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Review

Air Pollution Monitoring Changes to Accompany the Transition from a Control to a Systems Focus

Daniel A. Vallero

U.S. Environmental Protection Agency, National Exposure Research Laboratory, Research Triangle Park, NC 27709, USA; vallero.daniel@epa.gov; Tel.: +1-919-541-3306

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Abstract: During the 20th century, air pollution control technologies grew at an amazingly rapid rate. Air quality in much of the industrialized world greatly improved as the efficiencies of these technologies improved. This continued improvement in pollution control has more recently been complemented with measures to prevent the emission of air pollutants. The previous, exclusive focus on treatment requires systems thinking. This review provides a framework for this Special Issue of *Sustainability* by describing the new tools that are needed to support this new, broader focus, including life cycle assessments, exposure models, and sustainable design.

Keywords: air pollution control technology; life cycle assessment (LCA); exposure potential; design for environment (DfE); design for disassembly (DfD); pollution prevention; systems engineering

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1. Introduction

Since the industrial revolution in the 19th century, the air quality in many parts of the world has been threatened by an array of pollutants. Combustion, mining, agriculture, transportation and many other societal practices have been associated with the emissions of gases and aerosols that threaten the health and quality of life of billions of people, as well as eroding the quality of ecosystems and endangering other species [1,2].

Control technologies were developed and deployed to address the air pollution that accompanied worldwide industrial expansion concomitantly. Indeed, these were the exclusive approaches employed until the end of the 20th century. The predominant choices involved the extent and type of treatment, ranging from no controls to increasingly sophisticated technologies designed to address specific pollutants. For example, electrostatic precipitation and fabric filter technologies have continued to improve to remove particulate matter (PM) from stack and vent emissions. At first, these technologies collected all size ranges of PM, but as research demonstrated that smaller particles were more respirable and could penetrate the lungs more deeply [2,3], engineers designed equipment to remove these smaller particles [1].

Air pollution research and practice can benefit from systems thinking and sustainability tools. The research community has recently made strides in integrating life cycle and green engineering tools with air pollution control and prevention, such as design for the environment (DfE), design for disassembly, human exposure modeling, and multi-criteria decision analysis. One of the means of achieving this is by expert elicitation, where professional judgment is used as a first step in screening for potential exposure and risk of large numbers of chemicals that are either air pollutants or which may be transformed into pollutants.

The transition toward more sustainable approaches must be accompanied by enhanced tools that take advantage of technological advances and systems thinking. This begins with an appreciation of how science and engineering is changing to address air quality needs.

2. Trends in Sustainable Air Quality Solutions

The articles in this Special Issue indicate a number of trends, including the increased focus on near-field exposures, the variability among regions and nations in the ability to adopt sustainable air quality programs, the complexities in both the scientific and policy aspects of 21st century air quality programs, and the need to address both traditional air pollution problems (e.g., China) and emerging scenarios (e.g., in-vehicle exposures).

Historically, air pollution has been addressed mainly as an engineering problem, which is usually focused on the source, e.g., a stack or vent from a factory or from the exhaust of an automobile. Engineering solutions were designed to fit the emission. The factory is an example of a stationary source and the automobile an example of a mobile source. Somehow, all the releases from these sources had to be connected to the air quality of a neighborhood, town, or larger area. Thus, if the concentration of a pollutant emitted from a stack or tailpipe could be decreased, the air quality would be expected to improve correspondingly.

Location is a key factor in air pollutant exposure. Time spent and activities undertaken in different locations are important determinants of air pollution exposure. Air pollution monitoring may provide reliable estimates of ambient concentrations of air pollutants at various sites in a region. However, most people spend the majority of their time in indoor locations [4], with distinctions among ambient (often defined further as outdoor), indoor, and personal-scale exposures. The locations where people spend their time, such as in a kitchen, bedroom, vehicle or garage, are known as microenvironments. The microenvironmental connections between outdoor and indoor, and between these and personal-scale concentrations, can vary substantially by type of pollutant and mechanisms. For example, indoor concentrations of fine particulate matter do not correlate closely with outdoor concentrations [5]. Elevated concentrations of ozone (O_3) in the outdoor air do not typically penetrate indoor environments, but can enter dwellings more effectively by mechanical and open windows [6].

