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A COMPARISON OF STATISTICAL METHODS FOR ESTIMATION OF LESS THAN DETECTABLE IONISING RADIATION EXPOSURES

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Methods were developed to estimate the ionising radiation dose below the detection level (DL) of personal monitoring devices for a case–control study of protracted radiation exposure and lung cancer. Exposure data were grouped by dosemeter type and monitoring period. Each group contained dosimetry data that were interval-censored from limitations in measurement precision and included left-censoring of observations below detection. The grouped data were fit to a three parameter hybrid-lognormal distribution by maximum likelihood estimation. Using the fitted distribution, bootstrap samples were either simulated by Monte Carlo or constructed by sampling with replacement. The resulting bootstrap sample distributions were then used to predict the missing dose values and the associated uncertainty in the estimate. Among study subjects, 1357 workers were monitored with film dosimetry. Among the 39,263 dose observations 20,416 were recorded as zero dose, indicating 52% left-censoring. The statistical methods estimated 0.31 person-Sv below the DL or ∼1% of the total collective dose for this study population.

INTRODUCTION

Analyses for epidemiological studies of relationships between protracted workplace external radiation exposure and disease may attempt to account for bias and uncertainty in exposure monitoring data. Retrospective dose assessment is often complicated by past recording practices for non-detectable personal monitoring results [i.e. recorded as less than the detection level (DL) of the analytic method]. This paper reports an estimation method for penetrating radiation doses below the measurement sensitivity of typical film dosemeters. However, these methods may be adapted to other exposure types.

The DL for film dosimetry varied with dosimetry practices and radiation properties, ranging between 0.1 and 0.4 mSv for most penetrating photon irradiations. If the DL value is substituted for true doses closer to zero, a positive bias in the exposure estimate will result. Likewise, a negative bias is observed when reporting zero for true doses below detection. For example, the DL of film dosemeters at the Portsmouth Naval Shipyard (PNS) was ∼0.20 mSv between 1950 and 1959[1]. Values <0.20 mSv were routinely reported as zero doses, which censors all actual doses below that value. Given that personal monitoring at PNS was conducted bi-weekly prior to 1959 and monthly thereafter, a considerable amount of missed dose could accumulate over the course of several years and may result in significant underestimation of a worker's actual cumulative exposure. Therefore, a method is needed to estimate these potentially 'missed' doses and remove bias that may influence the epidemiological study.

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Background

Methods to impute doses below detection have been used in previous studies. These methods can be generalised as either simple substitution or distributional imputation. The methods are frequently compared based on their ability to reproduce summary statistics[2,3].

Substitution

Nehls and Ackland[4] suggested replacing non-detects with a constant equal to one-half the limit of detection (i.e. $DL{\cdot}2^{-1}$). Likewise, the National Research Council (NRC) treated exposures recorded as less than the minimum detectable level (MDL) as half of the MDL in their examination of film dosimetry used for personnel during atmospheric nuclear testing[5]. The term 'MDL' refers to the point where laboratory uncertainty was estimated at 95% confidence to be +/− 100% (normally distributed). The NRC recognised the actual recording threshold (i.e. DL) may be less precise and may not satisfy this definition.

Hornung and Reed[2] evaluated substitution methods for lognormally distributed data and found the $DL{\cdot}2^{-1}$method was marginally adequate for highly skewed data [i.e. geometric standard deviation (GSD) > 3.0] with censoring <50%. Results were

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improved using $DL \cdot 2^{-0.5}$ when the GSD was <3.0. However, Horning and Reed[2] confirmed that substitution methods performed poorly in comparison with distribution fitting techniques.

Distribution fitting

Distributional methods use the characteristics of an assumed parametric distribution to impute values below the DL. Several distribution fitting options are available. Strom[6] fit annual external radiation doses to a lognormal distribution using log-probit analysis. Sont and Ashmore[7] fit annual external radiation doses to lognormal and hybrid lognormal distributions using maximum likelihood estimation (MLE) methods. More recently, Bayesian methods have been used to fit external radiation data to hybrid lognormal[8], lognormal[9,10] and gamma[11] distributions.

Previous fitting techniques were aimed at fitting individual dose distributions for improvements to worker dose estimates. Although working with individual dose distributions is clearly preferred when sufficient data are available, it is commonplace among radio-epidemiological studies that many workers have few exposure data available for an appropriate fit. This study focuses on distribution fitting techniques to determine whether improvements in dose estimates can be achieved using combined data sources.

METHODS

Hybrid lognormal distribution

The lognormal distribution is often used to describe occupational doses to external irradiation[6,9,12,13]. In the lower dose range above the DL, the variation of individual doses tends to obey the law of proportionate effects and exposure data are distributed lognormally[14]. However, a departure from lognormality is typically observed with increasing doses, which is attributed to the effects of administrative control limits or the physical constraints of dose rate and exposure time[6,13,14]. Only the data of magnitude below the lognormal departure point is recommended for use when fitting dose distributions, which invokes additional data censoring.

In contrast, Kumazawa and Numakunai[14] have developed the hybrid lognormal distribution model to account for the effect of limiting doses. The hybrid lognormal distribution is constructed such that doses in the lower dose range are lognormally dominant, whereas the normal distribution component is dominant in the higher dose range. This distributional shape was observed in several empirical radiation dose distributions[7,14,15]. The hybrid lognormal model better describes the actual dose distribution over its entire range and does not require right-censoring of data during the distribution fitting process.

