AIHA Journal

ISSN: 1542-8117 (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uaih20

Comparison of Task-Based Estimates With Full-Shift Measurements of Noise Exposure

Noah S. Seixas , Lianne Sheppard & Rick Neitzel

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AUTHORS
Noah S. Seixas[a]
Lianne Sheppard[a,b]
Rick Neitzel[a]

[a]Department of Environmental Health, Box 357234, University of Washington, Seattle, WA 98195-7234;
[b]Department of Biostatistics, Box 357232, University of Washington, Seattle, WA 98195-7234

Using a large data set of noise exposure measurements on construction workers, task-based (TB) and full-shift (FS) exposure levels were compared and analyzed for the sources and magnitudes of the error associated with this methodology. Data-logging dosimeters recorded A-weighted sound pressure levels in decibels using Occupational Safety and Health Administration criteria for every minute of monitoring and were combined with information from task cards completed by subjects. Task-related information included trade, construction site type, location, activity, and tool. A total of 502 FS measurements were made, including 248,677 min of exposure on five construction trades. Six TB models of varying degrees of specificity were fit to the minute-level data and the results used to obtain TB estimates of the daily FS exposure levels. The TB estimates were derived using the predictions alone and also including subject and shift-specific residual means and variances. The predictions alone, which ignore within-task variability, produced a significant negative bias that was corrected by incorporation of the residual variance. This bias is only an issue in this setting in which the exposure of interest is noise, which follows a nonlinear averaging relationship. These estimates explained 10 to 60% of the variability in FS measures; adding the residual mean produced estimates that explained about 90% of the variability. In summary, TB estimates are important for exposure estimation when task time varies substantially. However, TB estimates include a substantial degree of error when there is large interindividual or intershift variability in exposure levels for a given task. Methods to improve the prediction of task-associated exposure, or adjusting for individual and shift differences, are needed.

Keywords: construction, exposure assessment, noise exposure, task-based exposure assessment

APPLIED STUDIES

Partial support of this work was obtained through grant RO1 OH03912 from the National Institute for Occupational Safety and Health of the U.S. Centers for Disease Control and Prevention. The views contained are solely those of the authors.

Since the advent of the personal sampling pump, occupational exposure assessment has been based on full-shift (e.g., 8-hour) time-integrated average samples. As a throw-back to earlier methodologies, numerous researchers have been developing and advocating the use of task-based exposure assessment strategies for chemical exposures(1–5) and noise.(6) Task-based (TB) methods have distinct advantages over full-shift (FS) methods in that they provide a more direct understanding of the sources of high exposure, and therefore help target effective exposure control interventions. In an epidemiology study context, task-based methods are particularly useful in that exposure levels can be estimated for a whole range of task combinations or differing amounts of time an individual might spend at particular tasks. In addition, TB methods may also greatly increase the efficiency of a sampling campaign by focusing measurement effort on those component tasks with the greatest exposure level or variability.(7,8)

The advantages of TB exposure assessment are most significant for jobs that have a high degree of variability in the time spent at individual tasks from day to day, or in which different workers do similar tasks, but for varying lengths of time. Such conditions are typical of the construction industry, making TB methods potentially particularly appropriate in this setting. For instance, despite a high degree of interindividual variability in noise exposure among construction workers in four trades, little variability could be explained by trade alone, whereas a substantial degree of variability could be explained by the task being done and environment in which the worker was exposed.[9]

One of the key methodological considerations in the development of a TB assessment strategy is the definition of *task*. A task may be highly specific, identifying the detailed environment, tool, and physical activity involved, or may be quite generic, specifying only the general actions involved. For instance, consider the construction task of building concrete forms. Although this is a well-recognized activity in building construction, it can be defined as one activity or as a compilation of several more specific tasks: materials handling, sawing, hammering, and erecting. Each of these tasks could be further specified by their individual components such as the method of manual materials handling, the type of saw (fixed or handheld power or hand saw), power or hand hammer, and so forth. Each of these individual tasks might be further defined by the location in which they occur; indoors, outdoors, the type of construction site, and so on. Any of these factors could have an important effect on the noise exposure received on a minute-to-minute basis.