The emphasis of air pollution programs has been to decrease releases from stationary and mobile sources, especially for the so-called "criteria pollutants", i.e., particulate matter, carbon monoxide, oxides of nitrogen and sulfur, O_3, and lead. This has also been the main focus for the hazardous air pollutants, i.e., "air toxics". These have been addressed using the best or maximally achievable control technologies. However, personal exposure to most chemicals predominantly occurs within near-field exposure scenarios, e.g., exposure while using a product that contains the chemical or contact with an article treated with the chemical [7]. This is leading to new screening models and tools, including multi-criteria decision analysis (MCDA) and expert elicitation exposure-based chemical prioritization [8].

MCDA allows for the consideration of numerous variables, from various information sources. For near-field air pollution, the two main categories of variables are: (1) those associated with product use; and (2) the physical and chemical properties of the pollutant. Thus, one of the important gaps in data and tools needed for life cycle- and risk-based decision making to address and to prevent air pollution is improved exposure predictions. For example, human health characterization factors (CFs) in life cycle assessments (LCAs) have benefited from improved hazard, especially toxicity, information [9].

The Cs are weighting factors used in an important component of the LCA process, i.e., the life cycle impact assessment (LCIA). An air pollution LCIA converts emissions into impact scores for various impact categories [10]. Two important impact categories for air pollution are human health or global climate change. An impact score is a weighted sum of the damage due to all air pollutant emissions to one of these or other impact categories [11]. LCAs generally and LCIAs specifically are important sustainability tools in that they provide a systematic view of the costs and benefits of an entire process rather than a single stage of the life cycle. For air pollution, LCAs allow the engineer or process designer to compare among various alternatives. For example, a chemical compound may appear to be the best choice for manufacturing a product, but the LCIA may indicate that it will produce a toxic air pollutant in later stages, which will have to be treated. The treatment will add costs and risks that can be prevented by changes in process design or selection of safer chemicals which, if substituted, may obviate or greatly reduce the treatment costs. Likewise, the LCA may indicate that a choice of a substance may increase air and other pollutants in earlier stages, such as the extraction of ores, which may not be necessary if another substance with less extraction-related pollution is chosen.

Until recently, LCAs have underweighted exposure and relied more heavily on inherent toxicity estimates to indicate risks posed by substances in the human health CFs [12]. However, since health risk is a function of hazard and exposure, the human health CF also needs reliable exposure predictions. These depend on a number of factors that differ among air pollutants. One large gap is accounting for near-field scenarios and incorporating these into sustainability tools.

3. Sustainability Tools for Air Pollution Control Systems

3.1. Near-Field versus Far-Field Exposure Scenarios

The difference between near-field and far-field exposure scenarios can be quite dramatic. Until recently, air pollutants were predominantly approached from a far-field perspective, i.e., a substance is released from a stack, whereupon it is followed until it reaches the receptor. This called for measurements at the source and downwind on a path toward the receptor. For example, the dominant exposure pathways for the criteria pollutants and for chemically persistent compounds, e.g., polychlorinated biphenyls and dioxin, may be far-field, e.g., leaked into soil or emitted from a stack and ultimately reaching the receptor, such as humans or other species (see Figure 1). However, for many substances, the dominant exposure scenario is near-field, e.g., a product purchased and consumed or used in a residential setting. The difference is demonstrated in the flowchart depicted in Figure 2. Note that the flow leads to aggregate exposure estimates, i.e., all routes and pathways for a single compound. For cumulative exposure estimates, i.e., all routes and pathways for multiple chemical compounds, individual flow charts for all potential compounds that may contact the person would have to be combined.

