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William A. Heitbrink , Michael G. Gressel , Thomas C. Cooper , Thomas Fischbach , Dennis M. O'brien & Paul A. Jensen

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Video Exposure Monitoring—A Means of Studying Sources of Occupational Air Contaminant Exposure, Part 2—Data Interpretation

William A. Heitbrink, Michael G. Gressel, Thomas C. Cooper, Thomas Fischbach, Dennis M. O'Brien, and Paul A. Jensen
Department of Health and Human Services, Public Health Service, Centers for Disease Control, National Institute for Occupational Safety and Health, 4676 Columbia Parkway, MS R-5, Cincinnati, Ohio 45226

Excessive exposures to air contaminants can be determined by conventional sampling with pumps and sampling media; however, such results do not provide insights into the reasons for the excessive exposures. The analog or digital output from direct-reading instruments can be captured by using data-logging equipment. While data are being logged from direct-reading instruments, the activities in the workplace can be recorded using a video camera. These data can be analyzed to find reasons for excessive air contaminant exposures. Three approaches have been used to quantitatively present the results of real-time sampling. First is the use of descriptive statistics to describe the data. Frequently, useful insights can be obtained from descriptive statistics and graphs. When activities in question are sufficiently separated in time, this can be a very fruitful approach. At other times, a second approach, statistical analysis, may be needed to evaluate whether a certain activity is causing an increase in worker air contaminant exposure. Spreadsheet programs, which have statistical analysis and database capabilities, can be used to address the autocorrelation by deleting data and to perform statistical analysis. Because deleting data to remove autocorrelation can result in the loss of too much information, a third approach involving time series analysis techniques has been used to analyze the data. After analyzing the data by these techniques, changes in the workplace can be focused upon activities that are actually causing important increases in the worker's air contaminant exposure. Because the data analysis may involve a number of assumptions that may not adequately reflect physical reality, conventional air sampling techniques are needed to evaluate the effect of workplace changes upon worker air contaminant exposure. Heitbrink, W.A.; Gressel, M.G.; Cooper, T.C.; Fischbach, T.; O'Brien, D.M.; Jensen, P.A.: Video Exposure Monitoring—A Means of Studying Sources of Occupational Air Contaminant Exposure, Part 2—Data Interpretation. Appl. Occup. Environ. Hyg. 8(4):339–343; 1993.

Introduction

Although conventional sampling with pumps and sampling media is used to determine excessive air contaminant exposures, such sampling usually provides little insight into the exposure sources. While videotaping workplace activities, data-logging equipment can be used to simultaneously record the output of direct-reading instruments. As described in Part 1, the image of a bar, the height of which is proportional to concentration, can be placed on the video recording of a worker. This is a useful tool for explaining how a worker receives exposure to air contaminants.

To develop recommendations for controlling worker air contaminant exposures, National Institute for Safety and Health (NIOSH) researchers frequently study the association between workplace events and air contaminant exposures. Such analyses provide insights as to the exposure sources. The contribution of various elements of a job to the worker's exposure can be identified. This article's purpose is to provide an overview of data analysis techniques.[1–4] In addition, real-time concentration data can be used to estimate air contaminant generation rates and the effectiveness of dilution ventilation. The techniques for accomplishing this are beyond the scope of this paper and are discussed elsewhere.[5]

Assembling the Data Set

The concentration measurements and the description of workplace events are easily assembled in a spreadsheet. Data-logger software is usually able to format the data so they can be imported into a spreadsheet. The file imported into the spreadsheet will contain two or more columns of data. One column of data will contain time and the other column(s) will contain the output signal of the measuring instrument. After importing the exposure data into a spreadsheet, codes for explanatory variables, which de-

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scribe the workplace events occurring during each concentration measurement, are placed in separate columns of the spreadsheet. These variables may be qualitative (i.e., the performance of a specific work task) or they may be quantitative (i.e., the rate at which a chemical is being used). The qualitative variables may be coded as physical descriptors or as dummy variables (1's and 0's) corresponding to "yes" or "no" to indicate whether an event occurred. The coding of qualitative variables depends upon the type of data analysis and the ability of the data-analysis software to automatically generate dummy variables. After adding the explanatory variables, the data set exists as a time series in which each time has a concurrent concentration and explanatory variables.

This time series can be used to evaluate the association between workplace activities and exposures. However, data-analysis techniques are complicated by the time required to transport the air contaminant to the instrument and the time required for the instrument to respond to a change in concentration. As a result, concentration is a function of explanatory variables in the preceding measurements and concentration is said to lag in time behind the explanatory variables. The magnitude of the lag is determined through knowledge of the process or is addressed in statistical analysis of the data. When the statistical analysis software has the capability to generate lagged variables, there is no need to adjust the data to compensate for the lag between events and changes in exposure.

