periods, he used the ratio of the flow rate in 1979 (when the experimentally derived value was obtained) to the flow rates in the previous time periods to scale up the emission factor proportionally, yielding values of 0.21 and 0.41 respectively. He simultaneously, increased the uncertainty bounds around these estimates.

Expert 1 used the bimodal particle size distribution (psd) information to calculate a aerosol mass-weighted settling velocity. The psd was divided into 20 size intervals, and the settling velocity was calculated for the midpoint for each particle size range. These velocities were then weighted by the fractional mass of particles in each size range, and their average was obtained. This settling velocity was multiplied by the floor area (198×27.45 m) to yield the settling term, $V_s A$, in Eq. (5). The RSD of this term was given a value of 0.10. Expert 2 did not use the psd information, and ignored the settling velocity term in the model. Both experts also ignored other removal mechanisms, represented by *R* in Eq. (5).

The experts were provided a choice of two models for predicting building concentrations — the general ventilation model described earlier, and a two-compartment model that predicts near-field and far-field concentrations. Both experts decided that the general ventilation model was the more appropriate one to use in this context, given the level of uncertainties in the information provided to them. Both assigned probability weights of near zero to the two-compartment model, and near unity to the general ventilation model which reflected the confidence of the experts in each model. Expert 1 provided a value of 5 for the dimensionless mixing factor, *K*, with a RSD of 0.05. While Expert 2 used a value of $K = 4$, he was ambivalent about the use of this parameter in the

model. He did not want to provide uncertainty bounds for this parameter, reasoning that *K* is itself a protective, uncertainty factor that is used during design of ventilation systems. The *K* factor can be interpreted as a measure of the deviation of the model from the well-mixed case assumption, and thus a measure of model uncertainty.

There is an extensive literature on obtaining consensus among the experts (Winkler, 1986; Cooke, 1991; Clement and Winkler, 1999), ranging from mathematical functional aggregation techniques to behavioral methods. In this study, it was decided to not seek consensus among the experts. Thus the differences in scientific judgments of the two experts were made explicit.

Monte Carlo simulations to obtain expert priors

A commercially available software (Crystall Ball, Decisioneering, 1996) was used to obtain 100 000 independent samples consisting of sets of values for each of the input parameters, for each year. The samples were obtained by Monte Carlo sampling from the probability density functions provided by the two experts for the input parameters. The model in Eq. (5) was run for each of these 100 000 sets of input values to obtain a simulated probability distribution of values for aerosol concentration in the building. This distribution characterizes the uncertainty in the aerosol concentrations in the building for each year, given the assumed uncertainty in the input parameters, and the model structure. As an example, Fig. 4 shows the input parameter distributions and the output aerosol concentration probability distribution (between the 2.5th and the 97.5th percentiles) for one year (1965), using input from Expert 2.

Figure 5 shows the median nickel aerosol concentrations in the building for each year as obtained from subjective model inputs from both experts. The error bars represent the range between the 2.5 and 97.5 percentiles of the 100 000 Monte Carlo simulation outputs. For the years 1958–1960, the estimates of Expert 2 were higher than those of Expert 1 by a factor of 10. However, for the period 1961–1979, while the estimates of Expert 2 were systematically higher by a factor of 2–3, they were not statistically different from the estimates of Expert 1. The reasons are not hard to discern. For 1958–1960, Expert 2 had an emission factor that was more than twice that of Expert 1. At the same time, Expert 2 did not include the particle settling term in Eq. (5) while Expert 1 provided a value for the term that was as significant as the flow rate term. For 1961–1979, the emission factor estimates of the two experts became more similar, but the flow rates estimated by Expert 2 became much higher than Expert 1. These two factors led to the concentration estimates of the two experts becoming more closely aligned, even though the differences regarding the settling term remained. Thus, even though the two experts used different distribution

