Integrated Environmental Assessment, Part I

Estimating Emissions

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A key element of industrial ecology involves estimating the environmental impact of products and processes. This assessment generally entails an evaluation of pollutant emissions and sometimes of fate and transport in the environment, exposure of humans or other environmental receptors, and the resulting health, ecological, or economic effects. When all of these steps are effectively executed, the process is often called integrated environmental assessment.

The analysis of emissions is especially salient in life-cycle assessment (LCA), where the inventory and impact assessment of emissions from the various stages in the life cycle of a product is a critical component of the overall environmental evaluation. Analysis of emissions plays a similarly central role in substance flow analysis (SFA), another tool widely used in the industrial ecology community. A review of the state of the art of systems modeling for each of the steps in an integrated environmental assessment is provided in a series of columns, beginning with this evaluation of methods for emissions estimation and modeling.

Knowledge of uncertainty helps prevent overconfident use of emissions estimates in industrial ecology applications and enables an evaluation of the robustness of comparisons of alternative processes and product designs.

Good emissions inventories are necessary as the first step in predicting environmental impact, but they also play an essential role when assessing trends and progress in industrial ecology, evaluating international treaty compliance, and in the enforcement of environmental regulations. This column reviews the principal methods used to estimate emissions and the critical need to recognize and characterize the uncertainty in the resulting estimates and inventories.

Estimating Emissions

The major techniques for estimating emissions include the following:

- Direct *measurement,* using either grab, periodic, or continuous monitoring
- The calculation of a *mass balance,* with emissions computed as the difference between material inputs and products
- The use of *emission factors* that relate emission rates to activity levels (e.g., product production, employment, or, in the case of mobile source emissions, "vehicle miles traveled")
- The use of more advanced *process models* for emissions
- The application of *inverse inference* from observed ambient concentrations

Source testing through direct measurement is usually preferred among these options; however, accurate emissions monitoring requires the measurement of both fluid flow rates (e.g., of air or water from discharge stacks or pipes) and pollutant concentrations, and this is difficult to achieve in many applications. Although new technologies for emissions monitoring are always being developed,[1] certain emission profiles are nearly impossible to measure directly, especially for diffuse, nonpoint, or fugitive sources.

e-supplement available on the *JIE* Web site

Volume 7, Number 1

Material balance calculations are always correct in theory, but suffer from inaccuracy when the emissions are (as usually hoped) a very small fraction of the system throughput. Emissions factors provide a standardized approach for estimation, but suffer from inherent simplifications and errors because they typically ignore differences between processes and factories or, for example, in the case of mobile emissions, differences in vehicles, fuels, traffic conditions, and driver behavior.[2] Some of these simplifications can be addressed with more sophisticated engineering process models. Examples include models for electric power plant operations and industry-wide models for sectors of the chemical industry. Ideally, when pollutant emissions are included as part of an industrial process design and simulation model, process emissions can be estimated under a variety of different operating conditions (Diwekar and Small 1998, 2002).

Back-inference methods use observed concentrations in the air, soil, or water to infer the emissions from nearby sources. Such methods must be coupled with an appropriate pollutant fate-and-transport model and are especially helpful for estimating nonpoint, area source or fugitive emissions.

Characterizing Variability and Uncertainty in Emissions Estimates

Although a single number is often preferred for an emission estimate, the reality is that emission rates vary from one source to another within a given source category and temporally for any given source. Emissions vary over time and from one source to another because of differences in design, feedstock compositions, ambient conditions, and maintenance and repair. Thus, there is inherent *variability* in emissions revealed by measurements on multiple sources or by repeated measurements of the same emission source. In contrast, *uncertainty* refers to our lack of knowledge regarding the true but unknown value of a quantity, such as the population average emission factor for a particular source category. The average emission factor is subject to uncertainty for several possible reasons: (1) random sampling errors, (2) measurement errors, (3) nonrepresentativeness of available data, (4) lack of information, and/or (5) data entry errors.