Although highly specific task definition might be ideal, there are limitations to the degree of specificity that can be associated with the exposure data. A relatively high degree of task specificity and accuracy may be expected if the work process is directly observed by the exposure assessor during each measurement. A lesser degree of specificity may be possible with worker self-reports, and even broader categories of task may be required when workers are asked to recall their tasks on later interview.[10] Nevertheless, the specificity of task definition and the accuracy of the assessment of the time spent at each task are as important as the exposure levels in applying TB methods.

Despite the increasing appearance of TB methods in the literature, no peer-reviewed studies were found directly comparing FS and TB exposure estimates. Using a large dataset of noise dosimetry measurements in the construction industry, such a comparison has been produced, taking advantage of the highly variable construction work environment and data derived from data-logging noise dosimeters.

METHODS

Data

Data used for this analysis came from two large surveys of noise exposure among construction workers, each using very similar methods. The first survey assessed noise levels among four trades (carpenters, laborers, operating engineers, and ironworkers) on four large commercial/industrial building sites.[9] The second survey focused on electricians working on another five building sites.[11] Volunteers on each site wore data-logging dosimeters (Quest Q-300 or Metrosonics db308; Oconomowoc, Wis.) for a full shift. The dosimeter models had identical response characteristics over the range of levels of interest (80–140 dBA). Data used in the current analysis were 1-min sound pressure levels in decibels (dB) recorded using the specifications of the U.S. Occupational Safety and Health Administration hearing conservation standard, including "A" frequency weighting, slow meter response, a 90-dB criterion level, an 80-dB threshold, and a 5-dB exchange rate.[12] During each exposure measurement, subjects filled out a "task card," recording each predetermined activity, tool used, and location (indoors, outdoors, partially enclosed, or other, which included unspecified). Start and stop times for each task were recorded using a time-line with at least a 15-min resolution. Each sample was further classified as to the trade of the subject and the site type (cast-in-place, tilt-up, multiple concrete methods, and tenant improvement). These methods are described in full in previous reports.[9,11]

TABLE I. One-Minute Noise Levels, L_{ijk} (dBA), by Categories Recorded on Activity Cards

Variable	Categories	N	Mean	SD
Overall		248,677	75.7	12.8
Trade	electrician	83,802	74.6	12.8
	carpenter	60,421	75.9	10.5
	laborer	54,342	75.9	12.3
	ironworker	25,306	75.9	11.3
	operating engineer	23,557	78.8	9.6
Site type	cast in place concrete	111,080	76.4	11.2
	tilt-up concrete	26,185	74.4	12.8
	tenant improvement	32,079	69.3	11.7
	multiple concrete	78,084	77.9	11.0
Location	indoors	72,238	72.9	11.7
	outdoors	44,489	78.6	11.0
	partially enclosed	87,779	78.4	10.7
	other location	42,922	72.2	11.8
Activity group	hand tool	56,503	75.8	12.0
	near machinery	34,151	80.1	9.6
	no tool	41,509	74.6	11.7
	other tool	36,948	70.2	12.8
	pneumatic tool	3046	85.1	15.8
	power tool	76,270	76.6	10.6
Tool group	electric	48,780	76.9	10.7
	gas	732	75.7	11.6
	hammer	19,527	79.7	9.2
	other hand tools	47,261	74.7	12.4
	heavy equipment	26,551	79.3	10.0
	pneumatic	4545	85.7	14.2
	none	83,242	72.7	12.6
	powder actuated	1071	78.5	8.7
	other	15,719	77.6	9.5

A total of 53 different activities and 42 different tools were recorded by the subjects. Each of these variables were reclassified into simpler activity and tool groups, which were defined a priori. Activity groups were defined by the predominant noise source associated with the activity, and tool groups were defined by the drive mechanism of the tool. Although these two variables have similar labels, there was significant variation within each category, allowing both grouped variables to be used independently. A list of the variables with which task was defined is given in Table I.

