United States
Environmental Protection
Agency

Solid Waste and
Emergency Response
(5306)

EPA530-R-95-010
PB95-191 235
April 1995

EPA

Guidelines for Assessing the Quality of Life-Cycle Inventory Analysis

EPA Contract Number 68-D2-0065
RTI Project Number 94U-5810-49 FR

Guidelines for Assessing the Quality of Life-Cycle Inventory Analysis

March 1995

Prepared for

Lynda Wynn
Eugene Lee

Office of Solid Waste
U.S. Environmental Protection Agency
401 M Street, SW
Washington, DC 20460

Prepared by

Jodi S. Bakst
Christopher J. Lacke
Keith A. Weitz
John L. Warren

Environmental Economics and Management
Center for Economics Research
Research Triangle Institute
Research Triangle Park, NC 27709

PREFACE

Life-cycle assessment (LCA) results can vary depending on how the sponsoring group defines the goals and scope of the LCA. With an increasing number of organizations using LCA for a wide variety of purposes, the need has arisen for objective, scientifically based guidelines for conducting LCAs.

EPA has responded to this need by supporting a multi-office LCA program that helps develop such guidelines. This multi-office program consists of representatives from the Office of Research and Development (ORD), the Office of Air Quality Planning and Standards (OAQPS), the Office of Solid Waste (OSW), and the Office of Pollution Prevention and Toxics (OPPT). The LCA program uses a consensus-building approach, coordinating closely with the Society of Environmental Toxicology and Chemistry (SETAC). Through the organization of a series of workshops, SETAC has laid the groundwork for the development of a technical framework for conducting LCAs.

Two of the first in a series of EPA LCA methodological guidelines documents, *Life-Cycle Assessment: Inventory Guidelines and Principles* and *Life Cycle Design Guidance Manual: Environmental Requirements and the Product System,* were published in early 1993. Supplementary LCA documents including *Life-Cycle Assessment: Public Sources of Data for the LCA Practitioner* and *Life-Cycle Impact Assessment: A Conceptual Framework, Key Issues, and Summary of Existing Methods* were completed in September 1994. Ongoing EPA LCA projects include life-cycle inventory case studies on residential carpeting systems, shop towels in industrial laundaries, and solvent alternatives; streamlined LCA methodology development; and product re-design through LCAs.

The purpose of this guidelines document is to provide practitioners with direction and to facilitate the use of a consistent approach for assessing and documenting LCI data quality. This document discusses key issues that make the assessment of LCI data quality unique, outlines a possible framework for assessing and documenting LCI data quality, and discusses specific techniques to support the LCI data quality assessment process. The relatively qualitative approach to data quality assessment outlined in this document is representative of the current state of LCA practice and data quality assessment techniques. As LCA and data quality assessment techniques evolve, it is expected that a greater level of statistical analysis will be used.

ACKNOWLEDGMENTS

This document was originally prepared for the U.S. Environmental Protection Agency (EPA) Office of Solid Waste, under EPA Contract No. 68-D1-0118, where Eugene Lee and Lynda Wynn served as project officers. Work was completed under the EPA Office of Air Quality Planning and Standard (OAQPS), under EPA Contract No. 68-D2-0065, where Charles French served as project officer. The technical work was originally conducted under Research Triangle Institute (RTI) Project No. 94U-5290-49 FR and completed under Project No. 94U-5810-49 FR. Carolyn Acree, Judy Parsons, and Andrew Jessup provided editorial, word processing, and graphics support for this document.

Technical guidance, review, and comments were provided by Dr. Roy Whitmore, Senior Statistician, RTI, Center for Research in Statistics. Additional guidance, reviews, and comments were provided by Mary Ann Curran (ORD/RREL), Tim Ream (OAQPS), Eun-Sook Goidel (OPPT), and Bruce Vigon of Battelle. Special thanks to S. Nasir Ali of Arthur D. Little, Inc. and Terrie Boguski and Robert Hunt of Franklin Associates, Ltd who participated in case study applications and technical review of these guidelines.

Peer Reviewers included Paul Arbesman, Allied Signal; Derek Augood, Scientific Certifications Systems; Bob Berkebile, American Institute of Architects; Terrie Boguski, Franklin Associates, Ltd.; Michael Brown, Patagonia; Frank Consoli, Scott Paper Company; Gary Davis, University of Tennessee; Richard Denison, Environmental Defense Fund; James Fava, Roy F. Westin, Inc.; Kate Gross, The Body Shop Inc.; Michael Harrass, Amoco Corporation; Frances Irwin, World Wildlife Fund; Greg Keoleian, University of Michigan; John Kusz, Safety Kleen; Arthur Weissman, Green Seal Inc.; Beth Quay, The Coca-Cola Company; Athena Sarafides, NJ Department of Environmental Protection; Jacinthe Sequin, Environment Canada; Karen Shapiro, Tellus Institute; Donald Walukas, Concurrent Technologies Corporation; and John Young, Hampshire Research Institute. Additional reviewers included John Wilkens, DuPont; David Wheeler, The Body Shop, Inc.; and Joel Ann Todd, The Scientifc Consulting Group, Inc.

CONTENTS

Chapter		Page
Preface		iii
Acknowledgments		iv
Key Terms, Definitions, and Acronyms		x
1	Introduction	1-1
1.1	The Current State of LCA Data Quality Evaluation	1-3
1.2	Purpose and Scope of These Guidelines	1-4
1.3	Areas Outside the Scope of These Guidelines	1-5
1.3.1	Peer Review	1-5
1.3.2	LCA "Code of Practice"	1-6
1.3.3	Life-Cycle Impact Assessment	1-7
1.3.4	Life-Cycle Improvement Assessment	1-8
1.4	Overview of Document	1-8
2	Key Data Quality Issues for Life-Cycle Assessment	2-1
2.1	Using a Variety of Data to Build an LCI	2-2
2.1.1	Data Sources	2-2
2.1.2	Data Types	2-5
2.1.3	Levels of Aggregated Data	2-6
2.2	Identifying "Key" LCI Data Sets	2-7
2.3	Aggregating Data in the LCI Data Development Process	2-8
2.4	Uncertainty Propagation	2-9
2.5	Using Nonparametric Samples in an LCI	2-10
2.6	Using Environmental Releases Data in an LCI	2-10

3 Assessing the Quality of Life-Cycle Inventory Data 3-1

3.1 Scope and Boundary Definition 3-3
3.2 LCI Data Collection Plan 3-7
3.2.1 Defining Data Quality Goals (DQGs) 3-8
3.2.2 Identifying Data Sources and Types 3-10
3.2.3 Identifying Data Quality Indicators (DQIs) 3-10
3.2.4 Developing a Data Questionnaire 3-12

3.3 Data Collection and Quality Assessment 3-15
3.3.1 Collecting Data 3-15
3.3.2 Assessing Data Sources Against Relevant DQIs 3-16
3.3.3 Assessing Data Quality 3-19

3.4 Evaluating Model Sensitivity and Results 3-22
3.4.1 Performing Sensitivity and Uncertainty Analyses 3-23
3.4.2 Determining Whether DQGs Have Been Met 3-24
3.5 Documenting and Referencing LCI Data Quality Results 3-25

4 Applying Sensitivity and Uncertainty Analysis Techniques to LCI Data 4-1

4.1 Sensitivity Analysis Techniques 4-2
4.1.1 Single System (One-Way) Sensitivity Analyses 4-3
4.1.2 Tornado Diagrams 4-3
4.1.3 Ratio Sensitivity Analysis 4-7
4.2 Uncertainty Analysis 4-9
4.2.1 Sources of Uncertainty 4-9
4.2.2 Qualitative Measures for Controlling Data Errors and Uncertainty 4-12
4.2.3 Quantitative Methods of Uncertainty Analysis 4-14

5 Compensating for Missing Data and Data Deficiencies 5-1

5.1 Missing Data and Data Deficiencies 5-1
5.2 Adjusting for Missing Data and Data Deficiencies 5-2

5.2.1 Imputation 5-3
5.2.2 Weighting Methods 5-7

Appendix A: Data Quality Indicators A-1
A.1 Acceptability A-2
A.2 Bias A-3
A.3 Comparability A-5
A.4 Completeness A-6
A.5 Description of the Data Collection Method and Limitations A-6
A.6 Precision A-8
A.7 Level of Reference A-11
A.8 Representativeness A-12

Appendix B: Bibliography B-1

TABLES

Number		Page
3-1	Case Study Example: LCI Scoping and Boundary Definition	3-5
3-2	Case Study Example: DQGs, Data Sources, and DQIs	3-9
3-3	Selected Data Quality Indicators Relevant to LCI	3-12
3-4	Case Study Example: LCI Data Quality Worksheet	3-21
3-5	Example Proof Statements for the Bias DQI	3-22
4-1	Hypothetical Sensitivity Analysis Worksheet	4-4
4-2	Hypothetical Tornado Diagram Worksheet for Product X	4-6
4-3	Energy Sensitivity Analysis on Two Production Systems	4-8
4-4	Uncertainty Propagation Formulas for Random and Systematic Errors	4-15
A-1	Sample Data to Calculate Bias	A-4
A-2	Sample Data to Calculate Precision	A-10

FIGURES

Number		Page
2-1	Example Data Sources, Data Types, and Levels of Data Aggregation	2-3
3-1	Life-Cycle Stages	3-2
3-2	LCI Data Development Steps	3-4
3-3	Example of a Partial LCI Data Questionnaire	3-13
4-1	Sensitivity of Air Releases for Product X	4-5
A-1	Relationship Between Precision and Bias	A-9

KEY TERMS AND DEFINITIONS

Aggregated Data	Data that are represented as summary reported values.
Data Aggregation	The aggregation of data within and between system components that occurs in the LCI data development process.
Data Quality	The degree of confidence an analyst has in a data source or a data value based on an evaluation of data quality goals (DQGs), data quality indicators (DQIs), and the role of the data in an overall LCI.
Data Quality Goals (DQGs)	Qualitative statements that define specifications for the adequacy of data used in an LCI or for certain LCI parameters.
Data Quality Indicators (DQIs)	Quantitative or qualitative terms defining data characteristics that serve as benchmarks against which data quality can be assessed to determine whether DQGs have been met.

Data Quality Indicators Used in this Document:

Acceptability	The degree to which the data source has been peer reviewed, evaluated against an accepted standard, or checked for errors through expert judgment.
Bias	The level of systematic error that causes the mean values of a data set to be consistently (over repeated samples) higher or lower than corresponding "true" parameter values. With respect to LCI data, "true" parameter values may not be known.
Comparability	The degree to which different methods, data sets, or decisions agree or can be represented as similar or equivalent.
Completeness	The amount of data available for the analysis compared with the amount of data needed or desired.
Data Collection Method and Limitations	The level of information describing the method of data collection, including any limitations associated with the data collection method.
Precision	The degree of spread or variability, expressed numerically if possible, in a set of data values or measurements compared to the mean of the data values.
Referenced	The degree to which data values reference the original data source.
Representativeness	The degree to which the data represent what the analyst is trying to describe or depict.