For equivalent doses, the probability density function of the hybrid lognormal distribution is given by

$$f\left(x|\rho,\mu,\sigma^2\right) = \frac{1}{\sqrt{2\pi}\sigma}\left(\frac{1}{x}+\rho\right)e^{-\frac{1}{2}\left[\frac{\ln(\rho x)+\rho x-\mu}{\sigma}\right]^2} \quad \left(\rho>0, \sigma^2>0\right) \qquad (1)$$

where x is dose. Let $\Omega(x|\rho, \mu, \sigma^2)$ represent the hybrid lognormal distribution function where values $\ln(\rho x)+\rho x$ are normally distributed with mean μ and variance σ^2 [e.g. $N(\ln(\rho x)+\rho x|\ \mu,\sigma^2)$]. As $\rho \to 0$, the distribution becomes lognormal and as $\rho \to \infty$ the distribution becomes normal.

Parameter estimation

MLE was used to estimate the parameters of the hybrid-lognormal distribution. The MLE technique followed a general formulation of the likelihood function (L) for a left-censored dataset grouped by a common DL:

$$L(\theta_1,\theta_2,\ldots,\theta_k) = \prod_{i=1}^{n} f(x_i|\theta_1,\theta_2,\ldots,\theta_k) \times \left[F(\mathrm{DL}|\theta_1,\theta_2,\ldots,\theta_k)\right]^{N_{\mathrm{DL}}}, \qquad (2)$$

where, x_i is a detectable data point above the DL and i = 1, 2, …, n detected data points; $\theta_1,\theta_2,\ldots,\theta_k$ are parameters of the distribution (e.g. ρ, μ, σ for hybrid-lognormal); N_{DL} is the number of left-censored data (e.g. data below the DL); $f(x)$ is the probability density function of x; and $F(x)$ is the cumulative distribution function of x.

Typically, exposure data above the DL are reported in increments where rounding occurs from measurement resolution. These data are interval-censored, where the random variable of interest (e.g. dose) cannot be observed exactly. The actual value lies in an interval $\left(x-\frac{1}{2}\Delta x, x+\frac{1}{2}\Delta x\right)$ where data resolution (Δx) is defined by the measurement process. For example, early PNS exposure data were reported in increments of 0.1 mSv. Therefore, a 0.4 mSv reported value is interpreted to lie between the interval 0.35 and 0.45 mSv. The likelihood function of interval-censored data is calculated by:

$$L(\mu,\rho,\sigma^2) = \prod_{i=1}^{n}\left[F\left(x_i+\frac{\Delta x}{2}|\mu,\rho,\sigma^2\right) - F\left(x_i-\frac{\Delta x}{2}|\mu,\rho,\sigma^2\right)\right], \qquad (3)$$

where n is the number of detected observations. Data resolution increased with monitoring improvements at PNS. Dosimetry records indicate resolution from

0.1 mSv to 0.01 mSv over the course of film badge monitoring.

The likelihood function can be modified for x equal to or less than the DL as follows:

$$L(\mu,\rho,\sigma^2) = \left[F\left(\mathrm{DL} + \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right)\right]^{N_{\mathrm{DL}}} \prod_{i=1}^{n}\left[F\left(x_i + \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right) - F\left(x_i - \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right)\right]. \quad (4)$$

It is more mathematically convenient to maximise the natural log of the likelihood [ln(L)] rather than L. Therefore, logarithmically-transforming Equation 4 yields

$$\ln(L) = N_{DL}\ln\left[F\left(\mathrm{DL} + \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right)\right] + \sum_{i=1}^{n}\ln\left[F\left(x_i + \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right) - F\left(x_i - \frac{\Delta x}{2}|\mu,\rho,\sigma^2\right)\right] \quad (5)$$

Estimates of the hybrid lognormal distribution parameters ρ, μ and σ^2 (i.e. $\hat{\rho}$, $\hat{\mu}$ and $\hat{\sigma}^2$) were solved by maximising ln(L). In practice, the SAS/STAT® Version 8 software NLIN procedure was used to estimate the distribution parameters by non-linear least squares regression such that −ln(L) was minimised through iteration by Newton–Raphson's algorithm[16].

Parametric bootstrap samples

Estimates of left-censored doses can be imputed by random sampling of $N(\ln(\hat{\rho}x) + \hat{\rho}x|\hat{\mu},\hat{\sigma}^2)$ and selecting substitution values corresponding to estimated points below the DL. However, the parameters $\hat{\rho}$, $\hat{\mu}$ and $\hat{\sigma}^2$ are also estimates and are subject to some uncertainty. This uncertainty can be significantly influenced by sample size and amount of data censoring. The accuracy of the missed dose estimate relies on the quality of fit to the extreme left tail of the distribution, where data fitting techniques are influenced by measurement resolution and the selection of the left-censoring threshold. To further examine these effects, modified parametric bootstrap simulation was used to estimate missed dose and its associated uncertainty. Using the parameter estimates of the fitted hybrid-lognormal distribution, synthetic datasets of size n_0 were generated by Monte Carlo simulation, where n_0 is the total number of initial observations (i.e. left-censored and interval-censored data). Given that $\ln(\rho x) + \rho x$ is normally distributed with distribution function $N(\ln(\rho x) + \rho x|\mu,\sigma^2)$, n_0 values of $\ln(\hat{\rho}x) + \hat{\rho}x$ were drawn at random from a normal distribution using estimated parameters $\hat{\mu}$, $\hat{\sigma}^2$. The Lambert's W function (W), which is defined for any (complex) z by $W(z)e^{w(z)} = z$, was used to solve for x (dose) where $x = W(e^Y)\,\rho^{-1}$ and $Y = \ln(\hat{\rho}x) + \hat{\rho}x$. Given that SAS does not provide explicit solutions for the Lambert's W function, uniform approximations suggested by Winitzki[17] were used to solve for $W(e^Y)$. These approximations are

$$W(e^Y) \approx \ln(1+e^Y)\left(\frac{1-\ln(1+\ln(1+e^Y))}{2+\ln(1+e^Y)}\right), \quad (6)$$

for $Y > 0$, and

$$W(e^Y) \approx \frac{(e^{Y+1})}{1+\left((2e^{Y+1}+2)^{-1/2} - \frac{1}{\sqrt{2}} + \frac{1}{e-1}\right)^{-1}}, \quad (7)$$

for $Y < 0$. The approximations were tested over for a range of $x\hat{\rho}$ from 10^{-20} to 500 and found to be within 0.4% [95% confidence interval (95% CI)]. After solving for x, data in each bootstrap sample were censored to provide Δx and the DL equivalent to the original dataset. For each of B bootstrap samples, MLE was used to find new parameter estimates ($\hat{\mu}_B$, $\hat{\sigma}_B$, and $\hat{\rho}_B$).

