British Occupational Hygiene Society
Working for a healthier workplace

The Occupational Hygiene Newsletter Insert

Bayesian Thinking in Exposure Assessment

Gurumurthy Ramachandran

Over the past few years, there has been an explosion of interest among occupational hygienists in a seemingly esoteric field called Bayesian statistics. Why are we, who pride ourselves on being practical and hard-headed realists, devoting time to such arcana ? Occupational hygienists try to ensure a safe working place, and one important way to achieve this is by understanding exposures and designing control strategies and systems to make sure that people are protected. How are Bayesian statistics connected to this ? In the Bayesian view, a measurement serves to refine previous knowledge of physical parameters by adjusting their probability distributions. Most industrial hygienists are Bayesian practitioners (even if unknowingly and informally) when they make initial educated guesses about exposures in a workplace (even if they are crude estimates of high versus low exposures) which are subsequently refined by actual measurements of exposures. The Bayesian mathematical framework formalizes this common sense approach to exposure assessment.

Bayesian statistics began with a posthumous publication in 1763 by the the Reverend Thomas Bayes, an amateur mathematician and Nonconformist minister from the small English town of Tunbridge Wells. Bayes theorem is a simple and uncontroversial result in probability theory. However, its specific uses have been controversial over the past century. The novel feature of Bayesian statistics is that probability is viewed as a degree of belief in a proposition, rather than the frequency of an event. This key insight allows us to combine qualitative information with quantitative (data) information to arrive at a more confident final, probabilistic output. This is similar to the scientific method, which involves collecting evidence that is either consistent or inconsistent with a given hypothesis. As evidence accumulates, our degree of belief in a hypothesis ought to change.

Bayesian statistics are used today in fields as diverse as medicine, image processing, astronomy, physics, economics, decision making and many others. Recently, methods for incorporating Bayesian methods into exposure assessment strategies have been developed that show promise in improving exposure judgments (Hewett et al., 2006; Ignacio and Bullock, 2006). These better judgments help to ensure that workers are protected adequately and that resources are focused on the most significant risks.

The Bayesian Hygienist

We will follow a new hygienist through a few scenarios to see if hygienists are Bayesian practitioners. A company that makes a variety of products has recently hired an IH for one of their medium size production sites. Our new IH has recently taken a professional development course which instructs participants on utilizing the comprehensive exposure assessment control banding strategy. She has also studied some recent publications on applying Bayesian methods to a control banding strategy. She has good practical experience and also reads technical journals, so we'll refer to her as "Super" since many would consider her a "super hygienist". With her new knowledge from several publications (1-4), Super decided to implement a comprehensive exposure assessment program using Excel spreadsheets to store qualitative assessments and sampling results. She has also found a freeware version of a Bayesian data analysis tool that she will use to analyze data and qualitative judgments. Super reviews past sampling data and related information to find jobs and areas for further refining her initial judgments.

Super collects and documents the basic characterization and qualitative exposure assessments for several jobs in her qualitative exposure judgment spreadsheets (Table I overleaf).

British Occupational Hygiene Society
Working for a healthier workplace

TABLE I. Basic Characterization and Qualitative Exposure Assessments

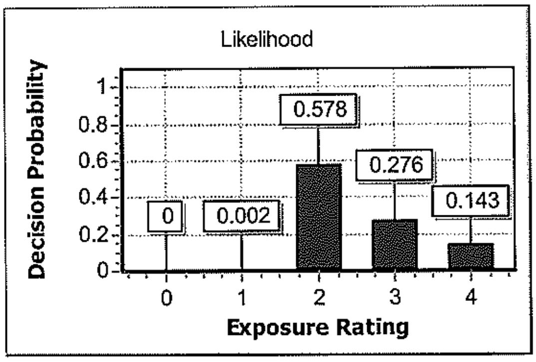
Job Title/Task Description/Agent	Duration/ Frequency	Equipment/ LEV Present	Agent/ Qualitative Exposure Assessment	Comments
Glue Operator / running "Blue / Quick Dry" glue mixer — charging bags of powers, charging solvents from process monitor, collecting several QC samples and monitoring process conditions / n-hexaneTWA = 50 ppm.	480 minutes per shift	Blue Glue Mixer / LEV = present	Category 2 (10–50% of TWA OEL)	Each glue batch is completed in one shift.
Maintenance employees / Unplugging bead extruder / ethyl acrylate STEL = 15 ppm.	20 to 60 minutes twice per week	Filter housing/no LEV present	Category 4 (>100% of STEL)	
Quality Lab Employee&Engineer/collect several QC samples through sample taps and submit to lab / methyl chloride STEL = 100 ppm.	15 mins each / 4 per shift	Various sample taps / LEV = No	Category 3 (10-50% of STEL)	Sample taps are located outside and no LEV is available.