It was common for up to three different activities or tools to be recorded at any particular time. To retain the potential contribution of these multiple tools and activities, while putting an appropriate weight on each, the data set was restructured to include a record for each activity and tool combination at any particular minute. Weights (w_{ijk}) were assigned to each record, inversely proportional to the number of categories reported during that minute. For instance, if two tools were reported for one minute, two records were produced, each with a weight of 0.5. If three tools and three activities were reported, nine lines of data were recorded, each with a weight of 0.11. All statistics were calculated using these weights. Although this solution is designed to minimize the misclassification of tasks, some error inevitably remains. Multiple tasks reporting occurred in fewer than 14% of the minutes, so the error is unlikely to have a major impact on the results.

1-Min Models

Six alternative linear models for the 1-min exposure data were developed for predicting task-associated exposure levels. The models were selected to provide a range of complexity and specificity. All models included an activity variable, in either the grouped (6 levels) or ungrouped (53 levels) form. In addition to activity, multiple variable models also included grouped tool, site type, location, and trade. Finally, these multiple variable models were also fit with the interaction between the activity variable and the other four covariates.

Calculation of FS and TB Exposure Levels

Full-shift exposure levels for individual i on shift j ($L_{ij,FS}$) were calculated using the standard method for averaging noise exposures measured over sequential time periods,

$$L_{ij,FS} = q \log_{10}\left[\frac{1}{\sum_k w_{ijk}} \sum_{k=1}^{n_{ij}} w_{ijk} 10^{L_{ijk}/q}\right] \tag{1}$$

where L_{ijk} are the 1-min average A-weighted noise levels measured over k=1 to n_{ij} time periods by the dosimeter, and q is the exchange rate (ER) divided by $\log_{10}$ of 2, or 16.6 for an ER of 5 dB.[13] In most cases the time periods were the single minute periods recorded by the data-logger. Where more than one task or tool was reported simultaneously, the periods were fractions of minutes with weights, w_{ijk}, corresponding to these fractions of minutes. Note that the sum of the weights is equal to the total number of minutes (M) of observation for an individual subject i, on shift j, that is, $\Sigma_{k=1}^{n_{ij}} w_{ijk} = M_{ij}$.

For exposures other than noise, the typical method of calculating a TB exposure estimate is a time-weighted average, with the average level for each task weighted by the time spent doing that task for each shift:

$$L_{ij,TB} = \frac{1}{M_{ij}} \sum_{t=1}^{T} (M_{ijt}\mu_t) \tag{2}$$

where the TB exposure levels ($L_{ij,TB}$) are calculated using (M_{ijt}), the total time each subject, i, reported on day, j, in each task, t, and where T is the total number of tasks, and μ_t is the average level associated with each task. Note that if a person does not perform a particular task, $M_{ijt}=0$. The analogous calculation for a task-based estimate for noise exposure, using the nonlinear averaging of noise exposure levels would be

$$L_{ij,TB} = q \log_{10}\left[\frac{1}{M_{ij}} \sum_{t=1}^{T} M_{ijt} 10^{L_t/q}\right] \tag{3}$$

where L_t is the average noise level in dBA for task, t. In this analysis the TB estimates were calculated in an equivalent manner, but using the 1-min data file as was done for the FS measurements. However, instead of using the 1-min average exposure levels, L_{ijk}, as was done in Equation 1, the authors substituted the model predicted task-associated levels, μ_{ijk}, which are equal to L_t for all k periods within task t. Thus, the FS measurements are based on the actual 1-min levels, and the TB estimates are based on 1-min predicted levels with a constant value for all time periods during which the same task was done:

$$L_{ij,TB} = q \log_{10}\left[\frac{1}{\sum_k w_{ijk}} \sum_{k=1}^{n_{ij}} w_{ijk} 10^{\mu_{ijk}/q}\right]. \tag{4}$$