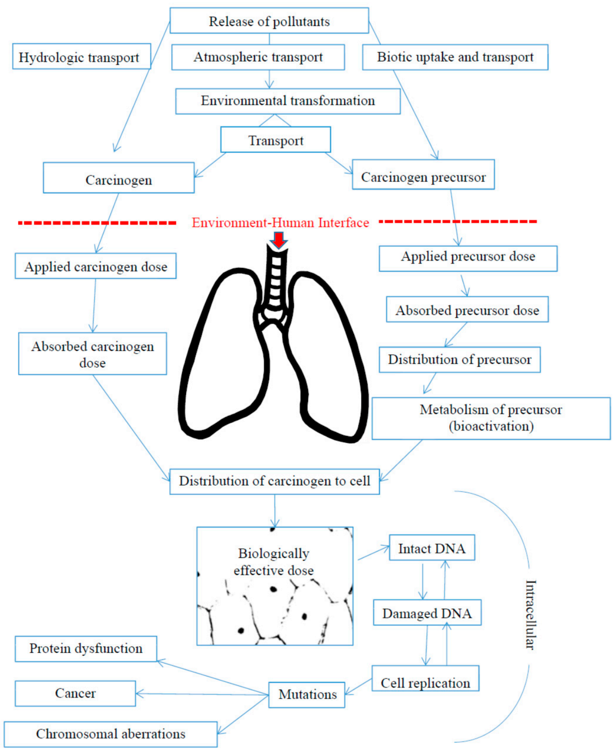

Figure 1. Far-field scenario of exposure to a persistent compound that has been emitted to the air, leading to uptake by a person. Sources: [1,13]. Bottom part of diagram adapted from [14]. Used with permission.

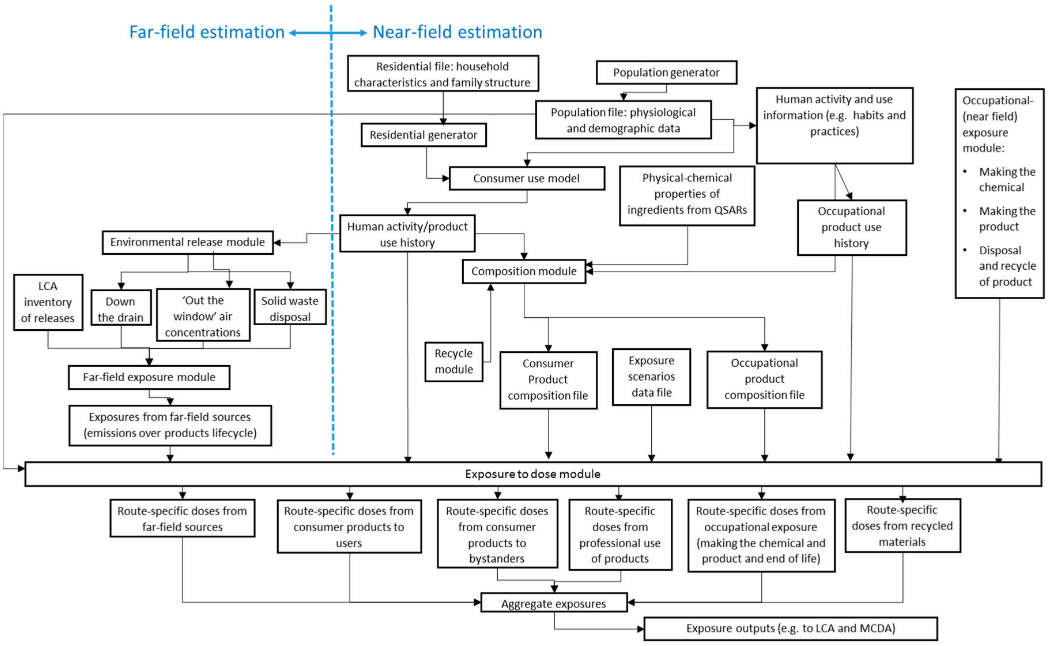

Figure 2. Information flow needed for a human exposure model that addresses both far-field and near-field exposure scenarios. LCA = life cycle analysis; QSAR = quantitative structure activity relationships; MCDA: multi-criteria decision analysis. Adapted from [15].

3.2. Dose Calculations

Chin et al. [16] measured the difference in near-field (indoor air) and far-field (outdoor air) pathways for exposure to para-dichlorobenzene (*p*-DCB). However, a more complete description to support green chemistry and the sustainable design of a product would follow the flow in Figure 1. The simplest example is a single consumer product whose main ingredient is *p*-DCB, i.e., solid pest repellent, commonly used in residential closets. Figure 3 demonstrates this difference by comparing Chin et al.'s results with consumer product doses modeled using SHEDS-HT [17], a high-throughput human exposure and dose-screening model for chemicals. The mechanistic model is based on probabilistic methods and algorithms of various exposure pathways, including oral, dermal, ingestion, and inhalation.