Scenario 1—Blender Operators/Running the Blue Glue Mixer

Super decides to first focus her efforts on the Glue Mixer Operators. The special "Blue / Quick Dry" glue uses n-hexane as the main solvent from which it derives its unique characteristics. After reviewing basic characterization information, she determines that the chemical with the most significant vapor hazard ratio is n-hexane (50 ppm 8-hour TWA: 2007 TLV). Super recently had completed a sampling survey for glue operators by collecting samples on three different production employees, on three different days on the Blue Glue Mixer, which is an important production unit in her plant. The unit runs three shifts per day and has three operators per shift.

Super would like to analyze the three full-shift samples (2 ppm, 12 ppm and 5 ppm) against the TWA TLV of 50 ppm. Using a freeware IH Bayesian tool (e.g., the tool IHDA Lite available at www.oesh.com), Super plugs in the three data points, presses calculate and looks at her Bayesian likelihood chart (Figure 1). The chart indicates that the three monitoring data are most consistent with a Category 2 (95th percentile between 10 % to 50 % of the occupational exposure limit), with about 14 % probability that it might be a Category 4 (95th >100 % of the OEL) exposure.

Figure 1. Bayesian likelihood chart for running the Blue Glue Mixer (three samples).



Super has talked with several glue operators and feels like the samples that she collected represent the full-shift exposure. The charging area and control station are well ventilated and she expects exposures to be well controlled. She decides that exposures are controlled, given all of the information and data. The blender operators will continue to be in the routine monitoring program, and no additional exposure controls are necessary at this time.

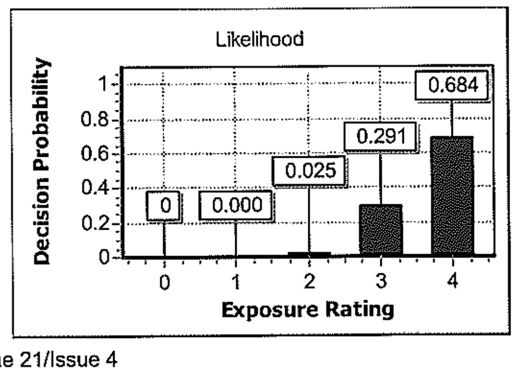
By combining her knowledge about the process controls and work-practices, along with sampling data to a final decision, is Super using a Bayesian thought process? It certainly appears to be the case.

Scenario 2—Maintenance Employees/Unplugging Extruder

During a visit to a crew health and safety meeting, Super hears concerns about a short-term task for which maintenance employees routinely unplug an extruder that makes resin pellets. Super looks in the file cabinet and finds a lab report where a sample was taken on a maintenance employee removing a plug in the extruder which had a result of 9 ppm. Keeping in mind that the STEL for ethyl acrylate is 15 ppm, she feels a bit uncomfortable, and continues to look through a few stacks of old reports but finds no other sample results for this task. Super is concerned that the workers who perform this short-term task probably exceed the STEL much more than five out of 100 times they perform the job.

Is Super concerned because her Bayesian intuition understands the probability of overexposure, given a limited set of data? Let's take a look at what the Bayesian likelihood chart would tell us (Figure 2).

Figure 2. Bayesian likelihood chart for changing filter task (one sample).



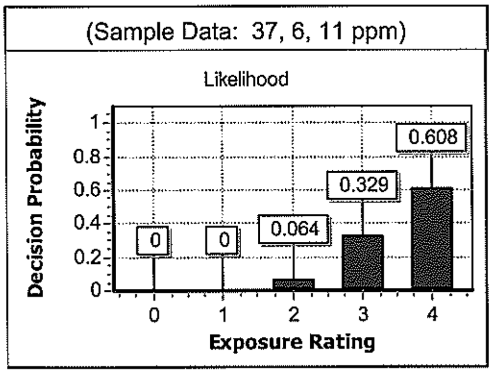
The Bayesian likelihood chart indicated that given her limited data, there is a greater than 68 percent chance that the true exposure profile will be an Category 4 exposure (95th percentile >100 percent of the STEL). Does this explain why Super was uncomfortable with the single result? It appears that the Bayesian likelihood matches Super's intuition.