Data Type	Data resulting from different data generation methods (e.g., measured, modeled, sampled, nonmeasured, and regulated data).
Goal Definition and Scoping	The definition of the LCA purpose and objectives; the identification of the product, process, or activity of interest; the identification of the intended end use study results; and the key assumptions employed.
Impact Assessment	The quantitative and/or qualitative classification, characterization, and valuation of impacts to ecosystems, human health, and natural resources, based on the results of an LCI.
Improvement Assessment	The identification and evaluation of opportunities to achieve improvements in processes that result in reduced environmental impacts, based on the results of an LCI or impact assessment.
Imputation	The procedure of replacing a missing value with a value considered to be a reasonable proxy or substitute.
Inventory Analysis	The identification and quantification of raw materials and energy inputs, air emissions, water effluents, solid waste, and other life-cycle inputs and outputs.
Key Data	A data point or data set that contributes significantly to the overall LCI results.
Life-Cycle Assessment (LCA)	A holistic tool used to evaluate the resource consumption and environmental burdens associated with a product, process, or activity through its entire life cycle. A complete LCA includes four components: goal definition and scoping, inventory analysis, impact assessment, and improvement assessment.
Life-Cycle Stages	The stages of any production process, including raw materials acquisition; manufacturing (including materials manufacture, product fabrication, and filling/packaging/distribution); use/reuse/maintenance; and recycle/waste management.
Measured Data	Data generated using analytical or physical measurement procedures, including survey questionnaires, sampling, or monitoring.

Modeled Data	Data generated as output from models.
Nonmeasured Data	Data generated through the use of engineering estimates, best professional judgment, educated guesses, etc.
Nonparametric Samples	Data that are typically chosen or developed from relatively small samples, that are not independent of each other, and often do not result in normal bell-curve distributions. Such data are often difficult to analyze using standard statistical techniques.
Nonstatistically Based	Any quantity or function that is not developed from the data in a probability-based sample, but developed, for example, from convenient or judgment-based samples.
Proof Statements	Statements that provide general rules by which data analysts can evaluate a specific data source.
Primary Data	Plant-specific, measured, modeled, or estimated data for conducting an LCI that the practitioner can directly access or for which the practitioner has input into the data collection process.
Random Sample	A sample of n units selected from a well-defined population in such a way that all possible samples of size n have the same chance of being selected. For example, a sample selected using n independent, equal-probability selections.
Secondary Data	Data that have not been collected specifically for the purpose of conducting an LCI and for which the practitioner has no input into the data collection process.
Sensitivity Analysis	A systematic process for evaluating the effect of variations of input parameters to a system on model results.
Statistically Based	Any quantity or function that is developed from the data in a probability-based sample.
Subsystem	An individual process that is part of a defined system.
System	A collection of operations that perform a desired function.
Uncertainty Analysis	The evaluation of uncertainty associated with inferences. Measures of uncertainty may be both qualitative (e.g., representativeness of the sample or choice of a model) or quantitative (e.g., sampling precision and bias).

Variability The fluctuation in variables over time or space. Variability can result from natural fluctuations or from the sampling and experimental design (e.g., through the use of experimental blocking factors, unequal probabilities of selection).

ACRONYMS

CV	Coefficient of Variation
DOE	U.S. Department of Energy
DQG	Data Quality Goal
DQI	Data Quality Indicator
EIA	Energy Information Administration
EPA	U.S. Environmental Protection Agency
LCA	Life-Cycle Assessment
LCI	Life-Cycle Inventory
QA/QC	Quality Assurance / Quality Control
SETAC	Society of Environmental Toxicology and Chemistry
SIC	Standard Industrial Classification
TRI	Toxics Release Inventory

CHAPTER 1
INTRODUCTION

The quality of life-cycle assessment (LCA) or any other decisionmaking tool is only as good as the quality of the information upon which it is based. Thus, assessing the quality of data utilized in a life-cycle inventory (LCI) is essential if the overall LCA results are to be properly interpreted and communicated. While LCA practitioners usually undertake some level of data quality assessment, the rigor with which that evaluation is applied—and the extent to which LCA reports discuss data quality—varies significantly. Practitioners are encouraged to continue and advance LCA data quality assessment practices.

KEY POINTS

- Greater clarity and consistency in assessing data quality is needed.
- These guidelines provide LCA practitioners with systematic procedures for assessing and reporting LCI data quality.
- These guidelines focus on assessing the quality of "key" LCI data sources.
- These guidelines or similar practices should lead to increased confidence in the final LCI results.

This document provides LCA practitioners with guidelines for assessing and communicating LCI data quality in a systematic manner. Although the focus of this document is on the inventory analysis component of LCA, some of the data quality issues and procedures will apply to LCA data as a whole. A relatively qualitative approach to LCI data quality assessment is taken in this document, representative of the current state of LCA practice and existing data quality assessment techniques. The consistent application of this or a similar framework should advance both the assessment and documentation of data quality issues in LCAs. As LCA and data quality assessment techniques evolve, it is expected that a greater level of statistical analysis will be used.

LCA is a holistic concept and methodology to identify the environmental consequences of a product, process, or activity throughout its entire life cycle and to identify opportunities for achieving environmental improvements. Life-cycle stages addressed in LCA include raw materials acquisition, manufacturing, use/reuse/ maintenance, and recycling/waste management.

The LCA approach consists of four interrelated components:

- **Goal definition and scoping:** the definition of the study purpose and objectives; the identification of the product, process, or activity of interest; the identification of the intended end use study results; and the key assumptions employed.

- **Inventory analysis:** the identification and quantification of raw materials and energy inputs, air emissions, water effluents, solid waste, and other life-cycle inputs and outputs.

- **Impact assessment:** the qualitative or quantitative classification, characterization, and valuation of impacts to ecosystems, human health, and natural resources, based on the results of an inventory analysis.

- **Improvement assessment:** the identification and evaluation of opportunities to achieve improvements in processes that result in reduced environmental impacts, based on the results of an inventory analysis or impact assessment.

A variety of organizations use the LCA methodology to serve a number of different purposes. Companies use LCA results internally to support management decisions on production processes, product design, and product packaging. Companies use LCA results externally to support product environmental claims. Government agencies use LCA results to support both technical policy and regulatory decisions. Consumer and environmental groups utilize LCA results to compare the environmental preferability of alternative products or production processes.

To date, most LCA practice involves practitioners compiling inventories and drawing conclusions based on simple data assessment techniques (e.g., the lower the amount of inputs or outputs, the lower the resulting environmental burden). Few practitioners have conducted impact assessments based on the results of an inventory analysis, largely due to the lack of development and consensus on specific impact assessment techniques. Guidelines for conducting improvement assessment, although widely practiced on an informal basis, also have not yet been established. As existing LCA tools and techniques are refined and new ones developed, practitioners are expected to conduct more impact and improvement assessments.

Completing an LCA typically requires the acquisition and synthesis of significant amounts of data. Given LCA's data-intensive nature and the importance of decisions that are made based on LCA results, data quality is a critical concern. Important problems can

arise if LCA results are based on poor or inadequate data. For example, if an internal analysis is based on poor quality data, misleading results could lead to process or product decisions that are unnecessarily costly. Likewise, conclusions based on external analyses that used poor quality data could mislead public perception about the environmental profile of a product or process. Due to such concerns, there is a growing consensus within the LCA community that data quality assessment procedures need to be integrated into LCAs and the results discussed more fully.

1.1 THE CURRENT STATE OF LCA DATA QUALITY EVALUATION

The evaluation of data quality for LCA studies was once considered a predominantly internal, informal exercise that relied heavily on expert judgment, with limited reporting in the final study results. LCA data quality assessment is still a largely judgmental process and will continue to be so for at least the near term. However, statistical information on some data is currently available and should be used whenever possible.

Recently, an international survey was conducted (Vigon and Jensen, 1992) to evaluate the current treatment of data quality and data base issues by LCA practitioners. Thirty-three European and North American organizations involved in LCA practice responded to questions addressing scope and boundary setting; data collection procedures; and data analysis, interpretation, and reporting. Following are highlights of the practitioner survey results.

Current data quality practices typically include an informal system of cross-check procedures. This analysis may involve a comparison through expert judgment of internal, primary data with other published or trade association data, or a comparison of estimated or measured data with theoretical values. Other approaches for checking data quality include internal project team discussions and third-party review. However, these procedures are often not clearly defined and documented in the final LCA results.

Practitioners are aware of the need for greater clarity and consistency in assessing and reporting data quality. Reflected in the survey responses is an acknowledgment of the lack of a systematic approach for determining the quality of the data being collected. Specific areas identified in the survey as needing improvement include techniques for sensitivity analysis, uncertainty analysis, and the quality of available data. Improvements

in these and additional techniques should result in more tightly developed conclusions and enhanced understanding of the impact of the data quality on LCA results.

Practitioners are aware of the need for greater clarity and consistency in assessing and reporting data quality.

This document addresses several of the data quality assessment and reporting needs identified in the LCA practitioner survey. In particular, Chapter 3 presents a data quality assessment framework which, if widely employed, will improve the consistency and clarity with which LCA data quality is assessed and reported. This framework is designed to complement the steps typically taken by practitioners during the conduct of an LCI.

1.2 PURPOSE AND SCOPE OF THESE GUIDELINES

The purpose of these guidelines is to provide guidance for LCA practitioners and others in assessing the quality of "key" LCI data sources (see Sections 2.4 and 3.4.2 for a discussion of key data sources). These guidelines address where and how data quality can be considered when conducting an LCI and describe a general, systematic approach for assessing LCI data quality based on data quality goals (DQGs), data quality indicators (DQIs), and documentation of practitioner judgments. The approach relies on a series of data quality worksheets for compiling and reporting data quality information on key data sources. These guidelines do not suggest conducting detailed assessment and documentation of every data source used, nor do they attempt to lay out each step an analyst should take to collect LCI data and assess its quality. The document also discusses sensitivity analysis, uncertainty analysis, and data compensation techniques. These guidelines have been tested through the conduct of two LCA practitioner data quality assessment case studies and modified accordingly.

The purpose of these guidelines is to provide a framework for LCA practitioners and others to assess the quality of "key" LCI data sources.

It is recommended that LCA practitioners incorporate data quality assessments into both internal and external LCAs. Internal LCAs must provide the stakeholders with high-quality information that is accurate as an engineering, marketing, and overall

decisionmaking tool. Practitioners may use external LCA results to educate the public about products and processes, to support product claims, or to advocate a particular public policy issue. Given the public nature of the information, characterizing the accuracy of external LCA results is an important concern. If practitioners follow these guidelines or similar practices when assessing and reporting data quality, users of LCA results should have increased confidence in the information. In addition to LCA practitioners, possible users of these guidelines include:

- analysts who are working to develop and improve LCA methodologies,
- analysts who need to assess the quality of data used in existing LCAs, and
- decisionmakers who use LCA results.

If practitioners follow these guidelines or similar practices when assessing and reporting data quality, users of LCA results should have increased confidence in the information.

Steps in the LCI data development process are complementary and iterative, and thus assessing LCI data quality is an iterative process. For example, if the collected data does not meet the previously defined DQGs, additional data must be collected or DQGs must be redefined. The interconnection between LCI data development steps is discussed further in Chapter 3.

1.3 AREAS OUTSIDE THE SCOPE OF THESE GUIDELINES

In addition to data quality concerns, four additional areas are important to the future development and use of LCA: the development of an LCA peer-review process, a code of LCA practice, and procedures for conducting LCA impact and improvement assessments. It is beyond the scope of this document to define or discuss any of these issues in detail. Here, they are addressed briefly in terms of their relationship to LCI data quality concerns.

1.3.1 Peer Review

The Society for Environmental Toxicology and Chemistry's (SETAC's) document, *A Technical Framework for Life-Cycle Assessment*, indicates that peer review is a necessary and important step for ensuring the technical and scientific credibility of LCAs

(SETAC, 1991). In response, the SETAC LCA Advisory Group collaborated with business, consumer, and environmental groups and with academia to develop an interim peer-review framework (SETAC, 1992). The framework recommends, among other things, the establishment of a peer-review panel early in any LCA that will be used in a public forum to review the following:

- the LCA study goals, scope, and key assumptions;
- data acquisition and compilation methodologies;
- compiled data and associated quality measures; and
- the communication of results in a draft final report (EPA, 1993b).