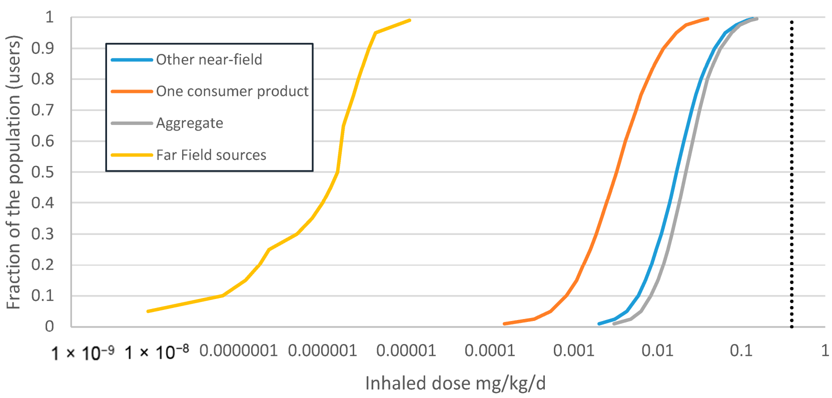

Figure 3. Distribution of doses of a volatile organic compound from inhalation of one consumer product, other near-field sources, far-field sources, and aggregate (total) e xposure. In this instance, far-field scenarios account for several orders of magnitude of less of the predicted dose compared to near-field scenarios. The doses were modeled using SHEDS-HT [17] from data in Chin et al. [16] and Csiszar et al. [18].

A case study by Csiszar et al. [18] to estimate potential exposures to *p*-DCB found that adding risk-based screening and aggregate exposure predictions to sustainability tools such as LCA can be used to compare product ingredients to help optimize formulations based on human toxicity, which can be considered along with other life cycle impacts (e.g., climate change, resource depletion, ecotoxicity, etc.). While none of the case studies presented here calculated uncertainty, similar calculations may include uncertainty and variability, e.g., seasonal, geographic and population variability.

The exposure information becomes increasingly complicated for products containing more than one chemical ingredient, as well as when considering co-exposures to chemical compounds other than those in the product; for example, airborne substances in a home may react with those of the product, generating new degradation products [19], and/or exposures to these other substances may change the susceptibility of the exposed person to the product ingredients [20,21].

3.3. Screening Tools

Protecting and improving air quality, like other environmental media, relies on credible data and models. Increasingly, evidence-based risk assessments are being augmented or even supplanted by precaution. This is particularly important for decisions in which there is a reasonable likelihood that an adverse effect is severe and irreversible [22]. Thus, tools will be needed to screen chemicals for deleterious effects. This is most common for consumer products, but could also be applied to fuels and industrial materials in early life stages which, when used, could result in emissions of air pollutants at some later stage. For example, expert elicitation has been used to identify and prioritize chemicals that may have high exposure potentials before they reach the marketplace [8].

This is useful for both sustainability users, e.g., LCA, and risk assessment users, e.g., substituting fuels and chemicals in early life stages that prevent a future air pollutant [23]. The prioritization must address both parent compounds and degradation products. For example, a chemical used in an industrial process may be relatively safe within an industrial life stage if workers are wearing proper personal protection equipment, but in downstream life cycle stages may result in an indoor air pollutant, e.g., an incidental, harmful ingredient in a product.

Screening can merge hazard and exposure information. For example, exposure prioritization can complement and/or be integrated into decision tools, such as the recently released CompTox dashboard [24], which includes individual chemical structures for over 700,000 compounds. The dashboard combines bioassay screening data, exposure modes, and product categories. Screening tools can be beneficial in identifying analytics associated with data-poor and emerging substances, e.g., nanomaterials, by showing rankings of chemicals based on hazard and exposure potentials [8]. Such screening tools can be also support the evaluation of a hypothetical portfolio of products (e.g., cleaning products, cosmetics) for various life stages of a product. A portfolio of products and an accompanying set of their chemical ingredients can allow decision-makers to rank products according to potential risk, including the likelihood of causing air pollution, which may lead to health risks [25].

3.4. Enhanced Characterization of Activities within Micro-Environments

This Special Issue of *Sustainability* provides examples of how the focus of air pollution modeling and measurement has shifted from almost exclusively concentrations of pollutants in the ambient air, especially outdoors, to concentrations in various microenvironments, e.g., rooms, vehicles, and garages. A number of microenvironments are not well characterized in terms of air exchange, activities of inhabitants, and source of contaminants, e.g., stored products. Since concentration is needed to calculate exposure, this paucity of information translates in uncertainties about potential exposures to particular air pollutants, e.g., carbon dioxide in vehicle compartments. Note that exposure estimates require that such concentrations be combined with behavioral and activity information:

$$E = \int_{t=t_1}^{t=t_2} C(t)\,dt + \int_{t=t_2}^{t=t_3} C(t)\,dt \ldots + \int_{t=t_n}^{t=t_{n+1}} C(t)\,dt, \quad (1)$$

where E is a person's exposure from time t_1 through time t_{n+1} (e.g., one day) and C is the concentration of the air pollutant of concern. Thus, an accurate depiction of exposure must include a person's location where the activities occur. For example, the breathing rate will differ substantially if a person is sleeping versus engaging in vigorous exercise.