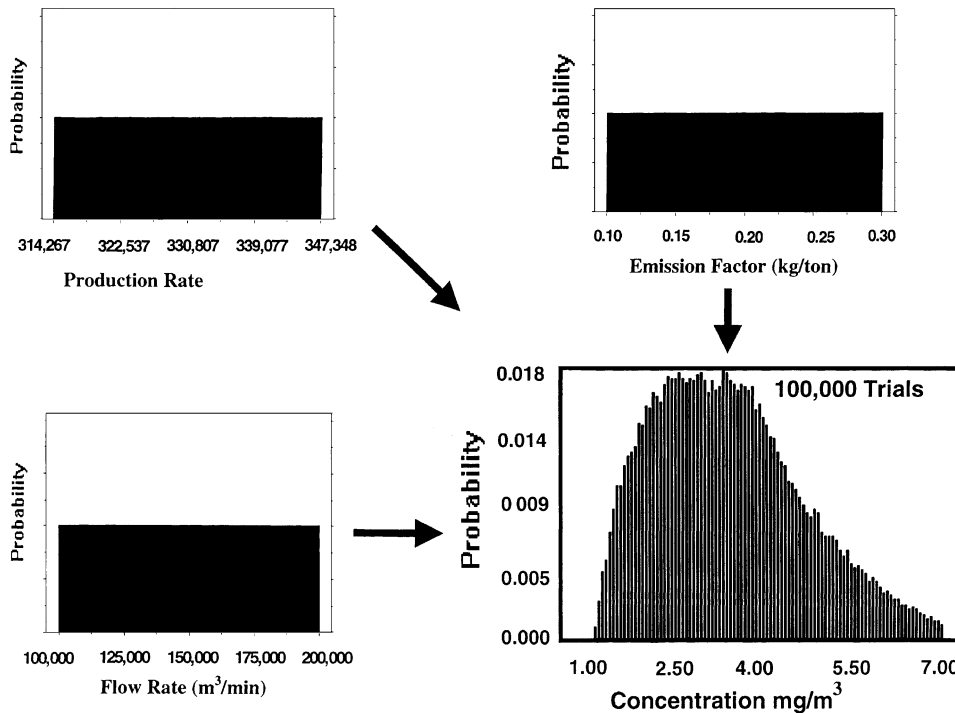


Fig. 4. Distributions of input and output parameters for Monte Carlo sampling to determine expert priors. Input parameter distributions include production rate (tons/yr), flow rate (m^3/min), and emission factor (kg/ton of matte), and the output parameter is the aerosol concentration (mg/m^3).

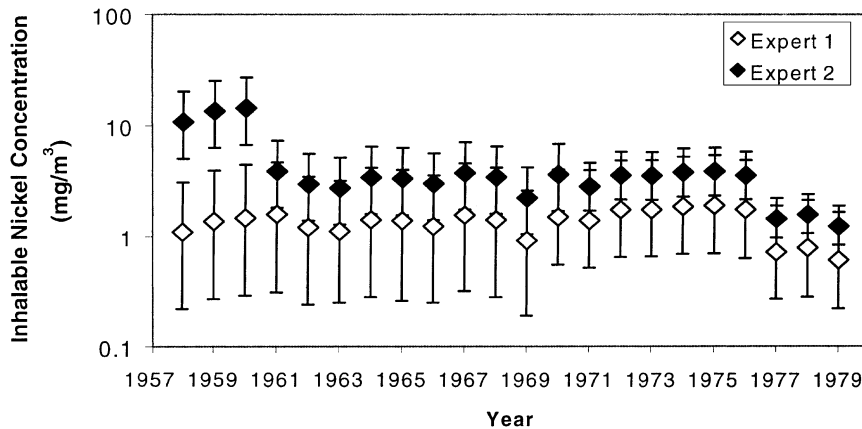


Fig. 5. Outputs of Monte Carlo simulations using expert inputs to a predictive model for inhalable nickel concentration. 100 000 sample runs were performed to obtain the distribution of model outputs for each year, using the set of input parameters provided by each expert. These are the expert prior probability distributions. The error bars represent the range between the 2.5th and the 97.5th percentiles of the outputs.