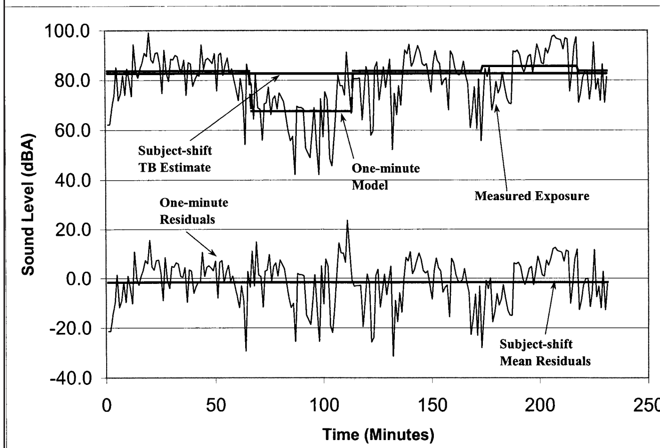

FIGURE 1. Illustration of minute-to-minute exposure levels with corresponding TB estimates and model residuals

Again, weights, w_{ijk}, were used for minutes in which more than one task was noted.

When calculating the TB estimates from the 1-min data file, additional important information can be obtained from the residual variation of the measured exposure compared with the modeled estimates. Figure 1 illustrates the relationships between the measured exposure levels (L_{ijk}), and the task-associated estimates (model prediction) for four different tasks during this sampling period. The difference between the model estimate and the measured values, that is, the residuals, are shown fluctuating in the lower part of the graph. The mean ($\bar{\varepsilon}_{ij}$) and variance (σ^2_{ij}) of the residuals within each subject-shift describe the two components of the error associated with the TB estimates.

In this way, the minute-long exposure levels can be described in terms of the TB model using these three components of the model: the simple prediction alone (i.e., using Equation 4), the residual means, $\bar{\varepsilon}_{ij}$, and the residual variance, σ^2_{ij}, estimated as the variance of ϵ_{ijk}. Under assumptions stated in the Appendix, Equation 4 can be expanded to:

$$L_{ij,TB} = 1 \log_{10}\left[\frac{1}{\sum_k w_{ijk}} \sum_{k=1}^{n_{ij}} w_{ijk} 10^{\mu_{ijk}/q}\right] + \hat{\bar{\varepsilon}}_{ij} + \frac{\hat{\sigma}^2_{ij}}{2q}. \tag{5}$$

Derivation of this equation is given in the Appendix. Equation 5 indicates the three components of the task-based estimate of the shift-specific exposure: the task-based predictions, the residual mean, and the residual variance. Different estimates of $L_{ij,TB}$ can be obtained by including one or more of these terms. It is important to understand that these two additional components of the model are available only within the data being used for model development. That is, if the TB estimates are used to predict exposures for individuals or days without exposure data, the residual mean and variance components would not be directly available.

The TB estimate using the predictions alone, or supplemented with the residual variance and residual mean, were compared with FS measurements by regressing the TB estimates on the FS measures.

RESULTS

A total of 248,677 minutes of exposure were recorded on 502 work shifts on 189 subjects. An average of 2.7 shifts was

TABLE II. Model Fit (r^2) for 1-Min Regression Models Used to Estimate Task-Associated Exposure Levels (dBA)

Model Type	Covariates	Grouped Activity (G)	Ungrouped Activity (U)
Single variable (S)	none	0.05	0.12
Multiple variable (M)	trade site type tool type location	0.12	0.15
Multiple variable with interactions (MInt)	trade site type tool type location plus interactions with activity	0.14	0.20

monitored on each subject, with 71 subjects providing only a single shift of measurements, and a maximum of 12 shifts of measurements on one subject. The 502 FS noise levels calculated using Equation 1 were approximately normally distributed with a mean (±SD) of 82.6 (±6.2) dBA. The 1-min exposure levels were analyzed by trade, site type, location, tool group, and both grouped and ungrouped activity (Table I; only grouped activity shown). The 1-min exposure levels averaged 75.7 (±12.8) dBA, with relatively small variation observed between trades.

Using the 1-min measurements, six regression models were developed to estimate the average levels associated with alternative definitions for task. These models are shown in Table II. As a result of the large minute-to-minute variation in recorded levels and the rather crude predictor variables, the models explained a relatively small portion of the overall variance. Activity alone produced model r^2 of .05 for the grouped variable and .12 for the more specific ungrouped variable. Adding four covariates to these models increased the r^2 substantially, to .12 and .15, respectively, and interactions further increased the model fit, with the r^2 up to .20.