These guidelines also recommend incorporating peer or expert review into the data quality assessment process. Peer review is recommended from a data quality perspective because it provides an additional set of checks and balances on the use of LCI data. Peer review should improve the conduct of LCIs, increase the understanding of the results, and aid in further identifying and subsequently reducing any environmental consequences of products or processes (EPA, 1993b). However, peer review of data sets and their quality is expected to remain largely internal for at least the near term because of confidentiality issues and the need to have a high level of expertise at the process or product level.

Although EPA supports the use of peer reviews, this document does not attempt to define an appropriate peer-review process for LCI data quality assessment or LCAs in general. SETAC will continue to identify and develop LCA peer-review procedures.

1.3.2 LCA "Code of Practice"

Inconsistencies and uncertainty in LCA results have resulted in the recognition of the need for a standardized LCA methodology (Denison, 1992). These guidelines present operating principles for the evaluation and reporting of LCI data quality. They do not, however, outline a code of practice for the entire LCA process; the development of such principles is being undertaken by SETAC.

This LCA "Code of Practice" is not a standard for conducting LCAs. Instead, it provides guidance on the process and on the methodological aspects of conducting an LCA, emphasizing that

- LCA is a complex, multi-dimensional tool;
- LCA methodology has yet to be described in full (of the LCA components, only inventory analysis has been well documented);
- inventory analysis and subsequent improvement decisions are the state of the art in 1993; and
- new issues will arise as practitioners expand the application of LCA (SETAC, 1993a).

Although SETAC does not have regulatory powers or the authority of a standards organization, it hopes that this LCA "Code of Practice" will be recognized as authoritative and will serve to enhance the use of LCA as a tool for environmental management (SETAC, 1993a).

1.3.3 Life-Cycle Impact Assessment

Data quality concerns associated with conducting an impact assessment extend beyond those of the inventory. A framework for conducting an impact assessment, including the key issues related to the impact-assessment phase of an LCA and possible methods for conducting impact assessment, are addressed in EPA's "*Life-Cycle Impact Assessment: A Conceptual Framework, Key Issues, and Summary of Existing Methods*" (EPA, 1994b), and SETAC's *A Conceptual Framework For Life-Cycle Impact Assessment* (SETAC, 1993b).

Impact assessment is generally used to determine the environmental effects attributable to inventory items. Conducting an impact assessment typically involves a range of models and analytical methodologies that often require extremely complex data manipulations compared to those used in inventory analysis. Thus, the quality of impact assessment data and the results produced by these models will be much more difficult to assess than those of the inventory component.

In general, impact assessment focuses on a greater number of data values than inventory analysis because it focuses on the relative harm of inventory items, which is not solely a function of their magnitude. For example, 10 pounds of xylene released to a river may not be considered as significant as 10 tons of carbon dioxide (CO_2) released to the air based on absolute values. However, the environmental impact of xylene would be very important, probably more so than the larger amount of CO_2. Thus data values that may not be considered key to the inventory may be critical to the impact assessment, and

quality assessment is not as straightforward as focusing on a few key data values based on degree of effect on final LCI results.

1.3.4 Life-Cycle Improvement Assessment

Data quality concerns also exist when conducting the improvement assessment phase of an LCA. Although widely practiced on an informal basis, there is no consensus on procedures for conducting a life-cycle improvement assessment. Vigon and Curran (1993) have outlined one possible framework for conducting an improvement assessment, but it has not yet been discussed in a public forum. Because it is in the improvement assessment component of LCA where options for achieving environmental improvements are evaluated, accurate and reliable data are critical. The lower the quality of data used in improvement assessment, the higher the risk of making the wrong decision.

One data quality concern relating to both impact and improvement assessment is that of compounding uncertainty, where imperfect information developed in the inventory is used as input data for imperfect impact and improvement assessment models. These and other issues will need to be researched and addressed as methods for conducting impact assessment continue to develop.

1.4 OVERVIEW OF DOCUMENT

The LCI data quality assessment guidelines are outlined as follows:

Chapter 2 identifies key issues that make data quality for LCI unique, reviews the data sources and data types typically used when conducting an LCI, and discusses potential problems with data quality.

Chapter 3 provides a detailed discussion of the steps involved in building the LCI and discusses where and how data quality can be evaluated. Chapter 3 also defines DQGs and DQIs and examines their applicability to an evaluation of LCI data quality.

Chapter 4 explains the concepts behind sensitivity and uncertainty analysis methodologies and their applicability to LCI data.

Chapter 5 discusses some alternatives for handling missing or deficient data and summarizes existing data compensation techniques.

CHAPTER 2
KEY DATA QUALITY ISSUES FOR LIFE-CYCLE ASSESSMENT

"Data quality" can take on a variety of meanings. For the purposes of these guidelines, data quality is defined as the degree of confidence an analyst has in a data source or data value based on an evaluation of data quality goals (DQGs), data quality indicators (DQIs), and the role of the data in an overall LCA. (See Chapter 3 for a detailed discussion of DQGs and DQIs.)

Data quality is the degree of confidence an analyst has in a data source or a data value based on an evaluation of data quality goals (DQGs), data quality indicators (DQIs), and the role of data in an overall LCA.

Ideally, data of the highest possible quality for use in LCIs would consist of measured values with ranges and standard errors, which would be developed using methods documented and approved by an accepted standards organization, measured and reported by individual material component (i.e., chemical species), and reported on the basis of a specific time frame. In practice, most of the data used in LCIs does not fit this ideal, and in many cases may not need to meet these stringent criteria. Therefore assessing and communicating the quality of LCI data is critical.

KEY POINTS

- Data used in LCIs are typically a mixture of different types from a variety of sources.
- A subset of "key" data sets may contribute proportionately more to the overall quality of the LCI data.
- Uncertainty occurs and can be compounded at a number of stages in the LCI data development process.
- Much of the existing environmental data was developed for purposes other than building an LCI.

LCA practitioners and interested parties have recognized key issues that make data quality assessment unique in the context of LCI:

- a variety of data are used to build an LCI which may vary by source, type, and level of aggregation;
- some subset of "key" data sets may account for a larger amount of variability;
- aggregating data sets is inherent in the LCI data development process;

- uncertainty propagation in the LCI data development process;
- the use of nonparametric samples in an LCI; and
- the use of existing data sources which have not been specifically developed for LCI use.

This chapter discusses each of these issues as they relate to LCI data quality. The purpose of this discussion is to provide the reader with a general understanding of key LCI data quality issues, as they provide the foundation for many of the LCI data quality assessment steps and procedures discussed in Chapter 3.

2.1 USING A VARIETY OF DATA TO BUILD AN LCI

LCI data sets can be comprised of data that varies by the primary or secondary nature of the data source, the type of data employed (e.g., measured, modeled, or nonmeasured), and the level of data aggregation (e.g., individual plant or industry average data). It is important that practitioners recognize these characteristics among data sets and consider how their use may affect the outcome of the LCI. For example, secondary data sources are generally less specific than actual measured or monitored plant-specific data found in most primary data sources. Similarly, aggregated data may provide little indication of the variability in a parameter of interest, such as facility-specific air emissions. Nonaggregate data, on the other hand, often can be used to calculate statistical measures, such as the mean, median, standard deviation, and kurtosis, to provide an indication of the central tendency, variability and skewness in the data. Examples of data sources, data types, and different levels of aggregation are shown in Figure 2-1 and discussed in the following sections.

2.1.1 Data Sources

Data sources have been defined fairly consistently throughout the LCA literature, and authors agree on the definition of a data source within the context of an LCA. A data source is where LCA data are found and includes, for example, industry reports; government documents, reports, and data bases; journals; and reference books (see Figure 2-1).

Data Sources (primary and secondary)

- industry data, reports, data bases, or consultants
- laboratory test data
- government documents, reports, data bases, or clearinghouses
- other publicly available data bases or clearinghouses
- journals, papers, books, and patents
- reference books
- trade associations
- related life-cycle inventories
- product and process specifications

Data Types

- measured
- modeled
- sampled
- nonmeasured
- regulated

Levels of Aggregated Data

- individual observations
- temporal averages
- spatial averages
- normalized (per unit) averages

Example: A data source could be the Census of Manufacturers, the data type could be measured data for SIC 2911, and the level of aggregation could be industry averages per annum.

Figure 2-1. Example Data Sources, Data Types, and Levels of Data Aggregation
Sources: SETAC, 1991; EPA, 1993b; EPA, 1994a.

The EPA's *Life-Cycle Assessment: Inventory Guidelines and Principles* (EPA, 1993b) identifies sources of government documents, including the U.S. Department of Commerce's *Census of Manufactures*, the U.S. Bureau of Mines' *Census of Mineral Industries*, the U.S. Department of Energy's *Monthly Energy Review*, and EPA's Toxic Release Inventory (TRI) data base. SETAC's report, *A Technical Framework for Life-Cycle Assessment* (SETAC, 1991), also refers to data sources in general categorical terms and provides specific examples of information sources within the different source categories.

EPA's report *Life-Cycle Assessment: Public Data Sources for the LCA Practitioner* (EPA, 1994a) is a reference document on public data sources potentially useful in LCAs. This report identifies and describes major types of public data sources potentially applicable to LCA and evaluates data bases for LCA applicability. Other sources of data discussed include bibliographic data bases, relevant documents and

directories of literature, electronic data base clearinghouses, foreign data bases, and ongoing studies.

Data used in LCIs are typically a mix of primary and secondary data. Because secondary data are typically collected for purposes other than LCA, additional data quality issues are often applicable. The following sections discuss data quality issues related to the use of primary and secondary data in the LCI data development process.

Primary Data

Primary data are plant-specific, measured, modeled, or estimated data that the LCA practitioner can directly access or for which the practitioner has input into the data collection process. In most cases, primary data are preferred for use in LCIs because they are specific to the product or process being evaluated and are more amenable to assessing data quality concerns. Companies conducting or commissioning LCIs have usually classified their primary data as proprietary. Under this circumstance, the data and the associated collection methods are unavailable for review or simply not released to the public. In some cases, summary results are made available but they do not include the actual plant-specific data. Consequently, verifying the quality of these data can be difficult. If an LCI involves the use of proprietary information, the level of data quality rests largely on the reputation of the company providing the data.

Although plant-specific data are often more representative, they are not always preferred to industry-based data. Situations can arise where plant-specific data are less representative than aggregate industry figures. For example, a steel-can manufacturer may buy steel on the metals market but may not be able to specify how or where the steel was manufactured. In this case, an LCI that used plant-specific manufacturing data may be less representative than one using data that reflect the mix of plants and processes that constitute the steel commodities market (Arthur D. Little, Inc., 1993a).

Secondary Data

Secondary data include data that were not collected specifically for the conduct of LCI and for which the practitioner has no input into the data collection process. Secondary data sources can be more difficult to evaluate from a data quality perspective. The data source may not include an explanation of the data collection methods and data variability. Secondary data may be specific to a product or process under evaluation or they may be aggregated values. In the latter case, the data may require some form of

manipulation before values suitable for use in LCIs can be generated (see the discussion in Section 2.1.3 on aggregated data).

2.1.2 Data Types

A data type is defined by the method used to generate the data. Data types generally include measured data (statistically or nonstatistically based), modeled data, and nonmeasured data (e.g., educated guesses or estimates).