functions, and ranges for those functions, the model outputs resulting from the inputs from the two experts are not very different. This might be due to the use of plant historical information that was provided to the experts as anchoring information. It was initially assumed that the direct experience of the expert with the specific workplace might be important. Therefore, one expert chosen was not familiar with the plant and the other one was reasonably familiar with the pro-

cesses at the plant. The results show that this did not make a significant difference to the model outputs.

Spatial and total variability in measurements

Table 3 lists the mean inhalable concentrations and the variability at each station in the converter aisle area of the smelter complex by year. In the table, the italicized numbers refer to the 95% confidence intervals (with zero as the lower limit), and the numbers

Table 3. Average inhalable concentrations (converted) and their variability including systematic biases (in italic) and number of measurements (in bold) by year and location (station) in the workplace. The locations of the Hi-Vol, workroom and personal 37-mm measurements are unknown. The last column contains overall average inhalable concentrations and their total variabilities

Year	Konimeter inhalable dust Station 60 (mg/m ³)	Konimeter inhalable dust Station 49 (mg/m ³)	Konimeter inhalable dust Station 56 (mg/m ³)	Konimeter inhalable dust Station 57 (mg/m ³)	Konimeter inhalable dust Station 1 (mg/m ³)	Hi Vol inhalable total dust (mg/m ³)	Workroom inhalable total dust (mg/m ³)	Personal inhalable (mg/m ³)	Inhalable dust entire workplace (mg/m ³)
1960									3.8 (0,18.1)
1961	2.7 (0,11.9) (2)		5.0 (0,23.9) (1)	2.5 (0,11.8) (1)					3.4 (0,15)
1962	5.3 (0,27.2) (2)	5.5 (0,27.8) (2)		4.1 (0,18) (2)					5.4 (0,26.5)
1963			2.9 (0,12.9) (2)	2.5 (0,12.1) (2)					2.8 (0,12.4)
1964			6.0 (0,27) (2)	3.2 (0,14.8) (2)					4.7 (0,21.9)
1965	2.2 (0,10.4) (1)		2.4 (0,11.4) (1)	3.8 (0,16.4) (2)					3.0 (0,13.4)
1966	3.3 (0,15.5) (1)	4.6 (0,21.6) (1)							3.9 (0,17.5)
1967			4.3 (0,20.7) (2)	13.4 (0,77.4) (2)					8.9 (0, 57)
1968	5.8 (0,25.1) (2)	6.6 (0,33.4) (2)							6.2 (0,28.5)
1969	6.5 (0,31) (1)	7.9 (0,37.7) (1)							7.2 (0,31.8)
1970	6.9 (0,32) (2)	6.8 (0,31.5) (2)							6.9 (0,30.7)
1971	6.9 (0,31.7) (2)	7.7 (0,33.6) (2)							7.3 (0,31.6)
1972	5.8 (0,25.5) (2)	6.6 (0,29.6) (2)							5.5 (0,25.8)
1973	6.6 (0,28.9) (2)	6.1 (0,27.4) (2)							5.5 (0,26.1)
1974	4.6 (0,20.1) (2)	3.9 (0,17.3) (2)							3.8 (0,17.4)
1975	1.5 (0,7.1) (2)	1.5 (0,7.1) (1)	5.7 (0,26.9) (1)	10.8 (0,51.4) (1)	0.9 (0,3.7) (5)	0.9 (0,3.8) (5)	1.7 (0,10.3) (118)	2.9 (0,21.9)	1.0 (0, 5.6)
1976					0.7 (0,3.3) (8)	0.6 (0,2.6) (16)	1.7 (0,10.3) (118)	5.2 (0,9.5) (50)	1.96 (0,9.8)
1977						0.6 (0,2.6) (16)	1.7 (0,10.3) (118)	5.2 (0,9.5) (50)	1.96 (0,9.8)
1978						0.6 (0,2.6) (16)	1.7 (0,10.3) (118)	5.2 (0,9.5) (50)	1.96 (0,9.8)
1979						0.6 (0,2.6) (16)	1.7 (0,10.3) (118)	5.2 (0,9.5) (50)	1.96 (0,9.8)