The range of uncertainty in emission factors can be substantial. For example, for light-duty gasoline vehicles, the uncertainty in the fleet average emission factor is as low as $\pm 10\%$ to as much as -90% to $+280\%$ (Frey and Zheng 2002a). The uncertainty in a statewide annual emission inventory for power plant NO*x* emissions is estimated to be -16% to $+19\%$ (Frey and Zheng 2002b). The positive skewness occurs because emission rates are highly variable, but emissions must be nonnegative.

The U.S. Environmental Protection Agency, U.S. National Research Council, and International Panel on Climate Change (IPCC) have all expressed concern regarding the level of uncertainty associated with emission factors and inventories and the need for development and application of appropriate methods for quantification of this uncertainty. Numerous challenges to the characterization of uncertainty in emissions exist. Some are philosophical, whereas others are methodological and organizational. Philosophical challenges typically center on the debate as to whether expert judgment is an acceptable basis for estimating uncertainty. Even methods that are based solely on the statistical analysis of available data involve many steps, each of which requires judgment. For example, the following key questions must be answered: Are the available data representative? What distribution is selected and fit to the data? What goodness-of-fit test is used? What criteria are used to reject a poor fit? Where data are unavailable or not representative, judgments regarding uncertainties can be encoded as probability distributions using expert elicitation protocols. These protocols are based upon an understanding of cognitive psychology and seek to avoid overconfident or biased estimates by countering the heuristics that people typically use to make judgments.

Common methodological challenges and problems that occur when characterizing emission variability and uncertainty include measurements below the detection limit, statistical dependence among multiple quantities, categorical data, and a lack of sample data. Although methods exist for estimating uncertainty for such distributions, empirical data may at times be composed of a mixture of two or more distributions, typically because different processes generate different portions of the database. In such cases, mixtures of distributions can be used to represent variability, and uncertainty can be inferred based upon the fitted mixture distribution. Two or more inputs to an inventory could be dependent upon each other. Where inputs are autocorrelated, vector autoregressive regression models can be used to account for both inter- and intra-unit dependence in the uncertainty of plant emissions.

In some cases, such as for chromium, mercury, arsenic, and particulate matter (PM) emissions, it is necessary to characterize the chemical speciation. For example, weight fractions of PM must be assigned to species categories, and the sum of the weight fractions must be equal to 1, which in turn induces a statistical dependence among the two or more weight fractions. For some inputs to an inventory, most typically activity factors, sample data are unavailable for making statistical inferences regarding uncertainty. In such cases, an expert judgment or modeling approach may be required.

Uncertainty analysis is most easily done if it is included as part of the original development of a database or a model. A key difficulty when trying to retrospectively develop uncertainty estimates is to obtain a well documented and complete database. As a first step to facilitate uncertainty analysis, we recommend that the developers of emission factors routinely report, at a minimum, the mean, standard deviation, and sample size of the data used to develop the estimate. This information should be provided as a part of the LCA and SFA public databases that are now under development. Furthermore, the data from which these statistics were estimated should be made available, including relevant process data and descriptive information. Knowledge of uncertainty helps prevent the overconfident use of emissions estimates in industrial ecology applications and enables an evaluation of the robustness of comparisons of alternative processes and product designs. With the central role that emissions estimates play in LCA and SFA, it is critical for industrial ecologists to ensure that they acquire and use the best methods and information possible, but also recognize the nature and implications of the uncertainty that remains.

Notes

1. A key advance in recent years has been the development of continuous emission monitors for selected air pollutants, such as SO_2, NO*x*, and CO_2, which have enabled market-based pollution control strategies based on cap and trade programs to be implemented with confidence. More information on emissions monitoring protocol is available at the U.S. Environmental Protection Agency Emissions Measurement Center ⟨www.epa.gov/ttn/emc/⟩ and the European Model Monitoring Training Accreditation Programme ⟨www.emmtap.eu.com/⟩.
2. References to research on this and other specifics mentioned in this column can be found in an e-supplement available on the *Journal of Industrial Ecology* Web site at ⟨http://mitpress.mit.edu/JIE⟩.

References

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