Measured Data

Measured data are monitored or sampled. These data can be collected under statistically based or nonstatistically based protocols. In addition to the general concerns expressed above regarding primary and secondary data, measured data present potential data quality problems. Monitored or sampled data could be inaccurate if an inappropriate sample design is used or if there is bias in the monitoring or sampling devices. It is important to have at least a description of the data collection methods or the statistical protocol to assess the validity of measured sources.

Modeled Data

Practitioners may use models to generate data for LCIs, or they may rely on secondary sources that use a model to generate the data. Models can be used to simulate an industrial process or estimate emissions from a production process. The potential shortcomings associated with modeled data primarily pertain to how the model is constructed. To provide simulated data with a high confidence level, models should be validated. Validation refers to the degree to which the model has been checked against a standard or reference value to determine if it represents what it is supposed to represent. If the model output equals or is reasonably close to the reference value, then the model is likely to generate relatively accurate results. Validation techniques include using expert opinion to determine whether the model presents an adequate representation of the process or using the model to reproduce an historical data set. A model that is not validated and verified may produce apparently useful results that may in fact have very little relation to the true values desired.

It is often easier to verify and validate primary modeled data than secondary modeled data because practitioners usually have access to their own models and can assess the accuracy of the model and results. Secondary data sources may provide neither the full model nor information regarding the author's verification and validation activities.

Nonmeasured Data

Nonmeasured data include estimates based on best professional judgment or other educated guesses. Many nonmeasured data sources do not describe the methods used to estimate the data or whether mathematical or other techniques were employed to compensate for missing data and data deficiencies. Assessing the quality of these data requires reviewing the evidence and assumptions that went into deriving the value(s). Without sufficient understanding of how and why the estimates were made, an analyst may make biased inferences using the data. Unless experts who developed the data can be consulted or there is adequate peer acceptance of the data source, the analyst may be unable to determine the extent of potential bias.

2.1.3 Levels of Aggregated Data

Aggregated data typically are presented as summary reported values. There are a variety of levels in which data can be aggregated:

- individual measures (i.e., unaggregated);
- temporal averages (monthly, annual);
- spatial averages (facility, industry, county, state, national); and
- normalized (per unit value) (EPA, 1993b).

Aggregated data are potentially useful when the LCI results are used for broad applications. Aggregated data are generally more representative of a composite function, such as an industry as a whole. In addition, such data can be made publicly available, are widely usable, and are more general in nature (EPA, 1993b).

The quality of aggregated data is often more difficult to assess than the quality of nonaggregated data because aggregated data sets usually do not list the intermediate values that were used in compiling the data. The data aggregation process can eliminate valuable information (e.g., variability in the data) needed to evaluate the quality of a data set. In addition, aggregated data also may require some sort of manipulation (e.g., interpolation, extrapolation, or back-calculation) to generate a value suitable for use in LCIs. Any uncertainty associated with the aggregated data may be compounded by the method used to produce appropriate LCI data values.

For example, the *DOE Monthly Energy Review* contains a section with monthly and yearly totals for residential and commercial, industrial, transportation, and utility

energy consumption. Within each class of end users, the data are broken down by the type of fuel used to generate the energy. To use these data in lieu of facility specific information to perform an LCI on a product (e.g., tires), an analyst would have to make assumptions about the percentage of industrial energy consumed in tire production. This percentage may be estimated using expert opinion/knowledge or using a mathematical model. The level of uncertainty in the aggregated consumption values could be compounded by the uncertainties associated with any assumptions used in modifying the data.

Nonaggregated data may or may not provide further information to assess data quality. Nonaggregated data can be used to calculate such statistical measures as the mean, median, standard deviation, and kurtosis—all of which may provide an indication of the central tendency, variability, and skewness in the data set. On the other hand, nonaggregated data may be composed of inputs from different plants within the same company. Differences in the data could be due to the way the parameter was measured (e.g., direct measurements, statistical sampling, engineering estimates, modeling); the different operating characteristics of the plants (e.g., fuel and raw material mixes or regulatory requirements); or the period of measurement (e.g., episodic, continuous, random sampling, or daily/monthly/annual). In these instances, nonaggregated data may provide no additional useful information unless the other sources of variability also are discussed.

2.2 IDENTIFYING "KEY" LCI DATA SETS

The complexity of the system being studied in the LCI can greatly affect data quality assessment. Even relatively simple systems may require collection, review, comparison, assessment, and validation of hundreds or thousands of data points (Franklin Associates, Ltd., 1993). While it is ideal to have high quality data for all data sources, time and resource constraints require that data quality assessment efforts of multiple large data sets be proportionately allocated to the most important or "key" data sets. Key data sets are defined as those that contribute significantly to final results and thus dictate the quality of the overall LCI. It is recommended that practitioners focus data quality assessment efforts on key data sets. However, it should be noted that key data for any particular analysis or conclusion may not be key for other analyses.

Identifying which data are key to the LCI thus becomes a critical aspect of data quality assessment. A number of qualitative and quantitative techniques are currently being used to help practitioners pinpoint these key data sets. For example, in the field of environmental labeling, "screening" matrices are often used to provide a more qualitative indication of the most significant life-cycle stages or environmental effects.

Formal and informal sensitivity analysis techniques may also be used to help identify key data sets. Formal techniques provide a more quantitative approach and require generating mathematical models to evaluate the relative importance of individual or multiple system parameters. Informal sensitivity analysis provides a more qualitative approach and relies on the analyst's empirical knowledge of the data set to determine which parameters are likely to contribute the most to LCI results. The results of an informal sensitivity analysis may be validated by formal sensitivity analysis techniques (Franklin Associates, Ltd., 1993). Specific sensitivity analysis techniques are described in further detail in Chapter 4.

2.3 AGGREGATING DATA IN THE LCI DATA DEVELOPMENT PROCESS

As used here, the term "data aggregation" refers to the aggregation of data within and between system components that occur in the LCI data development process. In short, data aggregation is a common technique in the LCI data development process that, when practiced correctly, can be a useful tool for presenting and managing LCI data. Typical primary and secondary LCI data vary widely on a variety of characteristics, including:

- the time frame over which the data were collected;
- the geographic scale represented by the data (e.g., facility-level observations versus national averages);
- product or process variations (i.e., multiple processes may be used to manufacture the same product, each with its own distinct quantity and mix of inputs and outputs);
- data value size (e.g., small versus large measurements);
- significant figures of data values (e.g., a rough estimate versus a number that has four significant digits);
- data collection process (e.g., actual measurement versus expert judgment); and
- data manipulations (e.g., normalizing per unit of output).

It is unlikely that any two LCI data points would have exactly the same characteristics. Therefore, the issue of data aggregation focuses primarily on the aggregation of disparate data points that typically occurs in the LCI data development process. Such aggregation of "apples and oranges" has the potential to misrepresent the system of interest, and may contribute to the propagation of uncertainty.

An issue associated with data aggregation is how the inclusion (or exclusion) of large versus small data values may potentially affect LCI results. In general, large data values contribute proportionately more to estimates of means and totals (typically final LCI results) and to the quality of the final results than do smaller data values. Different boundary settings may include or exclude potentially large data values. Thus, the dominance of large numbers is a key consideration when aggregating many numbers of different magnitudes and quality. Quality should be emphasized on the larger data values in the data set to reduce or compensate for uncertainty in the final results. However, small data values also can be important to data quality if they are measured or estimated poorly. The issue of large versus small data values is addressed in greater detail in Chapter 3.

2.4 UNCERTAINTY PROPAGATION

Uncertainty in data usually occurs and can be compounded at a number of stages in the LCI data development process. This can make it difficult for practitioners to develop accurate conclusions or decisions based on LCI results (Vigon and Jensen, 1992). Potential sources of uncertainty include:

- the data source itself,
- any assumptions and/or calculations used to manipulate LCI data, and
- aggregating very different data sources or values as described above.

Uncertainty analysis techniques may be used to identify which errors in input data are compounded as the LCI model is utilized. Determining the uncertainty or variability in data may also be accomplished through more qualitative means, which can help LCA practitioners ensure that their results are accurate and representative. Some of these qualitative activities, which are addressed more specifically in Chapter 4, include:

- careful planning and execution of the LCI process leading up to final results,
- formal and informal reviews of the LCI data development process,

- focusing data quality efforts on values that significantly influence LCI results, and
- ensuring that sample sizes for key data values are as large as possible, thus increasing the reliability of the estimates (Arthur D. Little, 1993b).

2.5 USING NONPARAMETRIC SAMPLES IN AN LCI

In many cases, a portion of the primary data that make up an LCI are nonparametric samples. Nonparametric samples refer to data that are chosen or developed from a relatively small sample size and where the data are not independent of each other. Nonparametric samples do not come from a probability sample and thus are often difficult to analyze using standard statistical techniques (Franklin Associates, Ltd., 1993). In the context of LCI, nonparametric samples would include data generated through engineering estimates, expert guess, and similar approaches where the shape of the "true" distribution of a parameter is not known.

Although methods for statistical analysis of nonparametric samples have been developed in other fields (e.g., limnology), little has been done in the area of LCA to develop statistical techniques with which to analyze nonparametric LCI data. Until such techniques and procedures are established, practitioner judgment will remain a substantial part of choosing data sources and assessing data quality in cases where only nonparametric samples are available. When using such practitioner judgment, whether in the context of nonparametric samples or otherwise, it is critical that all key steps and assumptions are checked, documented, and reviewed.

2.6 USING EXISTING ENVIRONMENTAL DATA IN AN LCI

Much of the existing sources for environmental data, whether public or private, have been developed for purposes (e.g., regulatory compliance) other than that of conducting an LCI (see EPA, 1994a). Although these sources may be readily accessible for use in an LCI, the quality of the data must be considered. Even when the quality of the data is considered to be good for the original purposes, the use of the data in an LCI may need be to be reconsidered. For example, TRI data are typically based on engineering estimates as prescribed by law; however, a greater level of certainty may be required for LCI—especially if the LCI is to be used in an external application. There is also a bigger issue of specificity regarding the use of TRI data. That is, TRI data are typically generated for generic waste streams and are not necessarily representative of the

specific waste stream data needed for an LCI that is often linked to a specific product or process. Practitioners should carefully evaluate existing environmental data to ensure that they accurately represent what is desired in the LCI.

In addition, many regulatory data bases report data on only a range of facilities for a subset of total environmental releases. For example, EPA's AIRS database covers point source emissions for primarily Clean Air Act criteria pollutants of sources emitting more than a threshold of 100 tons per year—except 5 tons per year for lead and 1,000 tons per year for CO (EPA, 1994a). The AIRS database also may report either actual or estimated emissions values, without stating which values are being reported. The lack of distinction between actual or estimated emissions is a common situation with environmental data sources which contain aggregated information.

While many existing data sources for environmental releases provide a readily available source of LCI data, it is recommended that practitioners exercise caution in using existing environmental data that has been developed for purposes other than conducting an LCI. Any limitations associated with such environmental releases data should be clearly identified and communicated in the final LCI results.

CHAPTER 3
ASSESSING THE QUALITY OF LIFE-CYCLE INVENTORY DATA

The LCI is the initial data generation and collection component of an LCA. As such, the quality of data used in the LCI directly affects the results of the overall LCA. This chapter outlines a framework for assessing the quality of LCI data that is designed to complement the LCI data development steps typically taken by practitioners. Although this framework focuses exclusively on the LCI component of LCA, some of the data quality assessment issues and techniques are likely to apply to LCA data as a whole.

The relatively qualitative approach to LCI data quality assessment outlined in this framework reflects the current state of LCA practice and existing data quality assessment techniques. The consistent application of this or a similar framework should advance both the assessment and documentation of data quality issues in LCAs. As LCA and data quality assessment techniques evolve, it is expected that a greater level of statistical analysis will be used.