in bold refer to the number of actual measurements. While the konimeter measurements were made at five well-defined locations (workstations) in the converter aisle, the locations of the Hi Volume, personal 37-mm measurements, and 'workroom' measurements (which were a combination of Hi Volume and personal 37-mm filter samples) are unknown. In Table 3, the Hi Volume measurements for each year between 1972 and 1975 have the same value, and the 'workroom' and personal measurements between 1976 and 1979 have the same value for each year. This is because the data set provided by the company collected all the measurements of each type made during those years into one group. We therefore assumed that the mean and standard deviation for each type of measurement are the same for each of those years. The variability was calculated using the converted measurements, so that each actual konimeter measurement translated into six converted inhalable measurements, and each Hi Volume measurement translated into two converted inhalable measurements. Within the converter aisle area, variability exists both spatially and temporally. Variability exists within a year at a particular workstation. This variability was determined by obtaining the standard deviation of all inhalable dust data within one year at one station and then accounting for systematic bias. In addition, the total variability across all workstations for each year was calculated. The last column lists the average inhalable concentration for the entire workplace and the total (spatial and within-year) variability. This was obtained by using all inhalable data across the entire building to obtain the 95% confidence interval. The confidence intervals were increased by a factor of 3.8/1.96 to account for systematic bias, and the lower limit of the 95% confidence interval was bounded to zero.

Concentration history for converter building: updating expert priors with historical measurements

An estimate of the mean inhalable concentration for each year, M , and the associated geometric standard deviation of the measurements, σ_M , was obtained in Table 3. These data were used to construct a likelihood function for the actual historical measurements, using Eq. (2). Next, the expert prior probability distributions for each year were updated using this lognormal likelihood function, to produce the posterior probability distributions. Fig. 6 shows the results of the Bayes updating for both the experts. A comparison with Fig. 5 shows that the posteriors are not very different from the priors, even though for most years the intervals within which 95% of the values lie are slightly narrower. This is seen more clearly in Fig. 7, which shows the cumulative probability distributions for the prior (according to Expert 2), the posterior, and the historical measurements for 1976. The historical measurement, which has a median value of 1.0 mg/m³ with a GSD of 2.85, covers a wide range. The

interval within which 95% of the values lie ranges from 0.1 to 10.3 mg/m³. The prior distribution has a median of 3.59 mg/m³, with the 2.5th percentile and 97.5th percentile values being 2.19 and 5.84 mg/m³ respectively. The prior has a much narrower distribution than the distribution of actual measurements, with the result that the measurements do not have any significant effect on the updating. The posteriors are, therefore, very similar to the priors. This finding does not change even when systematic errors in the historical measurements are ignored (with the effect of, roughly, halving the 95% confidence intervals for the measurements).

It is interesting to compare the concentration history in the converter building obtained using only the historical measurements with that obtained using Bayesian updating of expert judgment. Figure 8 shows that while the median levels obtained using the two methods are comparable, the error bars are greatly reduced for the Bayesian method.