Dose estimates were derived from the bootstrap sample parameter estimates and the cumulative probabilities of left-censored data. The sample data were ranked first to last where i was the rank assigned. The cumulative probability of a left-censored value was estimated for each value below the DL by median ranks approximation, where $p = (i - 0.3)(n + 0.4)^{-1}$. The inverse cumulative distribution function of $N(\ln(\hat{\rho}_B x) + \hat{\rho}_B x|\hat{\mu}_B, \hat{\sigma}_B^2)$ was used to estimate values of Y corresponding to each left-censored datum probability. Dose values were derived from Y as discussed previously except for censoring. The sum ($\hat{H}_B$) of the estimated doses from a sample dataset represents a single estimate of the censored collective dose from all left-censored values. Let the expected value from the distribution of $\hat{H}_B$ from B synthetic datasets be $\tilde{H}_C$, then $\tilde{H}_C$and its 95% CI provides a measure of the collective missed dose and the uncertainty in the estimate.

Non-parametric bootstrapping

As an alternative to parametric simulation, bootstrap samples were also constructed from the original dataset by random sampling with replacement using the methods suggested by Lubin *et al.*[18] Sampling in this manner is performed by selecting one record at random from the original dataset and then putting it back for the next record to be drawn until a bootstrap sample dataset equal in size to the original dataset is created. Some records are selected multiple times and other records may not be selected at all. The sampling process is repeated to construct B bootstrap samples. The remainder of the dose estimation methods using non-parametric bootstrap samples was identical to those discussed previously for simulated samples. Figure 1 is a schematic representation of the missed dose estimation methods.

Comparison of the estimation methodologies

Test datasets were constructed to ascertain the accuracy of dose estimates and to ascertain the relative performance of the two estimation methodologies. Test data consisted of 10,000, 1000 and

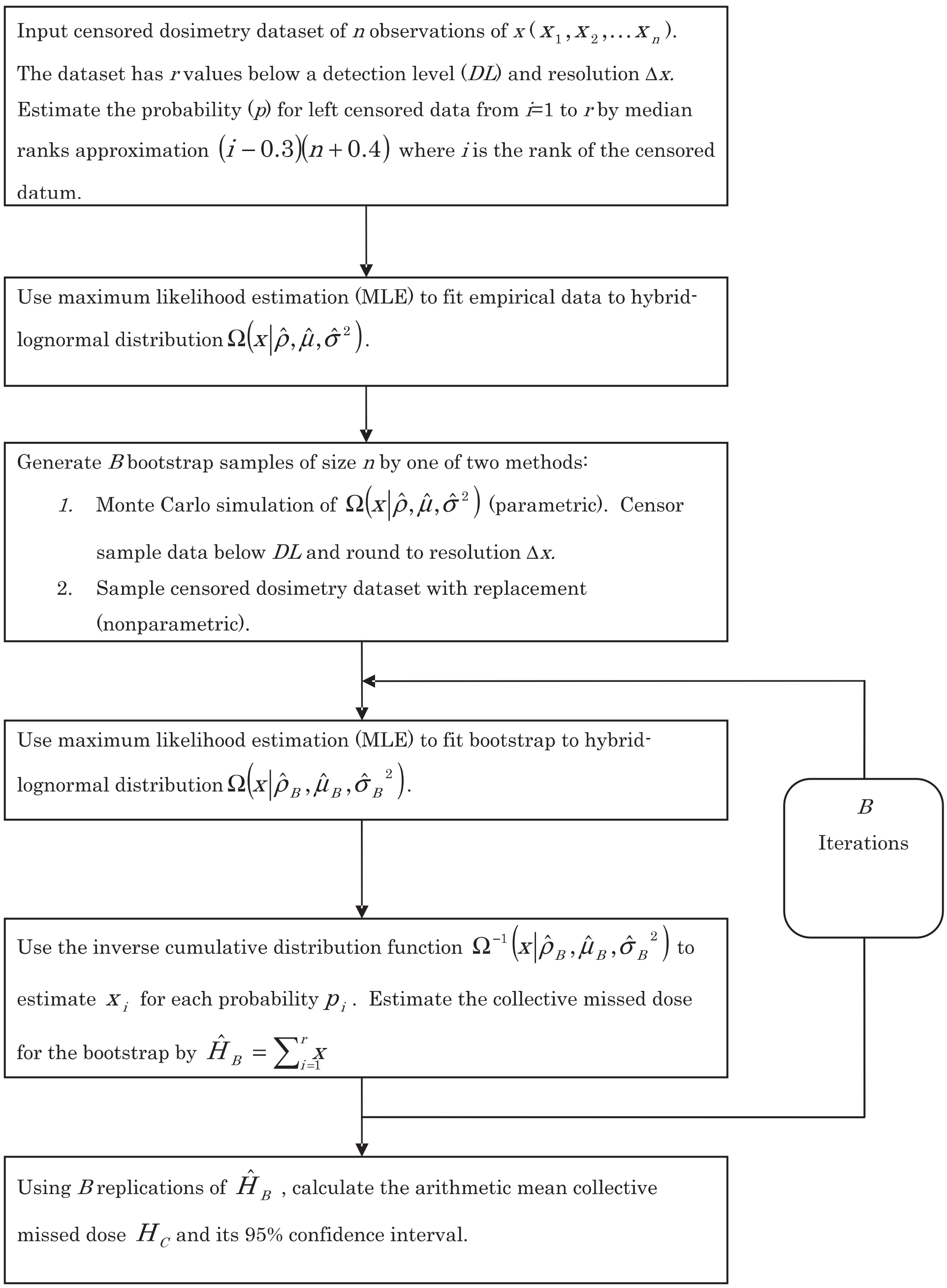

Figure 1. Missed dose estimation process diagram.