Generally, spreadsheet programs do not have the ability to generate lagged variables. To compensate for the lag between events in the workplace and changes in exposure, the spreadsheet can be used to "slip" the air contaminant concentration data with respect to the explanatory variables and time. To do this on a spreadsheet, the concentration data are moved up a few rows (to an earlier time). The difference between the time in the row to which the concentration is moved and the actual time of the concentration measurement is the lag. This move matches the concentration measurements with the causal events.

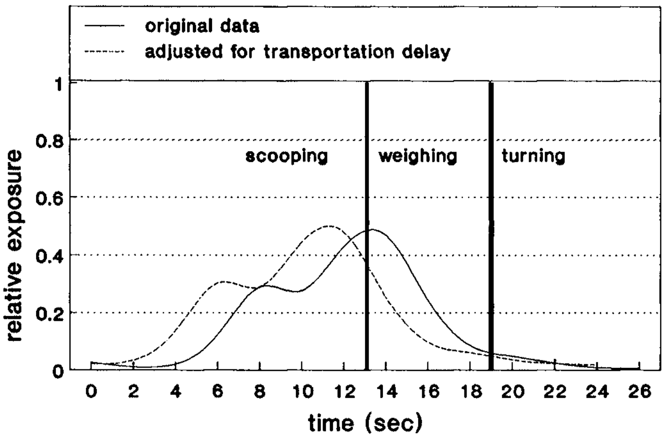

FIGURE 1. Data showing the effect of adjusting the data for the transportation delay. The annotations refer to the specific tasks during a weigh-out operation. These data were obtained by Gressel *et al.*[10]

Figure 1 illustrates the importance of understanding the magnitude of the lag. In this figure the original data and the data after adjustment for the transportation delay are plotted. In the original data the peak exposure occurs at the start of the weighing activity. Based upon a knowledge of the air flow patterns around the worker, at least 2 seconds are needed to transport the air contaminant into the worker's breathing zone. Thus, the peak exposure appears to be generated during the scooping activity. If the data had not been adjusted, the peak exposure could have been attributed to the wrong activity.

Exposure Source Identification

Worker exposure can be plotted as a function of time and the activities contributing to the exposure can be noted on the plot. For example, in Figure 2, the activity "PUSH" appears to be causing much of the dust exposure. Summary statistics can be used to estimate the fraction of the worker's total exposure caused by the events in the workplace. Such results are used to decide which components of a job should be controlled to reduce worker air contaminant exposure. When an investigator needs to evaluate whether activities are causing differences in concentration, statistical analysis is needed.

Spreadsheet programs such as Lotus 1-2-3® (Lotus Development Corporation, Cambridge, Massachusetts) can be used to perform multiple regression that evaluates whether a dependent variable is a function of the explanatory variables. Typically, the dependent variable is the contaminant concentration, but it also may be a concentration difference or other mathematical function of the concentration. In regression analysis the data are fitted to a model of the following form:[4,6]

$$\text{Exposure Concentration} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon_i \quad \textbf{(1)}$$

where:
β_0 = constant or intercept of regression line
$\beta_1 \cdots \beta_n$ = regression coefficients
$X_1 \cdots X_n$ = explanatory variables
ϵ_1 = the residual for each data point that is the difference between the measured and computed value of concentration. It has a mean value of zero and is assumed to be normally distributed.

The example spreadsheet shown in Figure 3 was prepared to facilitate the discussion of multiple regression in a spreadsheet environment. The explanatory variables are usually dummy variables that have a value of 1 or 0 to indicate whether the event, such as use of a specific tool, has occurred. In this model the intercept defines a base exposure level: sanding with tool A. The regression coefficients are the difference between the base exposure level and the exposure during the activity. In Figure 3 β_1 is the difference in exposure between sanders A and B.

Some spreadsheet programs supply enough statistical

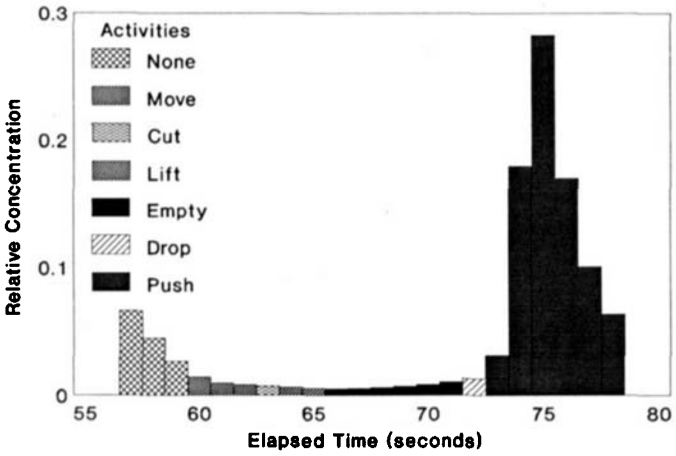

FIGURE 2. Relative exposure, as measured by aerosol photometer during bag dumping.(2) Empty bags were discarded by pushing and collapsing the bags into a drum that was located outside of the hood.