Exposure history for a specific job code

Using information about time spent by a particular job category in different microenvironments or workstations, and the concentrations of inhalable aerosol in those microenvironments, one can obtain the exposure history for that job category [Eq. (6)]. In this section, we will obtain the exposure history of job code 827, the 'skimmer converter' as an example. The historical measurements in each microenvironment and their associated uncertainties are given in Table 3. The expert priors (for the entire building) along with these microenvironment measurements were used to obtain posterior probability distributions for concentrations in these microenvironments. Workstations 49 and 57 are both similar skimmer platforms in different locations; likewise workstations 60 and 56 are similar puncher platforms in different locations. Exposures at these similar workstations are usually similar according to the plant industrial hygienist and, therefore, for the years where there is no data for workstation 49 or 60, we used data from workstations 57 and 56 respectively. The times spent by this job category in various microenvironments were provided by the plant industrial hygienist in the form of upper and lower limits of uniform probability distributions. For all years, the time activity pattern was unchanged — the worker spent 4.5–6 h in workstation 49, 1–2 h in workstation 60, and 2–3 h in workstation 1. Monte Carlo sampling ($N = 100\,000$) was done from the posterior probability distributions of micro-environments concentrations and the uniform probability distributions for time spent in these micro-environments. Using these samples in Eq. (6), the exposures for this job category were estimated for each year from 1960 to 1976. For the years 1977–1979, there were no microenvironment-specific measurements, and so the exposures were assumed equal to the building concentrations. Figure 9 shows

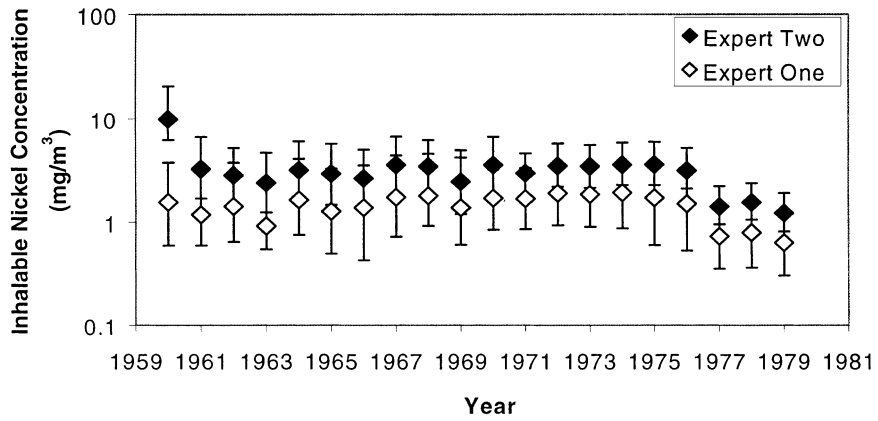


Fig. 6. Posterior probability distributions for the building air concentration of inhalable nickel. The error bars represent the range between the 2.5th and the 97.5th percentiles.

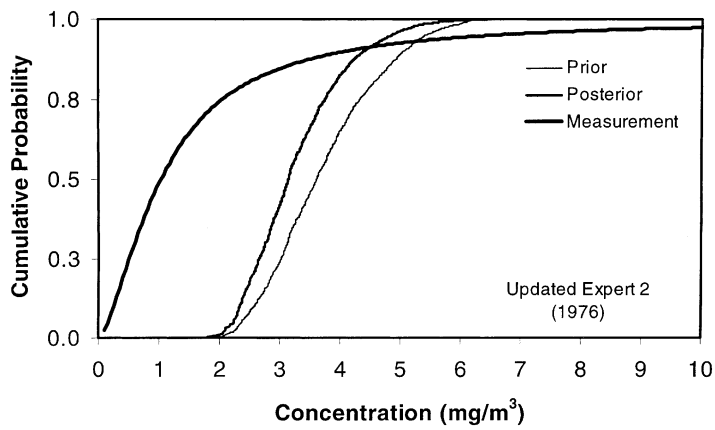


Fig. 7. Cumulative probability distributions for the prior (Expert 2), the posterior, and the historical measurements for 1976.