KEY POINTS

- The consistent application of this or a similar framework should advance both the assessment and documentation of data quality issues in LCAs.
- Practitioners should clearly define the system boundaries and explain how those boundaries were determined, as well as any limitations they may present.
- When evaluating data sources, it may be useful to apply DQIs to see if adequate information is provided about how the data were generated.
- A final LCA report should include a reference for each data source used and explicit information on the quality of the key data sources and any important assumptions.

The LCI data quality assessment framework presented in this chapter was tested in case studies by two recognized LCA practitioners. Using existing LCI data, the practitioners performed data quality assessments on selected data sources using this framework and documented their results. Where appropriate, examples from these practitioner case studies have been used to illustrate the application of the framework. SETAC (1991) and EPA (1993b) have prepared key LCA documents that outline procedures for conducting an LCI. As indicated in EPA's *Life-Cycle Assessment: Inventory Guidelines and Principles*, LCIs should contain data for the following life-cycle stages:

- raw materials acquisition;
- manufacturing (which includes materials manufacture, product fabrication, and filling/packaging/distribution);

- use/reuse/maintenance; and
- recycling/waste management (EPA, 1993b).

Each of the stages listed above receives inputs such as energy and raw materials and produces outputs such as waste streams (air, water, solid waste), recyclables, co-products, and final or usable products (see Figure 3-1).

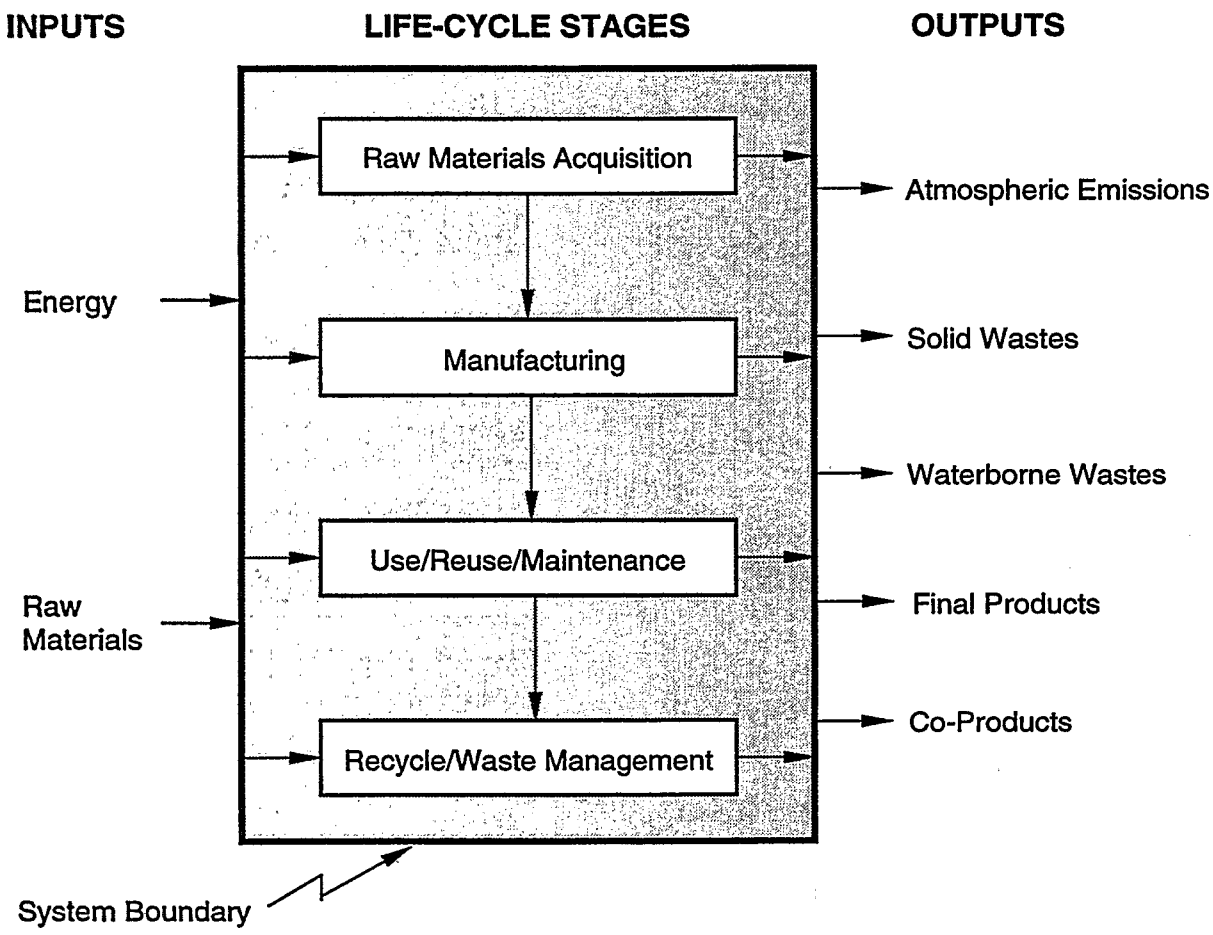

Figure 3-1. Life-Cycle Stages
Source: SETAC, 1991; EPA, 1993b

Practitioners undertake an involved process to build LCI data for each input and output associated with the system of interest. Figure 3-2 outlines the typical steps practitioners take in the LCI data development process and identifies points in the process where data quality activities should be incorporated. Steps involved in the LCI data development process include the following:

- defining study scope and boundaries,
- developing an LCI data collection plan,
- undertaking data collection and quality assessment,
- evaluating model sensitivity and results, and
- documenting and referencing study results.

Figure 3-2 also highlights the iterative nature of the LCI data development process. Although the process is depicted as moving in a linear direction, data limitations and other factors typically cause practitioners to continuously reconsider the scope and objectives of the LCI. For example, in moving from scoping and boundary definition toward documenting and referencing LCI results, a practitioner might recognize that a significant component of the life cycle was inadvertently excluded. In this case, the practitioner should re-evaluate and possibly refine the scope of the LCI, which would likely require collecting and assessing additional data. The following sections discuss the steps in the LCI data development process and their relationship to LCI data quality assessment.

3.1 SCOPE AND BOUNDARY DEFINITION

Defining the scope of the overall LCI is the first step in the LCI data development process. During this step, the overall purpose and objectives of the LCI are defined. This includes identifying the product, process, or activity under evaluation (e.g., process change or product comparison), the level of analysis undertaken (e.g., simple inventory calculations based on a "less is better" criterion or an impact assessment), and the end use of the final LCI results. With respect to the end use, practitioners should identify whether the final LCI results will be used in an internal or external manner, and whether the LCI will be absolute or comparative (i.e., evaluating one product or process versus multiple products or processes). Table 3-1 shows a case study example for LCI scoping and boundary definition.

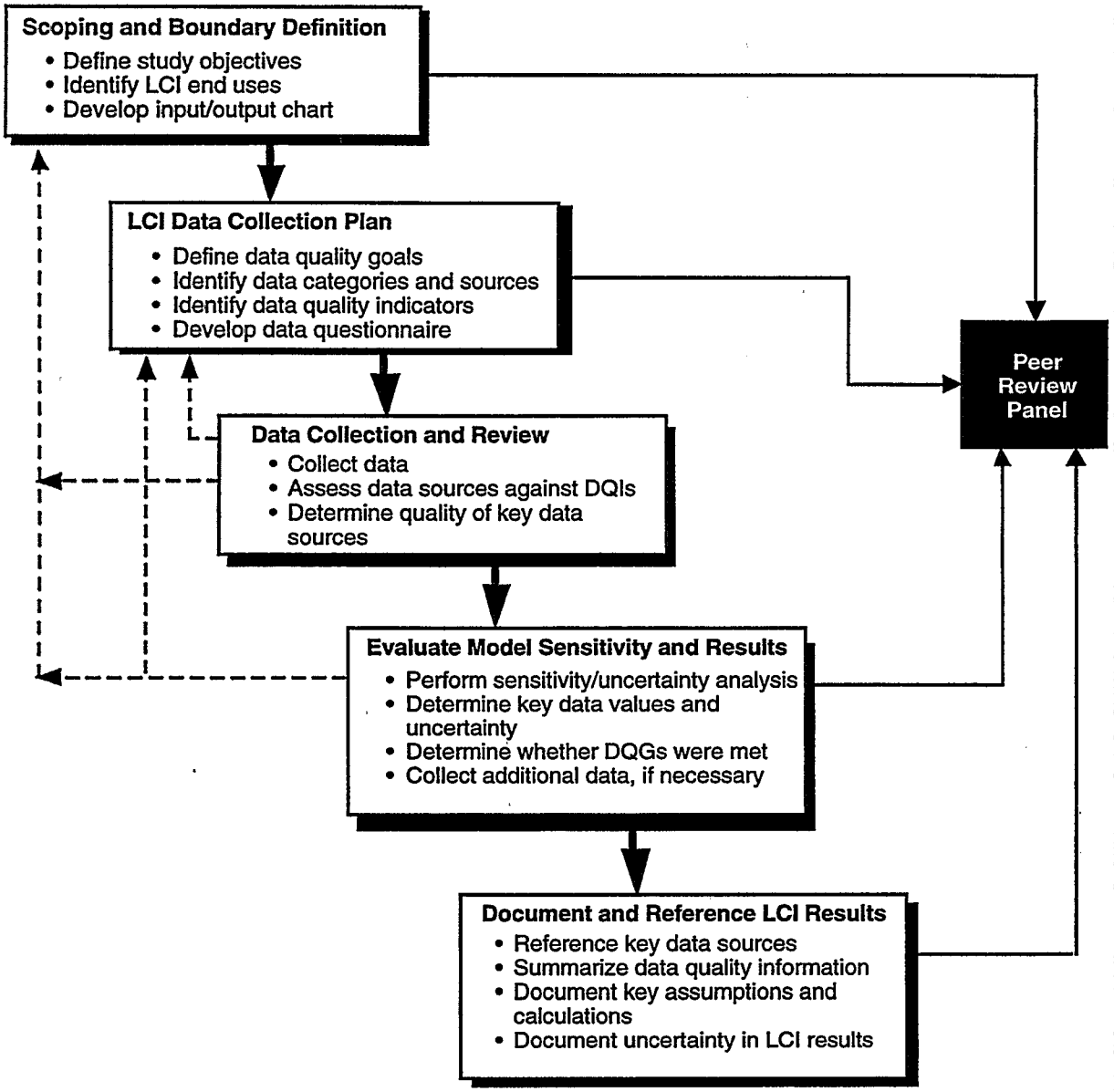

Figure 3-2. LCI Data Development Steps

Practitioners should also consider data quality as they define the scope of an LCI, including the type of data needed for the analysis and the level of data quality necessary to support the intended purpose of the LCI as well as the overall LCA. In addition to defining the objectives of the LCI, practitioners need to determine where data quality will be stressed—this might be thought of as developing initial, broad data quality goals (DQGs). For example, if an LCA is concerned with initiating a manufacturing process change, the quality of LCI data may be less significant for raw materials or transportation

TABLE 3-1. CASE STUDY EXAMPLE: LCI SCOPING AND BOUNDARY DEFINITION

Study Goal:	To assess the environmental performance of the process for manufacturing product X and to identify opportunities for environmental improvements.
Study Objectives:	• Develop a working data base of baseline environmental data for the manufacture of product X. • Evaluate the working data base for the most critical pollutant types. • Develop a final data base containing pollutant types considered to be most critical. • Identify areas where critical pollutant types may be reduced.
Study Scope:	A confidential industry data source will be used to develop baseline environmental data for one of the client's major product lines. The resulting data base is to be used on an internal basis only. Primary data will be collected from nine separate facilities. Study boundaries include raw material and energy inputs, water consumption, air emissions, water effluent, and solid waste generation associated with product manufacturing at these facilities. One of the foreseeable limitations in developing this data base will be that all nine facilities are multiproduct manufacturers. As a result, facility engineers may be required to use their best judgment to allocate aggregate waste streams to product X.