parameters to test whether the regression coefficients differ significantly from zero. In Figure 3, the standard errors for the regression coefficients are supplied. To obtain the significance level for the regression coefficient, a t-statistic can be computed by dividing the regression coefficient by the standard error. The probability for the t-statistic, which can be obtained from a table of t-statistics in many statistics textbooks, is the probability that chance could have caused the observed value of the regression coefficient.

Generally, real-time data do not consist of simple sets of independent measurements. Each concentration measurement may be some function of the preceding measurements. This phenomenon, called autocorrelation (also referred to as serial correlation), causes an underestimation of the variability in the data and an overstatement of the level of confidence for concluding that the explanatory variables affect the worker's exposure. Autocorrelation can occur because instruments do not respond immediately to changes in concentration and because time is required for the air contaminant to mix in the worker's breathing zone. The response of an instrument to a change in concentration is somewhat analogous to the effect that a change in inlet concentration has upon the outlet concentration of mixing a tank.(7) Figure 4 illustrates how the outlet concentration responds to changes in the inlet concentration. In the mixing tank the outlet concentration is a function of the inlet concentration in the preceding time intervals. Because of the mixing in the worker's breathing zone and in the instrument, real-time data generally involve some autocorrelation.

To evaluate the degree of dependence or autocorrelation, a regression equation is used to model the residual (ϵ_i) as a function of lagged residuals, which are the residuals in the previous readings. As was done in Figure 3, a regression coefficient, standard error, and a t-statistic are computed for each of the lagged residuals. If the real-time data are independent, the absolute value of the observed t-statistics should be less than the t-statistic for the 95th percentile of Student's *t*-distribution. If the probability for a larger, absolute value of an observed t-statistic at exclusively a lag of one time interval is less than 0.05, each residual is dependent only on the residual preceding it. Then, the autocorrelation can be removed from the original data set by eliminating every other data point and then performing a regression on the reduced, time independent data set. Similar data removal can be performed if a time dependence exists for readings separated by two, three, or more time intervals.

At times, censoring the data to remove autocorrelation results in the loss of too much information. Then, time series analysis methods can be performed to study the relationship between the explanatory variables and air contaminant concentrations.(8,9) The objective of the time series analysis is to remove the autocorrelation from the concentration measurements so that the effect of the explanatory variables upon concentration measurements may be studied.

Frequently, time series analysis involves several iterations of a two-step process.

1. Develop an explanatory model similar to Equation 1 that relates exposure to events in the workplace.
2. Using the residuals ϵ_i obtained from step 1, a time series model is developed to describe the relationship between sequential exposure measurements.

	A	B	C	D	E	F
1						
2	AN EXAMPLE SPREAD SHEET					
3	*One worker uses two tools (A&B) to perform his job.*					
4	Which tool causes the greatest exposure?					
5						
6		Measured			Predicted	
7	Time	Concentration	Tool	Constant	Concentration	Residual
8		(Y)	(X1)	(X2)		
9	0.0	1.0	0.0	1.0	1.1	-0.1
10	1.0	1.0	0.0	1.0	1.1	-0.1
11	2.0	1.2	0.0	1.0	1.1	0.1
12	3.0	1.3	0.0	1.0	1.1	0.2
13	4.0	1.0	0.0	1.0	1.1	-0.1
14	5.0	4.0	1.0	1.0	3.6	0.4
15	6.0	4.0	1.0	1.0	3.6	0.4
16	7.0	3.0	1.0	1.0	3.6	-0.6
17	8.0	2.0	1.0	1.0	3.6	-1.6
18	9.0	5.0	1.0	1.0	3.6	1.4
19						
20		MODEL	Y = β_1*X1 + β_0 * X2			
21			Exposure = 2.5 * TOOL + 1.1			
22						
23			Regression Output			
24		Constant			0.0 <--Forced through 0	
25		Std Err of Y Est			0.81	
26		R Squared			0.75	
27		No. of Observations			10	
28		Degrees of Freedom			8	
29						
30					Tool	Intercept
31		X Coefficient(s)			2.5	1.1
32		Std Err of Coef.			0.5	0.36
33		t-statistic			5.0	3.05
34						
35		Exposure when using tool "A"				For "A", TOOL=0
36			EXPOSURE = 2.5 * 0 + 1.1			
37			EXPOSURE = 1.1			
38						
39		Exposure when using tool "B"				For "B", TOOL=1
40			EXPOSURE = 2.5 * 1 + 1.1			
41			EXPOSURE = 3.6			

FIGURE 3. An example of spreadsheet data analysis. Typical data analysis would involve much more data.