Super takes the Bayesian likelihood chart to the maintenance supervisor and explains that there is a high probability of an unacceptable exposure and, consequently, that employees will need to wear respirators when unplugging a hot extruder. She tells the supervisor that respirators are required until she can work with the operators and engineers to collect more samples and implement engineering controls as needed.

Scenario 3—Quality Technician & Process Engineer / QC Sample Collections

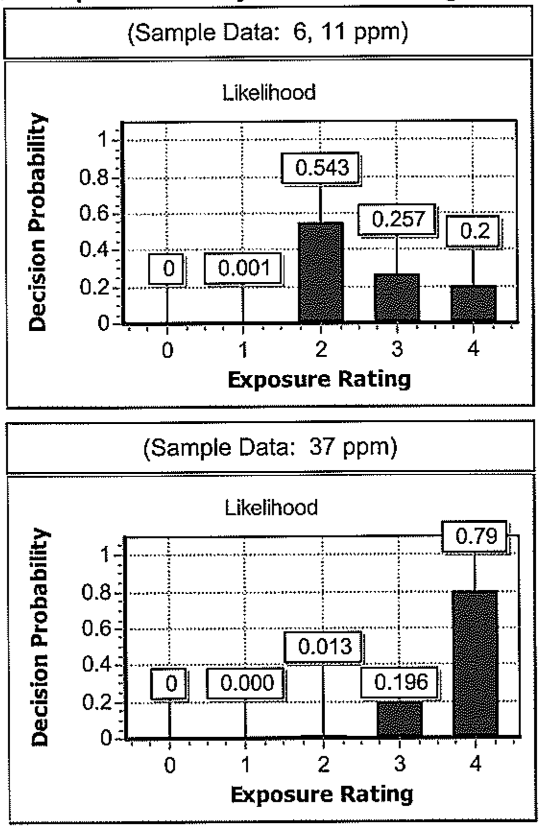
After interviewing a few Glue Operators when collecting samples, she finds out that the Quality Control Technician and Engineer both collect the QC samples twice per shift in a location that has poor ventilation. Super decides to collect some short-term samples on both the Quality Technician and Engineer during the QC sample collection tasks to see if her initial exposure judgment was correct. She collected three short-term samples : 37 ppm (Engineer), 6 ppm and 11 ppm (Quality Technician). The Bayesian likelihood analysis shows that there is greater than an 60 percent chance that the population exposure profile exceeds 50 ppm, which makes it a Category 4 (>100 percent of the OEL) exposure (Figure 3) for the duration of this task.

Figure 3. Bayesian likelihood chart for QC samples (all three personal air samples).



Notice that the likelihood analysis shows that Super's initial qualitative exposure assessment of Category 3 (Table 1) does not match the data analysis of Category 4. It appears that there may be some significant differences in exposure between the Quality Technician and Engineer (Figure 4). Based on these results, she decides to talk with the engineer and quality technician so she can better understand the determinants and variability of exposure.

Figure 4. Individual Bayesian likelihood charts for QC samples for Quality Technician & Engineer



Super decided to implement a voluntary use of respirators for the Engineer and Quality Technician until further sampling and / or exposure controls can be implemented. Super discusses several options to reduce exposure, such as adding local exhaust ventilation or enclosing the sample taps to reduce exposure on the QC sampling task. She expects that this also will help reduce the overall full-shift exposure. Super then reviews the procedures in the QC laboratory to ensure that samples are properly handled. Because Super's analysis of the data showed that this task was most likely a Category 4 exposure, she updated her exposure assessment database and published the industrial hygiene reports. This feedback on her initial judgment helped Super identify other similar jobs where follow up may be needed and offered insight into improving her qualitative judgments. Super is well on the way to implementing the continuous improvement process known as comprehensive exposure assessment and management.