Source: Modified from Arthur D. Little, 1993b.

input data (Arthur D. Little, 1993a). Practitioners should ask the following questions when defining the scope of the LCI:

- Will the data be used for LCI only, or will the data be used to conduct an impact assessment?
- What type of decision will be made using the data (e.g., modifying a product or an industrial process, imposing a regulation, or comparing one product to another)?
- How will altering the scope of the study influence data quality needs?
- How will altering data quality affect overall LCI results?

- Can data commensurate with the scope of the study be acquired given the available resources?

Note that if the answer to the last question above is "no," there is a need to reevaluate the study scope and/or the amount of resources allocated to the study. After clearly defining the scope and the general level of data quality, appropriate system boundaries must be delineated. System boundaries are typically summarized in an input/output flow chart or matrix, which identifies all inputs and outputs of the overall system and its subsystem components.

The input/output parameters needed for an LCI have been thoroughly discussed in the SETAC (1991) and EPA (1993b) documents. These documents state generally that all inputs (e.g., energy, raw materials, and water) and outputs (e.g., air emissions, water effluent, solid and hazardous wastes, and co-products) of the system under evaluation should be identified clearly. System boundaries are typically chosen to accurately portray the system being studied and to control the uncertainty and cost of the LCA; there is no single "correct" way to define them.

When delineating system boundaries it is important, especially for external applications, to indicate clearly which life-cycle components are excluded by the system boundaries and how including these components may affect the LCI and the interpretation of the overall LCA results. Practitioners should also consider how different boundary settings can affect the outcome of the LCI and the overall LCA. For example, a comparative study of two existing LCAs for corrugated cardboard production by Ekvall (1992) found significantly different results, even though the two facilities were located in the same country and produced the same product using similar processes. It was generally concluded from this study that differences in system boundaries, surrounding conditions (e.g., recycling rates, available resources), and data used in the analyses led to differences in the overall results (Ekvall, 1992).

Practitioners should also consider which LCI data sets would be included or excluded if boundaries were drawn differently (i.e., these data sets which will dictate the quality of overall LCI results). It is critical that practitioners clearly define the system boundaries and explain how those boundaries were determined, as well as any limitations to the study they may present. Clearly defined boundaries not only help place LCI results into proper context but are essential for decisionmakers and other interpreters of the results.

It is critical that practitioners clearly define the system boundaries and explain how these boundaries were determined, as well as any limitations to the study they may present.

Once the scoping and boundary issues have been addressed, SETAC recommends that practitioners submit this information to a previously established peer-review panel (SETAC, 1992). Depending on the intended use of the study, a peer-review panel can be made up of members of the organization sponsoring the LCA or persons outside the process. In examining study scope, boundaries, and assumptions, the peer-review panel should consider:

- the purpose for conducting the LCA;
- boundary settings;
- the choice of functional unit and range of alternatives; and
- any assumptions used in determining study boundaries and functional units.

Later reviews will also consider:

- anticipated data availability;
- proposed data aggregation procedures;
- anticipated data variability and sample sizes; and
- the consistency of goals and objectives, boundaries, assumptions, and data availability (SETAC, 1993a).

Review efforts are intended to help practitioners determine whether the identified scope, boundary, and data categories are reasonable. Such efforts help in enhancing the quality and credibility of the LCI data used and the overall LCI results.

3.2 LCI DATA COLLECTION PLAN

After the scope and boundaries of an LCI have been defined, practitioners can outline an LCI data collection plan. Because data collection is a significant part of an LCI budget, the data collection plan is typically prepared before the project is funded (Franklin Associates, Ltd., 1993). Key elements of a data collection plan include the following:

- defining data quality goals,
- identifying data sources and categories,
- identifying data quality indicators, and
- developing a data questionnaire.

In developing a data collection plan, the DQGs should be aimed at ensuring accuracy and representativeness of the final results, and data questionnaires should facilitate the collection of appropriate data (Arthur D. Little, 1993b).

3.2.1 Defining Data Quality Goals (DQGs)

The first step in developing an LCI data collection plan is defining DQGs to indicate where data quality is a high priority and the level of effort necessary to obtain data of a desired quality. DQGs are qualitative statements that define specifications for the adequacy of data used in an LCI or for certain LCA parameters. DQGs identify which data categories are important to the analysis and the features that are desired in data. For example, if an LCI is conducted to determine the impacts from energy usage and solid waste generation for a particular industrial process, the practitioner may desire precise energy and solid waste data, but may be willing to accept more uncertainty in the other life-cycle parameters. Sometimes a practitioner may plan to use existing data for less critical aspects of the study and collect new or site-specific data for the more critical aspects (Franklin Associates, Ltd., 1993). This type of requirement can be summarized in DQGs.

Data quality goals (DQGs) are qualitative statements that define specifications for the adequacy of data used in an LCI or for certain LCA parameters.

DQGs provide a framework for balancing available time and resources against the quality of the data required to make a decision or statement of overall environmental or human health impact (EPA, 1986a). DQGs are closely linked to overall study goals and serve two primary purposes:

- to aid practitioners in structuring an approach to data acquisition based on what data quality will be stressed in the analysis; and
- to serve as data quality performance criteria.

At a basic level, DQGs should identify the level of data quality sought for individual data sources used in the LCI. DQGs may also identify the level of data quality sought for groups of LCI parameters (e.g., major inputs, outputs, and life-cycle stages) or for the overall LCI. Because there presently are no standard requirements for developing DQGs, practitioners will determine both the number and nature of DQGs necessary to meet the goals and scope of the LCI. Table 3-2 shows an example of a DQG and other inputs to a data collection plan. Other examples of hypothetical DQGs include the following:

TABLE 3-2. CASE STUDY EXAMPLE DQGS, DATA SOURCES, AND DQIS

DQG:	Facility-specific data are required for raw material and energy inputs, water consumption, air emissions, water effluent, and solid waste generation.
Data Source:	Confidential industry data source.
Data Type:	Data used will be primary measured, modeled, and nonmeasured (i.e., estimated through best engineering judgments) data.
Relevant DQIs:	Acceptability Bias Completeness Comparability Representativeness

Source: Modified from Arthur D. Little, 1993b.

- Approximate data values are adequate for the energy data category.
- Air emission data should be representative of similar facilities in the U.S.
- Primary data for the recycling/reuse data category should be used, rather than national averages.

The goals and scope of the LCI and the accompanying DQGs can impose a structure that enables practitioners to assess the quality of key data prior to final use in an LCI. DQGs also provide a clear indication of where in the LCI data quality was made a priority. It

should be a regular practice to report in detail the objectives of the LCI and the related DQGs.

3.2.2 Identifying Data Sources and Types

Once DQGs have been identified, practitioners should have an understanding of the type and quality of data needed for the LCI. As discussed in Chapter 2, LCI data sets can be comprised of data that varies by the primary or secondary nature of the data source, the type of data employed (e.g., measured, modeled, or nonmeasured), and the level of data aggregation (e.g., individual plant or industry average data). It is important that practitioners recognize these characteristics among data sets and consider how they may affect the LCI results. For example, secondary data sources may be less specific than actual measured or monitored plant-specific data (i.e., primary data). Although primary data are typically more accurate for a specific process, they are not always preferred to secondary data. The manufacture of basic commodities that are used as inputs to many production systems, for instance, may be better represented by secondary data that reflect the mix of plants and processes that constitute the commodities market, then by data from one or a few plants.

Similarly, aggregated data may provide little indication of the variability in specific parameters, such as facility-level air emissions. However, industry aggregated data may be preferable when the LCI results are to be used for broad application across the industry (EPA, 1993b). Nonaggregated data, on the other hand, can be used to calculate statistical measures, such as the mean, median, standard deviation, and kurtosis, to indicate the central tendency, variability, and skewness in the data. For examples of data sources, data types, and different levels of aggregated data, refer back to Figure 2-1.

3.2.3 Identifying Data Quality Indicators (DQIs)

The quality of LCI data can be assessed by evaluating the data using defined DQIs. DQIs are quantitative or qualitative terms defining data characteristics that serve as benchmarks against which data quality can be assessed to determine whether DQGs have been met. In addition to determining whether DQGs have been met, evaluating data sources against DQIs may also help practitioners to establish levels of confidence for particular data sources.

Data Quality Indicators (DQIs) are quantitative or qualitative terms defining data characteristics that serve as benchmarks against which data quality can be assessed to determine whether DQGs have been met.

Table 3-3 defines selected DQIs applicable for assessing LCI data quality. Appendix A provides a more complete description of these DQIs and discusses their application to LCI data. Although a large number of potential DQIs have been identified (see SETAC, 1994) and may be applied in LCIs, the list of DQIs in Table 3-3 has been condensed to eliminate any overlap between the DQIs. For example, a longer DQI list might contain both: 1) quality assurance/quality control (QA/QC)—the degree to which data were subject to quality assurance and quality control procedures; and 2) verification/ validation—the degree to which data have been checked for errors or evaluated against an accepted standard. The distinction between these potential DQIs can be unclear because they are both indicators of data acceptability.

In some cases, DQIs with similar meanings have been combined. For example, QA/QC and validation/verification were combined to strengthen the acceptability DQI. In other cases, some possible DQIs (e.g., data aggregation, accessibility, model documentation, model limitations, and statistical measures) were not included because alone they reveal little about the quality or utility of the data. While these DQIs can be used, in practice they may contribute information to a more encompassing DQI such as acceptability or representativeness.

The DQIs in Table 3-3 are expected to be the most practical DQIs for purposes of LCI data quality assessment. They are not, however, the only acceptable DQIs. Other DQIs may be used as long as practitioners take care to explain why and how they were applied. The intent is for practitioners to use and describe the DQIs that are most appropriate and applicable to the specific data source being evaluated.

TABLE 3-3. SELECTED DATA QUALITY INDICATORS RELEVANT TO LCI

DQI	Definition
Acceptability	The degree to which the data source has been peer reviewed, evaluated against an accepted standard, or checked for errors through expert judgment.
Bias	The level of systematic error that causes the mean values of a data set to be consistently (over repeated samples) higher or lower than the corresponding "true" parameter values. With respect to LCI data, "true" parameter values may not be known.
Comparability	The degree to which different methods, data sets, or decisions agree or can be represented as similar or equivalent.
Completeness	The amount of data available for the analysis compared with the amount of data needed or desired.
Data Collection Method and Limitations	The level of information describing the method of data collection, including any limitations associated with the data collection method.
Precision	The degree of spread or variability, expressed numerically if possible, in a set of data values or measurements compared to the mean of the data values.
Referenced	The degree to which data values reference the original data source.
Representativeness	The degree to which the data represent what the analyst is trying to describe or depict.

3.2.4 Developing a Data Questionnaire

The data questionnaire is the final component of an LCI data collection plan. Practitioners usually develop a data questionnaire to obtain primary data. Developing a data questionnaire is closely tied to, and iterates back, to the defined DQGs. For example, the more information collected on the system of interest through the questionnaire, the more information available for determining whether the DQGs have been met. If it is realized that the data will not be adequate to meet DQGs, the practitioner may need to redefine the DQGs. Figure 3-3 illustrates the types of information that an LCI data questionnaire might include.