Task-based estimates were calculated for each model using an increasing number of components from Equation 5. Using the model predictions alone, mean estimates of full shift averages were about 76 dBA, similar to the average of the 1-min levels. Because these two methods of calculation ignore the significance of within-task variability in decibel levels, they result in a substantial bias of about −6 dB compared with the average FS measurements (82.6 dBA) (first section of Table III). With increasing specificity of the 1-min predictive model, the variability of the estimates increases, with standard deviations increasing from 2.1 to 4.9 dBA. In addition, the percent of variation of the FS measures explained by the TB estimates (r^2) increases from an r^2 of .08 to .55 for predictive models of increasing specificity.

By adding the residual variance to the model, the TB exposure estimates averaged about 83.5 dBA, with only a slight bias left after accounting for the within-task variability (second section of Table III). The variability was also increased to a small degree, indicating that the shift-specific variance provided a small additional adjustment. Similarly, the percentage of variation explained by the variance-adjusted TB estimates was slightly improved for each model.

Adding the shift-specific residual mean into the TB estimate did not change the mean estimates, with the bias remaining virtually unchanged and small (last section of Table III). The variability of the estimates was again increased to a SD of about 6.9 dBA. This variability was achieved now by all TB model estimates, regardless of the specificity of the underlying 1-min predictive model. Using the residual mean adjustment, most of the error was accounted for, and the correlation between the TB estimates and FS measurements substantially improved, yielding an r^2 of about .9 for each model, again regardless of the specificity of the TB predictive model. However, it must be understood that this final "correction" of the TB estimates can be done only in this context in which the full shift exposure level is actually known. In a TB exposure assessment study these residual means would not be available, and this high agreement between the estimates and the unknown true exposure could not be achieved.

The relationships between the FS measurements and TB estimates for the six models using the prediction alone, and also adding the residual variance and the residual mean, are shown graphically in Figure 2. Note that the array of plots in Figure 2 is the same as the results displayed in Table III. These plots clearly show the increasing specificity of the six predictive models from left to right. Relatively poor correlation and a substantial bias was observed for the predictions alone (first row). The bias was corrected

TABLE III. TB Estimates of Exposure and Relationships (r^2) Between FS and TB Noise Exposure Levels (dBA) (n = 502)

	Model					
	1 GS[A]	2 GM	3 GMInt	4 US	5 UM	6 UMInt
TB L_{OSHA} (Pred)						
Mean	76.0	76.1	76.2	76.2	76.2	76.3
(SD)	(2.1)	(3.7)	(4.0)	(3.5)	(4.1)	(4.9)
r^2	0.084	0.30	0.38	0.30	0.38	0.55
T L_{OSHA} (Pred + RVar)						
Mean	83.4	83.5	83.6	83.6	83.6	83.6
(SD)	(3.9)	(4.6)	(4.8)	(4.5)	(4.9)	(5.4)
r^2	0.11	0.33	0.40	0.31	0.41	0.59
TB L_{OSHA} (Pred + RMean + RVar)						
Mean	83.5	83.5	83.6	83.6	83.6	83.6
(SD)	(6.9)	(6.9)	(6.9)	(6.9)	(6.9)	(7.0)
r^2	0.89	0.90	0.89	0.89	0.90	0.89

[A]Models described as G or U for grouped and ungrouped activity, and S or M for single or multiple predictors, respectively, and Int for interactions between activity and other covariates.