100 observations generated by computer simulation of a hypothetical hybrid-lognormal distribution with distribution function $\Omega(x|\ 1.5, -3.0, 25)$. To simulate left-censoring over a range of DLs, generated 'dose' values below the DL were set to zero and the DL was set at 0.2 and 0.4 mSv. Interval-censoring was simulated by rounding values above the DL to the nearest 0.01 and 0.1 mSv. Estimation of distribution parameters and missed doses followed the methods described previously and shown in Figure 1. A measure of bias was determined as the ratio of $\tilde{H}_C$ to H_C, where the variable H_C is the actual censored collective dose below the DL in the test dataset.

Exposure data analysis

Exposure data from a nested case–control of lung cancer mortality in workers at the PNS in Kittery, Maine, were selected for data analysis. Four age-matched controls per case were randomly selected from risk sets defined from the cohort of PNS civilian workers employed between 1952 and 1992.

Dosimetry data for each exposed worker were gathered from available site dosimetry records. Details of the PNS dosimetry programme and records collection supporting the epidemiological study are described elsewhere[15]. The exposure data were coded into a relational database and were not modified except for conversion to SI units. In addition to dosimetry records, information regarding dosemeter response and monitoring frequency was examined to characterise the monitoring methods used and to define monitoring eras. To promote homogeneity, dosimetry data were grouped by similarities in dosemeter type, monitoring period and DL. Threshold values were established at the reported DL for the dosemeter. The radiation exposure for each worker was assessed to the earliest of the index case age at death or study end date.

Cumulative dose

Up to this point, estimates pertain to the collective dose over a specified exposure period. However, the summation of a worker's dose over several years of exposure (e.g. cumulative dose) is of primary interest in the epidemiological analysis. A primary assumption of the presented methods is that all observations are independent, thus, ignoring the possible correlation of data for a single worker. However, repeated measurements for a particular worker within the same working environment are likely to have a high degree of correlation relative to the *between worker* independence. To examine potential correlation effects on missed cumulative dose estimates, a test dataset was constructed using exposure data between 1 October 1974 and 31 December 1996. During this period, the DT-526/PD calcium fluoride thermoluminescent detector (TLD) was used for personal dosimetry, with a minimum sensitivity of ~0.01 mSv[15]. Given the low DL, actual missed dose is expected to be minimal for this dataset. The exposure data were censored below 0.20 mSv to model left-censored results from typical film badge monitoring. The collective missed dose was then estimated using the previously described methods. To estimate cumulative dose, the arithmetic mean missed dose per observation was obtained by dividing the collective missed dose by the number of left-censored data. This value was used as a surrogate for each censored data point for each study subject. The 'actual' cumulative missed dose (D_A) was calculated as sum of the censored data for each worker. Likewise, the estimated missed cumulative dose (D_E) was the number of censored data multiplied by the estimated mean missed dose per measurement. Differences among estimated and actual values were examined by analysing the distribution of $(D_A - D_E)$ paired for each worker.

RESULTS

Test data

The results of the initial test datasets are shown in Table 1. In all scenarios, censored data comprised over 50% of the dataset. For large datasets ($n \geq 10^3$), predicted sums were within ±18% of the censored data sums in all scenarios tested. Similar results were not observed for small samples ($n \leq 10^2$). As expected, uncertainty increased with decreasing dataset size, reaching ±42% for estimates from test data comprising ~30 observations above the left-censoring threshold. The arithmetic means of the relative biases were near unity, with values of 0.96 and 0.97 for parametric and non-parametric methods, respectively. The difference between the means of the two methods was not statistically significant by *t*-test ($p = 0.87$). Therefore, both methods appear to provide comparable and unbiased estimates of the summed censored data.

Non-parametric bootstrapping was superior to parametric bootstrapping in the sense that the calculated uncertainties attached to the non-parametric bootstrapping dose estimates were generally smaller. The non-linear fitting procedures were influenced by outliers resulting from simulations performed for parametric bootstrapping, resulting in wider CIs on the point estimates. This effect was observed to increase with decreasing sample sizes; where models using non-parametric techniques appear more robust than the parametric models. Given that exposure data distributions are discrete, this suggests that it may be more appropriate to model the uncertainty using non-parametric methods. Although sampling with replacement appears to

Table 1. Analysis of censored hybrid-lognormal test data using parametric and non-parametric bootstrap methods ($B = 50$).