DATA FOR THE MANUFACTURE OF:

_____ **product**

_____ **quantity**

Prepared by: _____

Company Name: _____

Phone Number: _____

Raw Materials

_____ lb.
_____ lb
_____ lb

List Co-products, Recovered Heat or Steam Generated by Process

_____ lb.
_____ lb.
_____ lb.

Net Water Use

Water intake _____ gal.
Water output _____ gal.

Process Energy

Electricity

Purchased _____ kwh

Self-generated _____ kwh

Fuel

Natural gas _____ cu.ft.
Coal _____ lb.
Residual oil _____ gal.
Wood _____ thou.Btu
Distillate oil _____ gal.
Other _____
Steam _____ lb. _____ psig. _____ type of fuel

Self-generated Electricity

_____ type and quantity of fuel/kwh
_____ type and quantity of fuel/kwh
_____ type and quantity of fuel/kwh
_____ type and quantity of fuel/kwh
_____ qual/quant of cogen. steam/kwh

Transportation Energy

Average shipping distance to customer (miles) _____ rail _____ ship
_____ truck _____ air

Solid Wastes (please note if any of these materials are recovered for recycling)

Wastewater sludge _____ lb. _____ % moisture
Packaging mater. _____ lb.
Off-spec. product _____ lb.
Trim or scrap _____ lb.
Process wastes _____ lb.
Other _____ lb. _____ material

Atmospheric Emissions

Particulates _____ lb.
Nitrogen oxides _____ lb.
Hydrocarbons _____ lb.
Sulfur oxides _____ lb.
Carbon Monoxide _____ lb.
Aldehydes _____ lb.
Other organics _____ lb.

(controlled emissions only)

Methane _____ lb.
Odorous Sulfur _____ lb.
Ammonia _____ lb.
Hydrgn. Fluoride _____ lb.
Lead _____ lb.
Mercury _____ lb.
Chlorine _____ lb.

Waterborne Wastes

Fluorides _____ lb.
Dissolved solids _____ lb.
BOD _____ lb.
COD _____ lb.
Phenol _____ lb.
Sulfides _____ lb.
Oil _____ lb.
Suspended solids _____ lb.
Acid _____ lb.
Metal Ion _____ lb.
Chemicals _____ lb.

(controlled emissions only)

Cyanide _____ lb.
Chromium _____ lb.
Iron _____ lb.
Aluminum _____ lb.
Nickel _____ lb.
Mercury _____ lb.
Lead _____ lb.
Phosphates _____ lb.
Zinc _____ lb.
Ammonia _____ lb.
Carbon dioxide _____ lb.

NOTE: A complete data questionnaire would include information on chemical characteristics (e.g., toxicity, persistence, bioaccumulation) and possibly environmental information (e.g., location of release, ambient pollution levels).

Figure 3-3. Example of a Partial LCI Data Questionnaire
Source: Franklin Associates, Ltd., 1993.

Data questionnaires should be designed based on the expected respondent (e.g., corporate manager, facility engineer, or research scientist) and should solicit information to enable the validity and representativeness of the data to be assessed. When primary data are available, practitioners want to obtain data that are representative of the identified DQGs, information on applicable confidence measures (e.g., error limits and variances), and a description of the data collection methods (e.g., sampling, direct measurement, or engineering estimates). Where primary data are unavailable or not needed, practitioners will need to identify whether appropriate secondary data sources exist. This will require a search of the public literature, data bases, and reports.

Preparation of a data questionnaire is a multidisciplinary task that may best be accomplished through a formal or informal workgroup. Using the study scope as a baseline, the workgroup can perform the following tasks:

- outline specific descriptions of data requirements,
- review the draft data questionnaire, and
- modify the data questionnaire to address variations among facilities.

The resulting data questionnaire, whether prepared by a workgroup or not, should provide a clear understanding of what data are needed and how they are to be used in the LCI.

As part of the process of preparing the data questionnaire, the workgroup will also want to establish the manner, and level of detail, in which data collection procedures from all key sources (e.g., plant managers, process engineers, industry experts) will be documented. Such information on data collection procedures should include any assumptions employed and/or limitations of the data collection procedures.

Once the data collection plan is completed, it is recommended that the plan be reviewed by a peer-review panel. The purpose of this review is to ensure that the components of the data collection plan (DQGs, data sources and categories, and the data questionnaire) are consistent with the scope and objectives of the LCI. This review not only helps to validate the data collection plan but also may help to identify flaws in the plan so it may be modified accordingly.

3.3 DATA COLLECTION AND QUALITY ASSESSMENT

Data collection and quality assessment is a critical phase of the LCI data development process that includes the following:

- collecting data,
- assessing data sources against relevant DQIs, and
- determining data quality.

3.3.1 Collecting Data

LCIs typically contain a mixture of primary and secondary data. Collecting primary data often necessitates the development and use of a data questionnaire, as discussed in the previous section. Although data questionnaires are typically not needed for collecting secondary data, the secondary data values may need to be converted into units that are consistent with the overall LCI. The entire LCI data collection effort may benefit from using a checklist and accompanying data worksheets. (For examples of an inventory checklist and data worksheet, refer to EPA (1993b.) A checklist helps to guide data collection and validation and may be tailored to any given product or process. The data worksheet has a dual purpose:

- as a tool for the analyst to coordinate and assimilate data, and
- for use in requesting data from others.

The LCI worksheet is often designed on a module, or subsystem, basis. These subsystems comprise the basis for aggregating data from individual processes to the life-cycle stages (e.g., raw materials acquisition, manufacturing, etc.), and, ultimately, from the life-cycle stages to the overall system level.

Primary data collected from multiple facilities can be used to assess the validity and representativeness of the data values with greater confidence than data from a single source. Another benefit of collecting data from multiple facilities is the added understanding of the variability of particular processes (Arthur D. Little, 1993b). For example, the consumption of energy typically varies to some extent even when the energy values are normalized to a unit value (e.g., Btu per unit output). In addition, variations in data among multiple facilities for similar processes can be even more pronounced due to differences in equipment, technologies, or operating practices. Because the level of

resources needed to collect data from multiple facilities is necessarily greater, practitioners will need to consider whether the added confidence in the data and the added understanding of process variability will affect LCI results significantly enough to merit these additional resources.

When primary data are obtained through using a data questionnaire, the data should be carefully reviewed and analysts should address any questions they may have with one or more responses (Arthur D. Little, 1993b). When using data from secondary sources, it is important to determine how accurately the data represent the specific process under evaluation. For example, process input and output values are dependent on a number of different factors such as mix and quantity of inputs, use of pollution-control devices, and process technology. It is unlikely that any two processes will contain exactly the same combination of factors. Thus, secondary data must be carefully evaluated to ensure that they are adequately representative. The DQGs may provide a useful tool for informally screening potential data sources, including secondary data.

3.3.2 Assessing Data Sources Against Relevant DQIs

An important factor in identifying LCI data quality is determining which DQIs are most applicable to the analysis. The selection of DQIs is influenced by the following:

- the defined DQGs;
- the type of data (i.e., whether the data are primary or secondary and measured, modeled, or nonmeasured);
- manipulations made to the data (i.e., whether the data are extrapolated, interpolated, or back-calculated); and
- the type of data quality assessment being conducted (i.e., whether data quality is being assessed during the conduct of the LCI or by an analyst reviewing an existing LCI).

Each factor that influences DQI selection is discussed below.

DQGs

DQGs are qualitative statements that define specifications for the adequacy of data used in an LCI or for certain LCA parameters. DQIs are quantitative or qualitative terms defining data characteristics that serve as benchmarks against which data quality can be assessed to determine whether DQGs have been met. The link between the defined DQGs

and selection of DQIs is key. DQGs by definition will help practitioners determine which DQIs are most relevant for LCI data quality assessment. For example, a DQG that requires the LCI data be typical of that for manufacturing facilities nationwide will necessarily heighten the significance of the DQI's representativeness and comparability.

The link between the defined DQGs and the selection of DQIs is key.

DQGs may also, implicitly or explicitly, help practitioners determine the type of data that is to be used in the LCI (e.g., primary, secondary, measured, modeled, nonmeasured). Such data specifications will in turn determine the relevance of DQIs. For example, if the DQGs specify that primary measured data be used, then the precision and bias DQIs may be critical in gauging whether the primary data provide the desired level of accuracy.

Data Type

Although data are available from a variety of sources, data can be classified broadly as either primary or secondary. As discussed in Chapter 2, primary data are different from secondary data in that an analyst has direct access or direct input into the data collection process. Primary data may be measured pursuant to statistical or nonstatistical protocols, estimated through best professional or engineering judgments, or generated from models (see Figure 2-1). These data may be assessed against DQIs such as precision and bias (if statistical parameters are provided), representativeness, and completeness. Data generated through models can be evaluated in part based on whether the model was verified and validated.

Secondary data may be more difficult to evaluate from a data quality perspective because they come in multiple forms and may lack an explanation of the data collection methods and data variability. Like primary data, secondary data can be measured, modeled, or estimated. An example of estimated secondary data is EPA's TRI data base, which contains chemical release data. In addition to being monitored, sampled, or

modeled, the TRI data may also be based on professional or engineering estimates (referred to in this document as nonmeasured data).

Traditional DQIs—including measures of precision, bias, and completeness—are quantitative measures for evaluating primary data (EPA, 1993b; Johnson and Ford, 1986). While these DQIs may be applicable to secondary data, it is more likely that additional indicators will need to be employed because secondary data typically are not generated under statistical guidelines. Qualitative indicators (e.g., completeness, comparability) and understanding of the data collection procedures may offer better insight on the limitations of the data.

Another important factor that influences the selection of DQIs when evaluating secondary data sources is the availability of information sufficient for an analyst to assess the quality of the source. For example, a data source could contain perfect data, but if there is no way to discern this, the data may not be usable for an LCI to influence public policy that would require the documented use of any high quality data. When evaluating secondary data sources, it therefore may be useful to apply DQIs such as the level of reference or description of the data collection method to see if adequate information is provided about how the data were generated. Once it is determined that adequate information is supplied about the data to assess its quality, the practitioner can proceed with evaluating the actual data through using other quantitative DQIs.

When evaluating secondary data sources, it may be useful to apply DQIs such as the level of reference or description of the data collection method to see if adequate information is provided about how the data were generated.

For these and other primary or secondary nonmeasured data, which cannot be assessed with more quantitative DQIs, the acceptability DQI may be most important—indicating whether the data value is widely accepted by peers or colleagues in the field.

Data Manipulations

Data quality is influenced not only by the quality of primary and secondary data sources used, but also by any assumptions used or manipulations to make the data better suited for use in an LCI. Using poor assumptions or manipulations can result in the generation and use of inappropriate data values, even if the quality of a data source itself is found to be high. Therefore, it is imperative to assess not only the quality of the data source but also the assumptions and calculations used to generate the LCI data values.

For example, suppose an analyst has Department of Energy (DOE) energy consumption data for a particular industry. To determine the appropriate value for an LCI (i.e., for a facility or group of facilities), the analyst may need to back-calculate (a process to disaggregate data) from the aggregate DOE data. To do this, the analyst will develop assumptions and calculations to generate numbers suitable for use in the LCI. Under this scenario, DQIs (e.g., representativeness) may be necessary to assess not only the quality of the data source but also the assumptions and calculations used by the analyst to generate the LCI data values.