Several of the Special Issue's articles address various aspects of all three features, i.e., characterizing a person's "exposome" [26], meaning a complete profile of a person's exposure based on the biological uniqueness of the person combined the activities and the location of the person. For example, average ventilation (i.e., breathing) rates will vary by biology, e.g., the 50th percentile for the age group 16 to <21 years performing moderate activity is 50% higher for the older age group (2.06×10^{-2} $m^3 \cdot min^{-1}$) than the younger groups (for example, 3.14×10^{-2} $m^3 \cdot min^{-1}$ for age group 51 to <61 years) performing the same activity. Similarly, the ventilation rate is affected by the activity, e.g., the age group 16 to <21 years performing a high intensity activity is 5.05×10^{-2} $m^3 \cdot min^{-1}$; it is 5.59×10^{-2} $m^3 \cdot min^{-1}$ for age group 51 to <61 years performing the same vigorous activity [27]. It is important to keep in mind that ventilation rates are important indicators of the air pathway and inhalation route. However, air pollutant exposure can also result from dermal, oral, nasal, and ingestion routes. For example, an aerosol may deposit on a surface and be sorbed to skin or enter food, resulting in dermal and ingestion exposures, respectively [28–30].

This demonstrates that sustainability tools and models must go beyond concentration data and must also account for the influence of a person's or population's biology, activities and location, just as air pollution risk assessments have had to consider their impact on potential exposure and risk [31].

3.5. Citizen Science and Sensors

Science in general and environmental science specifically are beginning to make use of widely available communications and sensor applications and technologies to improve the coverage and granularity of environmental measurements [32]. Numerous air quality studies can benefit from greater participation, e.g., relationships between ecosystem conditions and air quality, climate change impact assessments, and pollution detection and compliance monitoring [33,34].

This trend will likely continue and grow. For example, prototype smart phone systems have been successfully deployed for suites of gas-phase pollutants [32]. The systems connect to the smart phone and are about the same size as the phone itself. Thus, they are compact, inexpensive (at least compared to research and fit-for-purpose equipment), and relatively easy to operate and maintain (using off-the-shelf hardware). In this instance, the system's precision and accuracy are maintained by calibrating with central, fixed monitoring stations, allowing the citizen scientist to calibrate to the central readings [32].

As mentioned, air pollution control has depended on ever-advancing technologies. Moving forward, sustainable air quality programs will continue to depend on these advances, not only to treat pollutants, but to monitor their concentrations in places that in the past would have been logistically and cost-prohibitive.

4. Discussion

This paper suggested ways that sustainability tools can be incorporated into air quality decision making, i.e., improved dose calculations based on near- and far-field exposures, better screening tools, and adoption of an exposome perspective that combines biology, location and activities. Recent changes in risk assessment call for a greater reliance on tools that prevent air pollutants from being generated, e.g., the substitution of safer chemicals upstream in a product or process life cycle. Air pollution prevention and control is also benefiting from technological advances that include better exposure and dose models and smart technologies that can support citizen science.

The articles in this Special Issue have approached these and other sustainability needs for air quality decision making at various scales and complexities.

5. Conclusions

Air quality decision making is changing, from less acceptance of the need to treat air pollution to a more proactive and sustainable view of preventing the pollution at the outset. This paper has discussed a number of ways to transition from an exclusive control approach to one that increasingly relies on systems tools to view the entire life cycle of a product or process. This will result in less waste and pollution, not only at the end-of-product life, but in all stages of the life cycle, from extraction to manufacturing to product use and beyond. Certainly, air pollution control technologies will be needed at numerous stages in the life cycle, but a systems approach may well prove to lessen the amounts and toxicities of substances in the atmosphere at all scales, which should translate into improved economic and operational efficiencies.

The systems perspective also allows for steps to generate fewer or even eliminate difficult-to-treat pollutants, which would translate into better compliance with laws and regulations. Sustainable air monitoring systems will become increasingly feasible and reliable with the advances in communications and environmental technologies. These convergent advances will improve the quality and coverage of air quality monitoring systems globally.

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