Characteristic of test data[a]			Bootstrapping by Monte Carlo simulation of hybrid lognormal distribution (parametric)			Bootstrapping by sampling original data with replacement (nonparametric)			Simple substitution[b] ($\frac{DL}{2}$)	
Trials	Left-censoring threshold (DL)	Data resolution (Δx)	Sum below threshold (H_C)	Estimated sum ($\tilde{H}_C$) (95% CI)	Bias ($\frac{\tilde{H}_C}{H_C}$)	Sum below threshold (H_C)	Estimated sum ($\tilde{H}_C$) (95% CI)	Bias ($\frac{\tilde{H}_C}{H_C}$)	$\sum \frac{DL}{2}$	Bias
10,000	0.2	0.01	176	176 (156–207)	1.00	182	165 (150–178)	0.907	670	3.68
		0.1	180	181 (147–207)	1.01	178	176 (159–195)	0.989	657	3.69
	0.4	0.01	370	342 (289–394)	0.924	382	379 (346–421)	0.992	1463	3.83
		0.1	363	388 (332–447)	1.07	374	378 (330–424)	1.01	1467	3.92
1000	0.2	0.01	18.4	21.3 (13.7–29.4)	1.15	17.6	20.7 (15.6–25.5)	1.18	67.7	3.85
		0.1	18.7	21.3 (12.9–32.3)	1.13	17.0	18.4 (12.1–24.6)	1.08	67.1	3.95
	0.4	0.01	40.8	37.0 (19.1–57.2)	0.907	39.8	43.6 (30.5–54.3)	1.10	147	3.69
		0.1	36.0	38.1 (18.6–55.6)	1.06	37.0	36.5 (19.6–53.1)	0.986	147	4.03
100	0.2	0.01	1.90	1.36 (<0.01, 3.81)	0.716	2.36	2.83 (1.51–4.00)	1.20	6.80	2.88
		0.1	1.89	1.10 (<0.01, 4.52)	0.582	2.19	1.06 (<0.01, 2.41)	0.484	6.50	2.97
	0.4	0.01	2.53	3.40 (<0.01, 13.1)	1.34	2.63	1.95 (<0.01, 6.23)	0.741	13.8	5.25
		0.1	4.34	2.72 (<0.01, 9.64)	0.627	3.37	3.42 (<0.01, 8.12)	1.01	14.2	4.15

[a]Test data generated from hybrid-lognormal distribution function $\Omega(x|1.5,–3.0,25)$
[b]Replacing values below censoring threshold with a constant equal to one-half the DL[4]

provide more precise estimates, the computations were more complex than those required by Monte Carlo simulation; making multiple analyses of large datasets by non-parametric means potentially time-prohibitive.

Table 1 also shows the results of substituting censored datum with a constant equal to one-half the censoring threshold. Substitution methods resulted in consistently positive biases that were much larger than that observed from both parametric and non-parametric methods. Although substitution methods are common in exposure assessment[2,4,5], this analysis suggests it may be less than optimal for skewed exposure data distributions that are highly censored.

The stability of the parameter estimates was examined for a range of DLs. Given initial test data ($n = 10{,}000$) with interval-censoring set at 0.1, parameter estimates were determined for a DL between 0.1 and 3 in 0.1 increments. The ratios of initial parameters to estimated parameters were plotted against the DL (Figure 2). The plot shows reasonable prediction of parameters with censoring in the range anticipated for PNS data. However, loss of model stability is observed beginning with DLs in excess of 0.6, which corresponds to data censoring of ~78%.

PNS exposure data

Exposure monitoring with film emulsions began at PNS on 1 July 1950 with significant modifications in July 1952, July 1957 and July 1969 until replaced by TLDs on 1 October 1974[15]. The DL for film dosimetry was 0.2 mSv per monitoring period until July 1969, when improved dosimetry resulted in a DL of 0.1 mSv[15]. Film badge monitoring was conducted bi-weekly through 1959 and was extended to monthly beginning January 1960[15].

Among the 4388 cases and controls, there were 1440 workers requiring dose assessment. Of these workers, 1357 had exposure data from film badge monitoring resulting in 39,263 observations. There were 20,416 observations with 'zero' recorded exposure, which is equivalent to 52% of recorded data below the DL. Data were stratified according to dosemeter type, DL, processing intervals, and sample size. There were four strata defined, each containing at least 100 observations (Table 2). Data were fit to a hybrid lognormal distribution to estimate the missed dose contribution. Figure 3 shows an example of the fit of exposure data between 1950 and 1957. These same data were fit to a lognormal distribution, which demonstrates the departure from lognormality in the high dose region beginning at ~3.0 mSv (Figure 3, dashed line). This departure is attributed to limiting worker exposures through administrative controls at PNS.

Using parametric bootstrapping, ~0.31 person-Sv was estimated to be censored or ~1% of the total collective dose for this study population (Table 3). The relative uncertainty in estimates is greatest for the earliest monitoring period given fewer data available, reduced measurement sensitivity and lesser measurement resolution. However, the contribution to the total missed dose is minimal compared with other time periods.

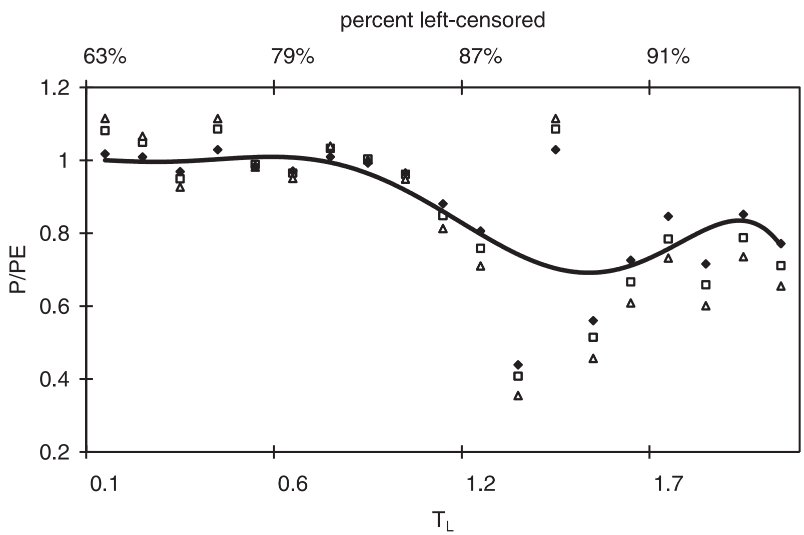

Figure 2. The ratio of the original parameters (P) to the parameter estimates (P_E) vs. left-censoring threshold (T_L). Simulated data ($n = 10{,}000$) from a hybrid lognormal distribution $p(x$: 1.5, −3, 25) with resolution (Δx) = 0.1. Legend: triangle = ρ, diamond = μ, square = σ. The trend line was calculated from sixth order polynomial fit.