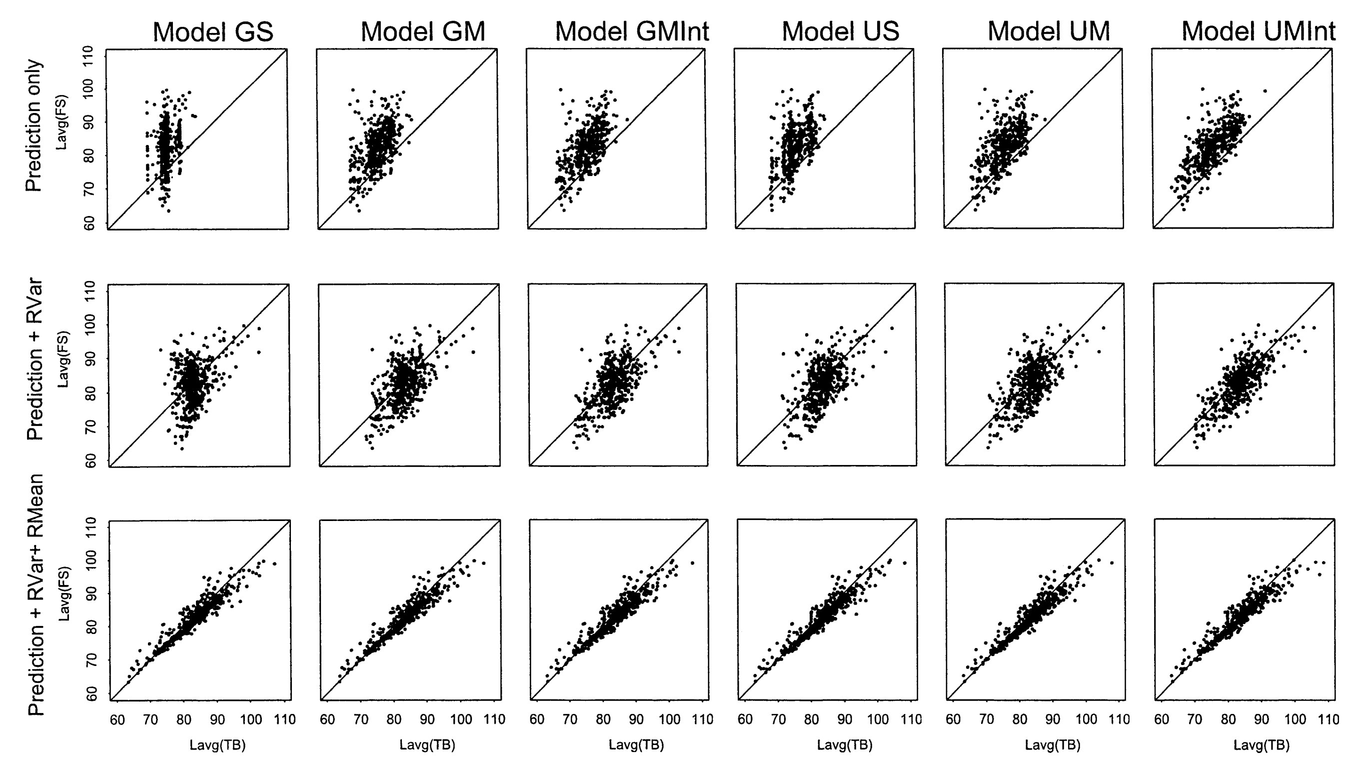

FIGURE 2. Scatter plots for six task models comparing TB with FS estimates

and the variance somewhat improved when the residual variance was added to the model (second row). The estimates were very close to the observed FS values after the residual mean was added to the model (third row).

DISCUSSION

Although TB strategies for assessing FS exposures have received a significant degree of attention in recent years, no explicit comparison of the two methods has been published. Exploiting a data set of continuous monitoring for noise exposure levels associated with relatively detailed task-cards on construction sites, a direct comparison of FS exposure measurements and TB estimates of the same exposures was possible. Depending on the specificity of the task definitions, the overall agreement between the TB estimates and FS measurements was relatively low—with r^2 ranging from less than 10% to as much as 55%. The higher range of these correlations appears encouraging; however, it would be rare to be able to achieve the level of model specificity provided by this multivariate model with interactions. Overall, this result suggests that a simple TB assessment strategy does not capture the full variation of FS exposures and therefore introduces a significant degree of measurement error into exposure estimates. Methods for improving TB estimates are needed.