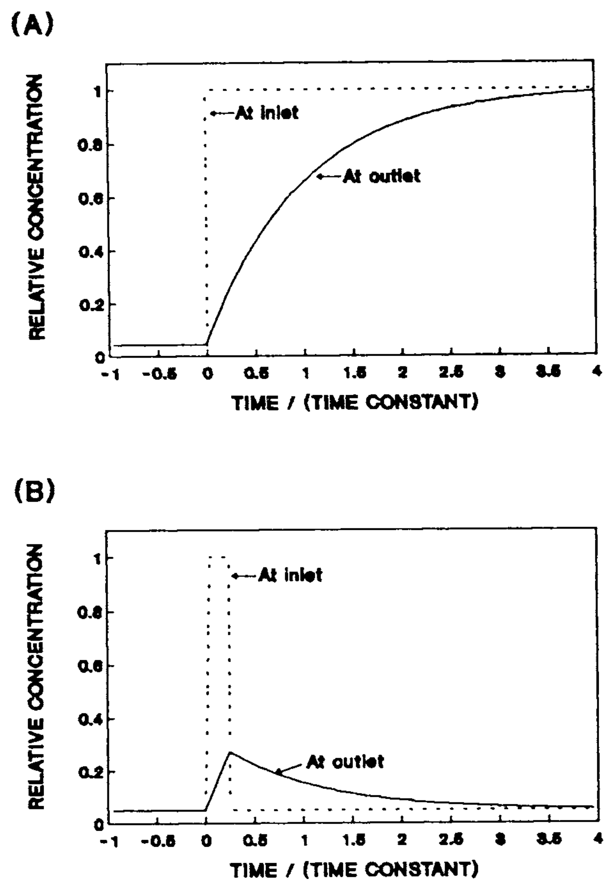

FIGURE 4. Time-dependent concentration at a mixing tank for: (A), a step change in concentration; and (B), a concentration pulse. The time constant for a mixing tank is the tank volume divided by the flow rate into the tank.

The explanatory model developed during the first step includes explanatory variables that describe workplace events, both in the time interval coincident with the worker's exposure and in time intervals preceding the worker's exposure. The time series model is used to transform the original data and regression analysis is performed to evaluate which parameters are affecting the worker's air contaminant exposure. Because the time series analysis uses residuals from a model that may not adequately fit the data, the estimate of the variability of the concentration data may be distorted. This may lead to a poor estimate of the transformation required to achieve independence. Therefore, the cycle of performing a time series analysis to estimate a transformation, which is then used to revise the real-time explanatory model, might be repeated several times. An example of such an analysis is presented elsewhere.[10] A less rigorous and less time-consuming approach, which needs further evaluation and development, is to include the lagged values of the worker's exposure as explanatory variables in the model (Equation 1) and to omit the time series analysis step completely. This may sufficiently adjust for autocorrelation and allow the data analysis to proceed in a routine fashion.

Conclusions and Recommendations

Thoughtful analysis of real-time data can provide useful insights that focus control measures upon actual exposure sources. Special care and considerations are needed throughout data collection and data analysis. Although vast amounts of data on video exposure monitoring can be collected, data coding and analysis can be very time-consuming. Thus, video exposure monitoring studies should be carefully planned.

In analyzing the data the transportation delays and effective response time are important considerations that affect how the data are coded and analyzed. The time required for the concentration to change limits the amount of subclassification that can be done to study the effect of job tasks upon exposure. Job subclassifications, which are shorter than the instrument's response time, may not be useful. In analyzing the data, exposure is usually modeled as a function of lagged explanatory variables. Experimental measurements of transportation time and effective instrumental response time should be helpful for determining whether the models used in the data analysis were reasonable.

The analytical techniques presented here assume that the data are being analyzed because of a need to implement changes in the workplace. In the course of this analysis, assumptions may be made that do not adequately reflect physical reality. Good industrial hygiene practice dictates that conventional sampling be done to evaluate the effect of workplace changes upon the worker's exposure. This presents an opportunity to evaluate the assumptions made in the analysis of the real-time data.

Disclaimer

Mention of company or product name does not constitute an endorsement by the National Institute for Occupational Safety and Health.

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