Table 2. Available dosimetry data for Portsmouth Naval Shipyard workers within a lung cancer case–control study.

Strata	Monitoring Period	Sample size (n)	Censored data ($x < DL$)	Detection level (DL) mSv	Processing Interval	Resolution (Δx) mSv	Recorded dose (person-Sv)
1	1 July 1950–30 September 1957	141	61 (43.3%)	0.2	Bi-weekly	0.1	0.335
2	1 October 1957–31 December 1959	3546	1587 (44.8%)	0.2	Bi-weekly	0.01	2.35
3	1 January 1960–30 June 1969	25,247	12,966 (51.4%)	0.2	Monthly	0.01	21.3
4	1 July 1969–30 September 1974	10,329	5802 (56.2%)	0.1	Monthly	0.01	5.15

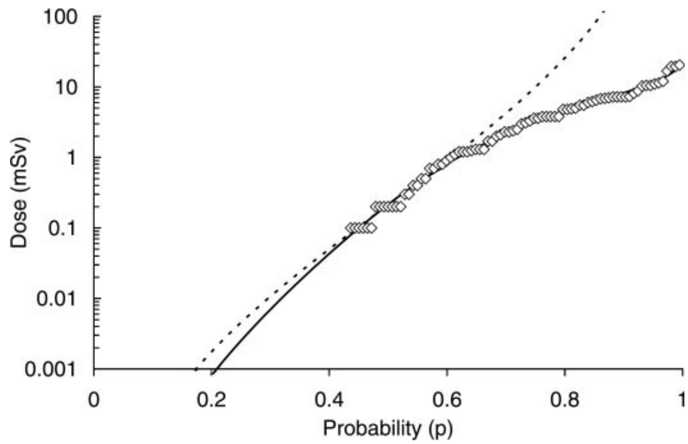

Figure 3. Probability plot for dose measurements at the Portsmouth Naval Shipyard between 1950 and 1957 (diamond). The plot also shows dose fit to a lognormal distribution (dashed line) and hybrid-lognormal distribution (solid line).

Table 3. Results of missed dose estimation for the PNS lung cancer case–control study with parametric bootstrap methods.

Strata	Estimated distribution parameters[a]			Expected values for bootstrap distribution parameters[b]			Estimated missed dose[c] ($\tilde{H}_C$) (person-mSv)	Percent of collective dose (%)
	$\hat{\rho}$	$\hat{\mu}$	$\hat{\sigma}$	$\tilde{\rho}$	$\tilde{\mu}$	$\tilde{\sigma}$		
1	0.889	−1.85	8.70	0.764 (0.319–1.72)	−1.90 (−3.29 to −0.674)	7.70 (4.67–12.5)	0.620 (0.015–2.21)	0.18
2	0.987	−2.38	4.17	1.39 (1.30–1.48)	−1.69 (−1.92 to −1.46)	4.59 (4.53–4.66)	19.8 (16.4–23.4)	0.84
3	0.543	−3.22	4.05	0.490 (0.460–0.497)	−3.25 (−3.32 to −3.22)	3.84 (3.77–3.91)	216 (204–223)	1.00
4	0.504	−4.10	3.62	0.437 (0.389–0.482)	−4.14 (−4.28 to −4.04)	3.41 (3.28–3.56)	70.5 (63.9–77.9)	1.35

[a]Estimates correspond to a hybrid lognormal distribution function $\Omega(x|\hat{\rho}, \hat{\mu}, s\hat{\sigma}^2)$
[b]$\tilde{\theta}$ is the arithmetic mean of B bootstrap sample parameter estimates $\hat{\theta}_B$ for a hybrid-lognormal distribution function with parameters μ, σ, and ρ. The 95% CI is shown in parenthesis
[c]$\hat{H}_c$ is the arithmetic mean of B bootstrap sample parameter missed dose estimates $\tilde{H}_c$. The 95% CI is shown in parenthesis

Similar results were obtained from non-parametric sampling methods (Table 4). However, non-parametric sampling methods were more stable with smaller datasets. These estimates were consistent with previous analyses of the PNS cohort (<1%) and a sub-cohort of 204 radiation workers (1.8%) using log probability regression[15].

Cumulative dose estimates

There were 9499 dose observations between 1 October 1974 and 31 December 1996 used for the cumulative dose test. Censoring doses <0.20 mSv resulted in ~221.8 person-mSv from 7124 individual monthly dose observations among 208 workers. The censored dataset was fit to a hybrid lognormal distribution $[\Omega(x|0.46, -4.47, 10.1)]$ using non-parametric methods (Figure 4). From the fitted distribution, the collective missed dose was estimated to be ~216.9 person-mSv, resulting in an average missed dose per measurement of ~0.030 mSv. Actual and estimated cumulative missed doses were calculated for each of the 208 workers. Paired sample analysis of $(D_A - D_E)$ resulted in a nearly symmetric distribution (Figure 5) with an arithmetic mean (0.02 mSv) not significantly different from zero at the 95% CI

Table 4. Results of missed dose estimation for the PNS lung cancer case–control study with nonparametric bootstrap methods.