The use of noise as the exposure of interest in this study introduces a complexity that is typically not present for other environmental contaminants. Because noise is characterized in decibels, which requires a logarithmic transformation of the actual sound pressure, noise levels measured in decibels follow nonlinear relationships. Thus, in summing or averaging noise levels, the sound pressure levels, not decibels, are used in the calculations. In the process of modeling the sound levels expressed in decibels, all of the variability within task is eliminated (actually shifted to the residual variance), and as a result the modeled TB estimates included only the between-task variability and none of the within-task. The loss of within-task variability introduces a significant bias in the TB estimates unless corrected. This bias could also be corrected with an overall estimate of variability, which in practice could be estimated along with the TB estimates. This bias is important for nonlinear exposure metrics such as noise and should not be overlooked by hygienists using a TB methodology for assessment. For instance, if a handheld sound level meter were used to estimate the sound levels associated with a particular task, and these levels were then used to produce full shift estimates, the lost within-task variability should produce a substantially biased estimate of exposure. For other agents that follow linear relationships this problem will not occur.

The nonlinearity of the equation used for characterizing average noise exposures also gives rise to more assumptions and thus a greater opportunity for assumption violations. For instance, the residuals were replaced with their expected values (the residual mean and variance terms in Equation 5) even though the normal distribution assumption for ϵ_{ijk} may not hold exactly. Although the model residuals appeared symmetrical, they had somewhat heavier tails than would expected in a normal distribution. Furthermore, our models, especially Equation 5, assumed that the 1-min TB model residuals are serially independent. However, a first-order autoregressive model fit the within subject-shift residuals fairly well with an average serial correlation of about .6. These assumption violations contribute to the small amount of positive bias seen for the TB estimates in the second and third sections of Table III. However, because the residual variance term does not explain much of the variation in FS measurements, they do not have a large impact on the relationship between the FS measurements and TB estimates.

The errors associated with the TB estimate derive from several sources. These include limitations in the accuracy and specificity of the self-reported activities, the model used to estimate the task-associated levels, the between-subject variability doing the same task, and the day-to-day (or task-to-task) variability in exposure. Although there has been significant attention to the within and between subjects variability in exposure measured on a full shift basis, these sources of error also operate on a task-specific level. These sources of error are minimized in the current analysis because the FS measurements were obtained using the same data on which TB estimates were derived. If task-associated exposures are extrapolated to an independent set of subjects or work conditions, the level of agreement is likely to be worse than shown here.

The model used to estimate the task-associated levels may be constructed at many different levels of specificity. The current analysis presents a range of task models, from a simple model with activities grouped into 6 broad categories (model GS), to a multiple variable model with interactions that includes a total of 755 possible categories. The variables in this model included both shift-specific variables (trade, site type) and variables that could change repeatedly within a shift (activity, tool, location). Despite the large number of possible "tasks" that a subject might feasibly do within a shift, the actual number of tasks in a day averaged about three, with a range of 1 to 10.

The specificity of the model has a number of important implications. As noted in the current analysis, the more specific models enhanced the agreement between the TB estimates and FS exposures. In addition, the more specific models also increase the variability of the estimates. Increased variability suggests that a greater range of actual exposures is being more effectively modeled, and the model is more effectively estimating the tails of the true exposure distribution. On the other hand, as the model gets more specific, the individual estimates are less robust—that is, they are more vulnerable to random variation in the model. This tradeoff between specificity and random error is analogous to contrast and precision in the context of exposure grouping in which the benefit of achieving a large contrast in exposure is traded off by having poor average precision in exposure groups.[14] In assessments that maximize contrast and precision, measurement error bias can be minimized.[15]

Although the current analysis would suggest that more specific task definitions produce better results, the practical feasibility of detailed task classification must also be considered. Only in rare situations is it possible to have an observer record detailed tasks for each exposure measurement. More commonly, workers are asked to fill out a task card diary (as done in the current study) or record tasks using an end-of-shift questionnaire. In several studies documented moderate to good agreement between worker task records and researcher observations were documented.[9–11] The extent of agreement appears to depend on the complexity and clarity of the task definition.[16] Even more difficult is the situation in which workers are asked to recall task information over a long period of time, as would be done for a retrospective or prospective study. At 6 months postexposure, workers were able to recall construction tasks with a remarkable degree of accuracy, however, using a relatively simple set of task definitions.[10]

The TB approach is perhaps most importantly limited in that it uses the average exposure level calculated for a task across all individuals and days for which monitoring data are available. In assigning this TB average (L_t) to all individuals, the interindividual and day-to-day variability in task-specific noise levels is ignored. However, part of the TB interindividual variability is addressed by allowing the time at task to vary by individual (M_{ijt} in Equations 2 or 3). In fact, allowing time-at-task to vary from day to day is the key advantage of the TB exposure assessment strategy. However, even after incorporating the daily time at task into the estimates, it has been shown that a significant degree of inter- and intraindividual variability remains, as represented here by the residual means and variances.