Accuracy in Judgments

The above examples show how an occupational hygienist can use professional judgment in a Bayesian framework to guide decision-making. While hygienists have always used professional judgment, the Bayesian framework forces them to be transparent in their judgments, and document them quantitatively. But inaccurate professional judgments can lead to bad decisions. Studies looking at systematic biases in exposure judgments are only just getting started. Preliminary findings suggest that these biases are similar to those observed among professionals in other fields, e.g., medicine, psychology, and economics. Nobel Laureates Kahneman and Tversky (1979) identified several heuristics that could lead to biases, and these are similar to the biases seen in occupational hygienists. For example, when hygienists are given small sets of hypothetical exposure data and asked to predict the exposure category, they typically underestimate the exposure category for the SEG. Figure 5 shows how a group of hygienists at the AIHCE in 2007s under-estimated the correct exposure category. There are other biases besides this one, e.g., being overconfident and being more influenced by the last data point rather than the data set as a whole. Thus, hygienists tend to use their instincts to evaluate data and sometimes their instincts can lead them astray. An effective way to overcome these biases is to use formal statistics every time for assessing data instead of relying on instinct. An even more important method is to use the results from the Bayesian likelihood analysis as a feedback mechanism to improve one's judgments over time. The use of physical-chemical exposure models is another mechanism. Hygienists should implement a process to review their qualitative judgments when sampling data becomes available. They need to look for ways to increase exposure understanding and the accuracy of their qualitative judgments.

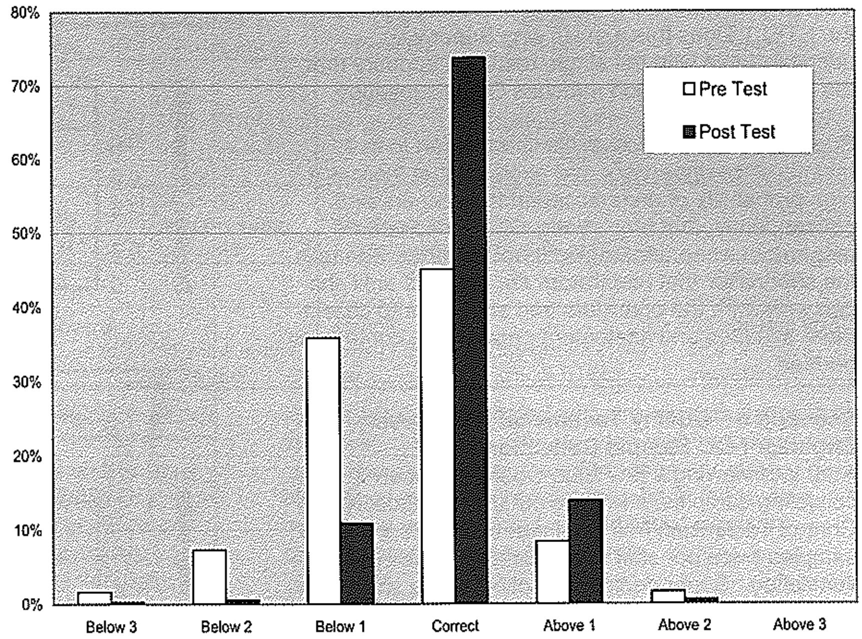


Figure 5

Summary

This short article shows that the routine process by which industrial hygienists combine qualitative and quantitative information to arrive at a final judgment is inherently Bayesian. But adopting a formal Bayesian framework in which decision making can be done provides greater transparency, can lead to efficient and effective decision-making, and serve as an criticial feedback mechanism to prevent systematic biases in exposure judgments. By using Bayesian tools, hygienists can get a better understanding of the factors and information that may be driving their decisions. Industrial hygienists routinely rely on their "intuition" or "professional judgment" when making decisions. We illustrate several examples where an industrial hygienist could be using Bayesian-like intuition to help guide his or her decision-making processes. It is very important to understand that just because a process is Bayesian that doesn't always lead to the best decision. If their professional judgment is inaccurate, then the final decisions may be incorrect. A fool with a tool is still a fool. Biases in professional judgment seen in other professions are also present in industrial hygiene. We all know that accurate exposure judgments are the foundation of efficient and effective exposure management. As a profession, we should work together to better understand what makes a hygienist's judgment more accurate.

References

Hewett, P., P. Logan, J. Mulhausen, G. Ramachandran and S. Banerjee: J. Occup. Environ. Hygiene, 3:568–581 (2006).

Ignacio, J. and B. Bullock, eds. A Strategy for Assessing and Managing Occupational Exposures, Third Edition. Fairfax, VA: AIHA Press, 2006.

Leidel, N.A., K.A. Busch and J.R. Lynch: Occupational Exposure Sampling Strategy Manual. NIOSH Publication No. 77-173 (available from the National Technical Information Service, Publication No. PB274792).

Kahneman, D., Tversky, A.: Prospect Theory: An Analysis of Decision under Risk, Econometrica, XLVII (1979), 263-291.

Gurumurthy Ramachandran, CIH, PhD, is a Professor at the University of Minnesota, Minneapolis. He can be reached at (612) 626-5428 or ramac002@umn.edu.