Strata	Estimated distribution parameters[a]			Expected values for bootstrap distribution parameters[b]			Estimated missed dose[c] ($\tilde{H}_C$) (person-mSv)	Percent of collective dose (%)
	$\hat{\rho}$	$\hat{\mu}$	$\hat{\sigma}$	$\tilde{\rho}$	$\tilde{\mu}$	$\tilde{\sigma}$		
1	0.889	−1.85	8.70	0.937 (0.428–4.14)	−1.95 (−5.35 to 0.502)	8.91 (5.19 –33.4)	0.30 (<0.001, 0.986)	0.09
2	0.987	−2.38	4.17	0.993 (0.816–1.22)	−2.37 (−2.61 to −2.18)	4.18 (3.69 –4.76)	16.2 (11.4–21.3)	0.68
3	0.543	−3.22	4.05	0.541 (0.494–0.608)	−3.22 (−3.32 to −3.14)	4.03 (3.85 –4.20)	197 (183–210)	0.92
4	0.504	−4.10	3.62	0.504 (0.452–0.549)	−4.11 (−4.09 to −3.90)	3.62 (3.46 –3.76)	62.3 (58.1–67.1)	1.19

[a]Estimates correspond to a hybrid lognormal distribution function $\Omega(x|\hat{\rho}, \hat{\mu}, \hat{\sigma}^2)$.
[b]$\tilde{\theta}$ is the arithmetic mean of B bootstrap sample parameter estimates $\hat{\theta}_B$ for a hybrid a hybrid-lognormal distribution function with parameters μ, σ, and ρ. The 95% CI is shown in parenthesis
[c]$\hat{H}_c$ is the arithmetic mean of B bootstrap sample parameter missed dose estimates $\tilde{H}_c$. The 95% CI is shown in parenthesis

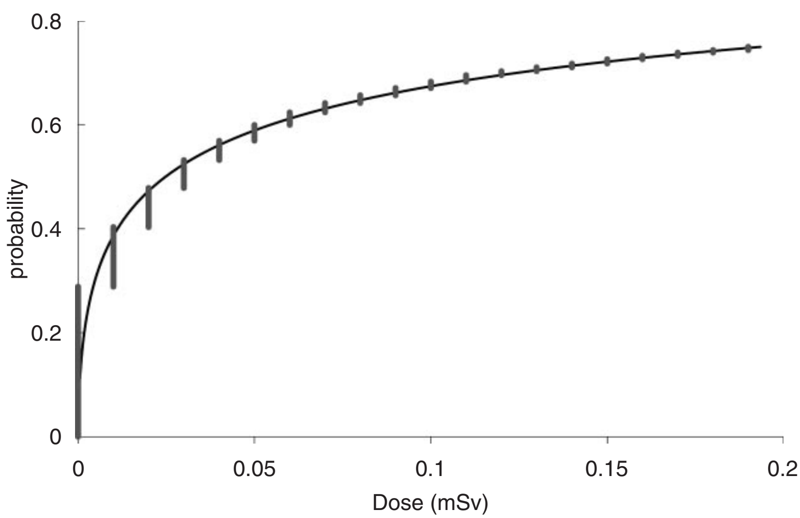

Figure 4. Cumulative distribution function of censored dose data between 1 October 1974 and 31 December 1996 (markers) and fitted hybrid lognormal distribution (solid line). $n = 9499$; $7124 < DL$; $DL = 0.20$ mSv.

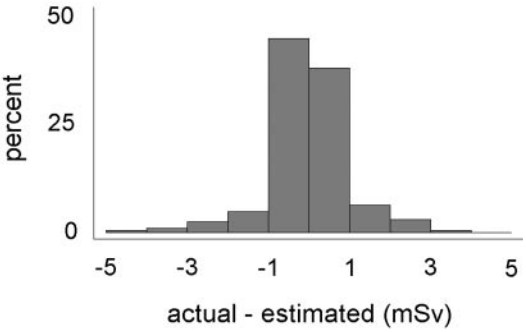

Figure 5. Histogram of the differences between actual cumulative doses (D_A) and estimated cumulative doses (D_E) for individual study subjects ($n = 208$) using missed dose estimation methods.

($p = 0.71$). The standard deviation of ($D_A - D_E$) was 0.93 mSv. These results suggest that the potential correlation among individual worker data may not significantly influence estimates of missed cumulative doses derived from the missed collective dose.

DISCUSSION

Methods are introduced to estimate censored doses from the dose distributions of similarly exposed workers instead of each worker's individual dose distribution. Estimated collective doses were examined as a simple means to assess the accuracy and precision of the methods used. However, the collective dose is of little use in an epidemiological study, where estimates of individual cumulative doses are most desired. A simple means to estimate individual worker cumulative doses was accomplished using the average missed dose per measurement obtained for a group of workers as a substitution for censored measurements of each worker. The test example suggested these methods were unbiased and appropriate for epidemiological study related to PNS exposures. Instead of substituting the average missed dose, censored data could be replaced with estimates imputed by random sampling of $N\left(\ln(\hat{\rho}x) + \hat{\rho}x|\hat{\mu}, \hat{\sigma}^2\right)$. Replacement values can also be drawn from the bootstrap samples, where $N\left(\ln(\hat{\rho}x) + \hat{\rho}x|\hat{\mu}, \hat{\sigma}^2\right)$ was used to simulate B bootstrap samples, which provide B sets of replacement values from $N\left(\ln(\hat{\rho}_B x) + \hat{\rho}_B x|\hat{\mu}_B, \hat{\sigma}_B^2\right)$.