In the current exploration, the authors were able to almost completely account for these unobserved variables by adding back into the model the known residual means. Obviously, in most situations this would not be possible or necessary if the FS data were available. One possible method that could be employed to correct for interindividual differences would be to take a small sample of measurements from each subject and use these to correct the individual-specific estimates. Such a strategy would be easily implemented in the future by assuring that each subject in a study had at least some minimal number of monitoring days, so that the subject-specific adjustment could be derived. This strategy was attempted within the current data set by taking a random sample of one exposure day per subject and using this as an estimate of the individual's residual mean for all days of monitoring. However, even with this adjustment, 40% or more of the variation of the FS measurements could not be explained by the TB estimates. This poor result was because the information contained by a single sample is inadequate to characterize interindividual exposure variation. Other novel approaches to estimating the individual residual mean should be further explored.

TB assessment holds a significant promise for improving exposure assessment for epidemiologic studies, especially when subjects vary daily in their task assignments or work environments. However, the success of the TB model depends on how well task can be defined and characterized, and on the ability to develop adequate models to account for the interindividual variability that is not addressed by the time spent in tasks. If there is little interindividual variability in exposure during a specified task in comparison to between-task variability, then TB methods may prove much more successful. However, in many environments such as construction, in which noise levels for any particular task vary widely with the tools used, the context in which it is done, and individual work methods, then TB methods of exposure assessment appear to have limited accuracy.

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APPENDIX

The expanded TB estimate equation (Equation 5) is derived from the FS measurements for subject-shifts (Equation 1) after converting to natural logarithms:

$$L_{ij,FS} = q'\ln\left[\frac{1}{\sum_k w_{ijk}} \sum_{k=1}^{n_{ij}} \exp\left(\frac{L_{ijk}}{q'}\right)\right] \tag{A.1}$$

where k indexes observation within subject i and shift j, and $q' = q/1n10$. Now let $L_{ijk} = m_{ijk} + e_{ijk}$, where μ_{ijk} are the predictions and ε_{ijk} are the errors, and assume $\varepsilon_{ijk} \sim N(\bar{\varepsilon}_{ij},\sigma^2{}_{ij})$. Then $E[\exp(\varepsilon_{ijk}/q')] = \exp(\bar{\varepsilon}_{ij}/q' + \sigma^2{}_{ij}/2q'^2)$. We assume μ_{ijk} and ε_{ijk} are independent and note that it is reasonable to replace $\exp(e_{ijk}/q')$ by its expected value when summing over all k. This yields

$$L_{ij,TB} = q'\ln\left[\frac{1}{\sum_k w_{ijk}} \sum_{k=1}^{n_{ij}} \exp\left(\frac{\mu_{ijk}}{q'} + \frac{\bar{\varepsilon}_{ij}}{q'} + \frac{\sigma^2_{ij}}{2q'^2}\right)\right]. \tag{A.2}$$

To obtain Equation 5, simplify and substitute the estimates $\hat{\bar{\varepsilon}}_{ij}$ for the subject-shift residual mean $\bar{\varepsilon}_{ij}$ and $\hat{\sigma}^2_{ij}$ for the subject-shift residual variance $\sigma^2{}_{ij}$ under the assumption that the ε_{ijk} are independent and identically distributed. Although the data indicate the normality assumption holds approximately, the ε_{ijk} within subject-shifts exhibit serial dependence. The residual disagreement between A.2 and A.1 (Table III, third row) results from these simplifying assumptions and is magnified when time-weighted averaging is not linear.

APPLIED STUDIES