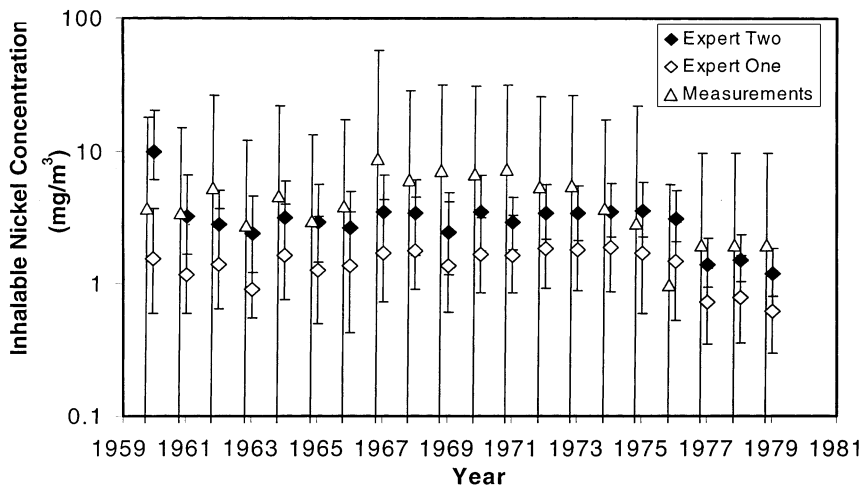


Fig. 8. Comparison of posterior probability distributions (for both experts) with historical measurements. The error bars represent the range between the 2.5th and the 97.5th percentiles.

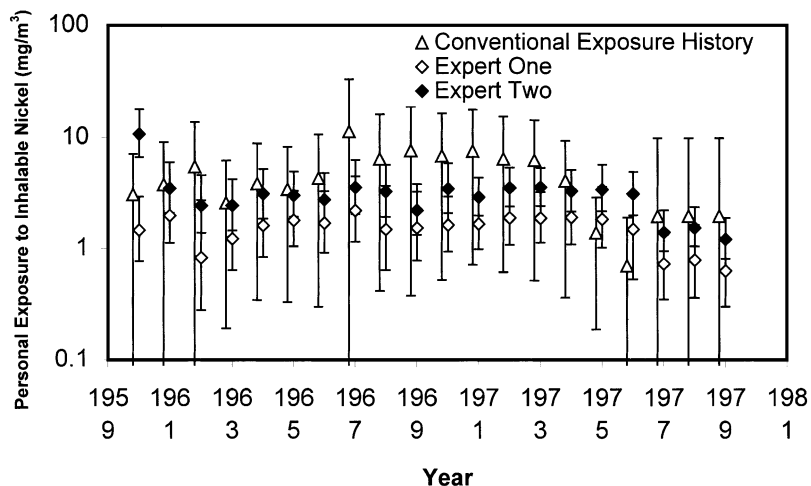


Fig. 9. Comparison of posterior probability distribution of exposure history of job code 827 (skimmer converter) for inhalable nickel aerosol with conventional exposure history.

a comparison of the Bayes posterior exposure distributions according to the three experts with the exposures obtained using the historical measurements along with the time activity patterns. The Bayes posterior distributions are much narrower than, and lie within, the distributions obtained using historical measurements alone.

CONCLUSIONS

Historical measurement data typically have large uncertainties associated with them that may not always be quantifiable. Retrospective exposure reconstruction based solely on such historical measurements leads to estimates with such large error bars as to be not useful for developing quantitative dose-response relationships for epidemiology. However, expert judgment, based on historical plant information in conjunction with physical models, in the form of probability distributions can be combined with sparse historical measurements. This requires the calculation of a likelihood function for the historical measurements, using the estimated variance in the measurements.