Both test data and PNS exposure data results suggest that non-parametric bootstrap sampling methods may provide better estimates than the parametric bootstrap (random sampling) methods. However, as a tradeoff, computational time may be prohibitive when applying non-parametric bootstrapping to multiple large datasets because of random sampling to construct each bootstrap sample. Lubin *et al.*[18] have shown that the number of bootstraps can be reduced using a non-parametric approach, thus improving computational time. Both methods should be explored and optimised to the source data. For this study, we have chosen to use parametric methods for uncensored datasets >100 observations.

LIMITATIONS

Adequate data must be available for an accurate fit to the dose distribution. This is particularly important when using parametric methods, since random sampling from a continuous and skewed distribution can result in 'outlying' dose values. As expected (and as shown by the test data analysis), significant uncertainty is likely when fitting highly censored data.

Second, a primary assumption for this modelling is actual exposures below some threshold are left-censored (e.g. non-zero dose) and distributed according to the fitted parametric distribution. For PNS workers, dosimetry was issued when entering a radiation area where some exposures were likely. Therefore, the recorded zeros are indicative of radiation work and most likely underestimate true exposures. However, recorded zero-doses can result as an artefact of the dosimetry file (e.g. placeholder) from processing unexposed dosimetry (e.g. true zero values). For example, by 1951, workers entering the main area of the Oak Ridge National Laboratory (ORNL) were monitored weekly regardless of their actual potential for exposure (West, CM. Letter to Cragle, Donna, 1 June 1992. Description of the ORNL external monitoring programme 1943–1961. Oak Ridge, TN). The monitoring was expanded to all employees by late 1953 with the integration of the dosemeter and security badge. The large number of recorded zeros may be indicative of exposures at or very near environmental background levels and may correctly report zero net exposures. In the case of ORNL data, dose estimation methods must be adjusted for expected zero exposures to prevent introducing a positive bias in assessed doses. For example, Tankersley *et al.*[19] and subsequently Watkins *et al.*[20] separated ORNL subjects into exposed and unexposed groups based on the observed proportion of recorded zeros among subjects and work groups. Missed dose was estimated only for the population likely to be exposed.

Third, the potential effect of correlations for the *within* and *between* worker components of variance must be taken into account. The effect of such correlations was studied herein by examination of the PNS exposure data. However, most PNS workers were exposed almost exclusively to gamma and X rays from activation products under very similar conditions involving work within the shielded volume of the reactor compartment onboard nuclear-powered submarines[15], which is expected to promote homogeneous exposure patterns. This exposure homogeneity is less likely in other radiation-exposed cohorts. Other cohorts may exhibit stronger correlations for the within worker exposures and greater dissimilarities in radiation types, energies and exposure geometries among groups of workers. Further work is necessary to examine these potential correlations. Although appropriate estimates of worker missed dose were determined by analysis of grouped data in this study, it is recommended that a hierarchical approach be used such that analysis of individual worker dose distributions are preferred over combined datasets when sufficient data are available.

Another limitation is the choice of an appropriate left-censoring threshold. In the presented examples, the left-censor threshold was the DL, which was easily observed in the monitoring data provided. However if annual doses are used, the number of censored data within the sum comprising the annual values is unknown. In this case, the departure from a fitted distribution is subtle and a left-censor threshold is difficult to discern. A range of thresholds must be examined, which introduces additional uncertainty in the parameter and dose estimates.

Finally, the study methods pertain only to the uncertainty associated with dosemeter sensitivity at PNS and assume that the grouped dose values either accurately represent true doses or demonstrate a pattern of exposure that can be adjusted given other known sources of uncertainty. Several other sources of uncertainty are indicative of film dosimetry and have been reported on extensively in the literature. As evident in the literature, some of these sources of error are likely to be of greater concern than the source described by this work. For example, the accuracy and sensitivity of film dosemeters can be largely affected by environmental conditions[21–23] the length of monitoring period[21] and the number of monitoring periods resulting in a cumulative dose[24]. Likewise Brodsky *et al.*[25] examined sources of error associated with random variations in film composition, sensitivity, methods of processing, densitometry and other laboratory techniques. General methods have been developed to adjust dosimetry values for these sources of errors[5,26]. Specific adjustment methods applicable to dosimetry from PNS and other nuclear facilities have been developed by Daniels and Schubauer-Berigan[27]. In that study, Daniels and Schubauer-Berigan examined sources of measurement uncertainty by facility and time period to make adjustments to reported dosimetry from changing environmental conditions (i.e. temperature and humidity effects), exposure geometries, exposure energies, and dosemeter calibration and processing procedures. Similar methods should be used to identify appropriate data analysis groups and to adjust recorded values prior to distribution fitting. As practical, the methods provided by this study should be carried out in concert with other methods accounting for uncertainty common to facility-specific dosimetry practices, both past and present.

CONCLUSION

Researchers are often challenged to improve exposure estimates for epidemiological study. Personal dosemeters used during the height of operations in most radiological facilities were designed to reliably assure exposures were below protective limits. As such, personal dosimetry design did not provide the sensitivity desired for epidemiological retrospective dose assessment. In response, estimation methods for exposures below the DL of film dosemeters were examined for an epidemiological study of workers at PNS. Although our example used computer programming to investigate uncertainties, the basic principles are adaptable to spreadsheet calculations similar to those described by Finkelstein and Verma[28]. These estimation principles provide a fundamental model that can be adapted to other exposure types.

The testing of the two dose estimation methods with simulated data revealed that the estimation process is unbiased and robust for its intended purpose. However, caution should be observed when applying these methods to highly censored data or when insufficient data are available to obtain an adequate fit. Unreliable results were shown when modelling small ($n < 100$) or highly censored (>70%) datasets. Therefore PNS exposure data were analysed in strata containing >100 observations and <60% censoring.

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Required Disclaimer

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