It is quite possible that, despite efforts to account for every source of uncertainty, the estimated variance might be an underestimate. But even with the levels of uncertainty that have been calculated, the posterior probability distributions are very similar to the prior probability distributions. Despite the considerable subjective uncertainties in the expert opinions regarding the input parameters to the physical model, the output of the model had a substantially lesser uncertainty than the uncertainty in the historical measurements. At the same time, the concentration ranges obtained from expert judgment lie completely within the concentration ranges obtained from the historical measurements. Thus the measurements are not adding any new information that might change the

prior probability distributions given by the experts. Hence the posterior probability distribution is very similar to the prior probability distribution. Thus, in a situation with very sparse historical concentration and exposure data, expert judgment in conjunction with physical modeling is a more preferable way to estimate past exposures. Since the historical data in this specific case add little new information, they are, to that extent, useless. This is even more so the case if the uncertainties in the historical measurements that have been calculated in this paper are an underestimate.

Nonetheless, it is possible to envision scenarios where the measurements do make a difference. This would happen if the prior probability distributions of the experts do not lie completely within the distribution of the historical measurements. In such cases, the posterior distribution will be different from the prior distribution. One scenario under which this could happen is if the measurements had a relatively small amount of uncertainty in them, e.g., in a company that had more detailed air monitoring and exposure records. Of course, in such a case, expert judgment may be quite unnecessary. A second scenario is if the expert priors have wider error bars than the measurements. This will occur if there are unreliable or non-existent records of plant historical conditions, and the experts will have no anchoring information for their judgments. This is a common situation in occupational hygiene where exposure records from many decades ago are available in databases even though the companies themselves are defunct. In this case, the posteriors will look very similar to the measurements, and expert judgment may be considered a waste of time. A third scenario is if there is a moderate amount of uncertainty in both the historical measurements as well as the expert judgment priors. In this case, the Bayesian approach will truly

come into its own, and provide a real synthesis of both.

Validation of retrospective exposure assessments, i.e., ensuring that the results are close to the 'true' values, always poses a significant problem. One method that has been proposed is to use the technique to predict current exposures for which, presumably, complete information is available (Ramachandran and Vincent, 1999). The limitation of this method is that expert judgment is better at predicting recent exposures than at predicting exposures that occurred several decades ago. Thus success of any method in predicting current exposures should not be taken as a validation of its prediction of past exposures. Cherrie and Schneider (1999) used the correlation between estimated and measured values as a measure of validity, although they recognized the obvious limitation that the measured values are sparse and contain substantial error. In this study, the correlations between the median values of the expert priors (and posteriors) and the measurements are $R_{adj}^2 = 0.6$ and 0.5 for the two experts respectively. All the expert posterior values fell within the confidence limits placed around the measurements, although this was because the measurements had very wide error bars. Another flawed measure of validation is that except for the very earliest years (1956–1960), the two expert priors (and posteriors) are remarkably similar ($R_{adj}^2 = 0.9$ for the median values of the priors and posteriors). This agreement between the experts, while reassuring, may also be due to their similar backgrounds (academic occupational hygienists with expertise in aerosol science).

Given the lack of objective measures of validity, the only reasonable alternative is to invoke the rationality of the methodology. The use of a physical model provides a rational framework for predicting exposures. While the inputs to these models are subjective probability distributions, they are anchored in actual historical plant information. Thus, an argument could be made that if one accepts that the physical model chosen is appropriate and the choices for input parameters are reasonable, then one logically has to also accept the results of the rational procedure described in this paper.

This paper presents the practical application of a Bayesian framework to retrospective exposure assessment in a nickel smelter. It was shown that using only the sparsely available historical measurements results in estimates with large associated uncertainties. However, additional information can be brought to bear on this process: (a) estimates of uncertainty in the historical data set, and (b) expert judgments informed by knowledge of historical plant production rates, emission factors, ventilation rates, and worker activity patterns. This information can be synthesized with the historical measurements using the Bayes formalism. The approach used here emphasizes the need for detailed information about the industrial operations,

materials, tasks, and other environmental variables obtained from company archives and site visits. Without such information, quantitative exposure assessment with manageable uncertainties would be impossible.

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