Type of Data Quality Assessment

The type of data quality assessment being conducted also influences the selection of DQIs. There are two basic types of LCI data quality assessments: those conducted by the practitioner while developing an LCI and those performed by analysts reviewing existing and/or published LCIs. For a data quality assessment conducted by the practitioner, the choice of DQIs to use will be a function of the goals and scope of the LCI as well stakeholder needs. When reviewing the quality of data in an existing or published LCI, additional DQIs may be needed to indicate, for example, whether the data have been referenced and if the data are accessible and reproducible.

3.3.3 Assessing Data Quality

After a practitioner has selected the relevant DQIs for a particular data source, the next step is to evaluate the quality of the data source against the DQIs. Assessing the quality of LCI data is important because it provides users with a frame of perspective with which to properly interprete LCI results. LCI results based on poor quality data may not be as significant as results based on higher quality data. Also, while higher quality data would likely be needed to support the external applications of LCI results for external applications, practitioners using LCI results for internal application should also consider how different levels of data quality affects the value of those results. DQIs are used in

the LCI data quality assessment process to determine whether DQGs have been met. As discussed in the previous section, the importance of individual DQIs is a function of the DQGs. Again, keep in mind that these guidelines do not suggest conducting a detailed assessment and documentation of every data source used, but rather promote the assessment of key data sources. The final LCI report should include any documentation of data quality issues and assessment results. In some cases, it may be more appropriate to provide a summary of data quality results in the text of the final report and place more detailed data quality information in an appendix.

Two aspects of assessing data quality are very important: (1) that each key data source be evaluated in a consistent and clearly defined manner, and (2) that the resulting data quality information be clearly communicated. Table 3-4 contains an example of an LCI data quality worksheet that provides a framework for evaluating and documenting the quality of key LCI data sources. The worksheet can be used to identify the relevance of each DQI to the data source (identified by high/medium/low) and the quality of the data with respect to each DQI (identified by high/medium/low). For example, as shown in Table 3-4, referencing the data source is considered to be of low relevance but receives a high data quality rating because the document was thoroughly referenced. On the other hand, representativeness of the data source is considered to be of high relevance and received a high rating because the data were collected from numerous facilities. In this example, it is more important to have a highly rated representative data source than to have a highly rated referenced data source.

It is recommended that each DQI rating be accompanied by explanatory comments that adequately convey the rationale for both the relevance and quality ratings for the DQI. Once the evaluation has been completed for each relevant DQI, an overall data quality assessment of good, fair, or poor may be assigned to the data source based on the relative importance of the DQIs and their respective ratings.

In addition to clearly explaining the specific relevance and quality rating for each DQI, practitioners may want to take the additional step of documenting the general criteria used for assigning high, medium, or low quality ratings for each DQI. These "proof statements" would provide general rules for each DQI by which analysts could evaluate a variety of data sources (Arthur D. Little, 1993b). Proof statements not only increase the clarity of data quality evaluation but may help increase consistency among practitioners in how ratings are made. An example of proof statements for rating the degree of bias in data is shown in Table 3-5.

TABLE 3-4. CASE STUDY EXAMPLE LCI DATA QUALITY WORKSHEET

Data Source:	Development Document for Effluent Limitations Guidelines, New Source Performance Standards, and Pretreatment Standards for the Pulp, Paper, and Paperboard and the Builders' Paper and Board Mills Point Source Categories. U.S. EPA, Office of Water, 1982.
Data Quality Goals:	• Effluent data for each compound will be typical for most US paperboard manufacturers. • Data must capture long-term trends in effluent releases.
Data Assessed:	Primary water effluent considered for this data source include: BOD5, TSS, pentachlorophenol (PCP), trichlorophenol (TCP), and zinc.

DQI	Relevance of DQI1 (A)	Data Quality Rating2 (B)	Comments
Acceptability	High	High	(A) It is important for the data to have undergone review by an independent party. (B) The data received extensive review, including being subject to an extensive QA/QC methodology.
Bias	High	High	(A) Bias in aggregated data can result from over-reliance on data from a new technology, a specific region of the country, or from specific processing method. (B) Data were collected from over 600 mills covering many technologies, processes, and geographic areas. The data were segregated into specific subcategories to avoid overlapping process technologies. Long-term sampling programs were employed which mitigate problems from cyclic variations (e.g., seasonal, business cycle).
Comparability	High	High	(A) It is important for the data to be comparable to long-term measures of industry effluent. (B) Several test sites were selected for long-term analysis to provide a comparable measure. Data values compared well to these standards.
Completeness	Medium	High	(A) Representativeness is deemed more important than completeness in this analysis. (B) There is considerable data in this data source on the target primary water effluent from 600 mills.
Data Collection Method and Limitations	High	Medium	(A) Given the broad universe of mills this data source captures, it is important for collection methods and limitations to be well documented. (B) An extensive description of the data collection methods used is provided in the text. Specific data quality limitations for each mill are not identified.
Precision	Medium	Medium	(A) Exact values are not needed, reasonable approximations are adequate for the study. (B) Few statistical measures are provided to assess the precision of the data. While single values are provided for each mill from which the variation across mills can be assessed, there is no consideration of the variation in the data collected.
Referenced	Low	High	(A) Thorough referencing of the data source is not critical given the wealth of effluent data collected from the 600 mills. (B) The document is thoroughly referenced.
Representative	High	High	(A) It is important for the effluent data in this report to reflect typical releases. (B) Although the data is dated 1982, it is the most recent comprehensive collection (from 600 mills) and is deemed to be representative of the industry.

[1]High, medium, or low. [2]High, medium, or low.
Source: Modified from Arthur D. Little, 1993b.

TABLE 3-5. EXAMPLE PROOF STATEMENTS FOR THE BIAS DQI

	Data Quality Rating		
DQI	Low	Medium	High
Bias	There is no clear indication that potential biasing effects have been considered.	Potential biasing effects are considered qualitatively, but only limited efforts are made to correct for these biases.	The data collection tool is structured to avoid any potential bias. Where bias is identified, additional data are collected or the results are adjusted to mitigate the impact of the bias.

Source: Arthur D. Little, 1993b.

3.4 EVALUATING MODEL SENSITIVITY AND RESULTS

As part of the process of collecting and evaluating LCI data, and building a computational model, practitioners will determine which data values are key to the analysis. While DQGs will provide overall guidance on where data quality should be emphasized. In addition, the following approaches can be used to determine whether a specific data source is key to the analysis:

- Sensitivity analysis, and to a lesser extent, uncertainty analysis, can be used to identify the parameters most important to LCI results (as discussed in Chapter 4).

- Practitioners can use their knowledge of the data source and its relevance/importance to the overall analysis to determine which data sources are likely to have the greatest effect on results.

In identifying key parameters, the objective is to determine which parameters are critical (i.e., contribute significantly) to final results and then estimate the level of error in the data that would significantly alter the final results. Finding that small changes in an individual parameter have significant impacts on LCI outputs would indicate that the parameter is important to the analysis and that high quality data is more critical for that parameter. For example, if an LCI comparing two alternative processes shows that

process A and B produce 10 and 11 tons of solid waste, respectively, it may be difficult to discern whether process A truly differs from process B. Sensitivity and uncertainty analysis techniques, discussed in Chapter 4, may help to determine how changing the values of these two numbers would affect LCI results. If a "reasonable" change in any parameter significantly changes final LCI results the practitioner should consider

- collecting additional data to get a more precise estimate of the parameter,
- compensating for missing or deficient data, or
- caveating final LCI results (e.g., provide ranges or a distribution of values).

Determining which model parameters are most sensitive to LCI results does not indicate whether data quality is adequate or not but does provide increased understanding of the significance of those parameters. This can help identify where additional resources should be directed to improve LCI data quality or where some degree of qualification is needed in study research.

3.4.1 Performing Sensitivity and Uncertainty Analyses

LCI data are generally collected on an iterative basis. After evaluating a data source against selected DQIs, practitioners may determine that collecting and reviewing additional data sources is necessary. Sensitivity analysis, and to a lesser extent, uncertainty analysis, can be used to indicate which parameters are most important to the analysis and where data quality resources should be directed or redirected.

Sensitivity analysis is a process for evaluating the effect of variations of input parameters to a system on model results. Sensitivity analysis can be performed on typical LCI data to determine the importance of individual LCI data values or combined values (e.g., total CO_2 emissions for the manufacturing stage) on overall LCI results.

Uncertainty analysis is a process for evaluating uncertainty associated with inferences, and may be applicable to analyzing uncertainty in LCI data and results. Uncertainty analysis may also help to identify the propagation of uncertainty throughout the LCI model, that is, where the uncertainty associated with various key data grows as the LCI model utilizes the data values and calculations before arriving at a final set of LCI numbers.

Statistical analysis of uncertainty can be difficult in an LCI, where the multiple data points needed to perform statistical analyses typically are not available. Thus, it is generally not feasible to calculate actual measures of error or uncertainty for LCI data. However, several alternative methods of expressing uncertainty in data or final results may be useful, including the following:

- presenting a discussion of possible sources of uncertainty,
- identifying estimates of uncertainty associated with specific data or results,
- calculating and presenting numbers with appropriate significant figures, and
- presenting data and results as ranges rather than absolute numbers (Arthur D. Little, 1993b).

Chapter 4 provides a more detailed discussion of sensitivity and uncertainty analysis techniques and their application to LCI data.

3.4.2 Determining Whether DQGs Have Been Met

Once key data sources have been identified and assessed against applicable DQIs and data values have been evaluated for their impact on LCI results, the practitioner can determine if the data source, and corresponding data values from that source, meet the defined DQGs. If the obtained data quality results meet the DQGs, then the practitioner proceeds with the study and documents the data quality results. If the DQGs are not met, the practitioner has a number of possible options, which reflect the iterative nature of setting and achieving DQGs:

- collect additional, better quality data which satisfies the DQGs,
- redefine the DQGs,
- revisit and possibly redefine the goals and scope of the LCI,
- proceed with the LCI and clearly communicate any limitations that should be placed on the results,
- abandon the LCI, or
- apply data compensation methods to address problems with the data (see Chapter 5 for a discussion of data compensation methods).

In all cases, whether or not DQGs are met, practitioners should also identify and clearly communicate any limitations that should be placed on the LCI results.

3.5 DOCUMENTING AND REFERENCING LCI DATA QUALITY RESULTS

A final LCA report should include a reference for each data source used and explicit information on the quality of the key data sources as well as important assumptions used to generate values. It is important for users to understand how relevant key data sources and assumptions are to the overall LCI and the corresponding quality of those data sources. For example, a practitioner may do a detailed data quality analysis of ten key data sources where the evaluation indicates that half of the data sources have "good" data quality and half have "fair" data quality. If the half with good data quality were more important to LCI results than the half with fair data quality, overall LCI data quality could be considered good.. Documentation of this information will enhance the clarity and transparency of the final LCI and LCA results.

A final LCA report should include a reference for each data source used and explicit information on the quality of the key data sources as well as important assumptions used to generate values.

In the final LCI report, practitioners should provide a worksheet, or other means of clearly conveying data quality, for each of the key LCI data sources. In cases where a large number of data sources were evaluated, practitioners may want to summarize data quality information by using summary graphics relating the quality of key data sources. While the use of summary graphics alone is not likely to provide sufficient level of detail, it may serve as a useful supplement to more detailed data quality information. Broad summaries of data quality information should not be provided in lieu of the more detailed information in the worksheets. Ultimately, internal and external users should be able to conduct their own quality assessment of key data sources and assumptions based on the information provided in the final report.

To the extent possible, the sensitivity and uncertainty associated with each important LCI parameter (or class of parameters) used in the analysis should also be reported. In addition to identifying data quality, the report should identify the degree of variation in each parameter. This information is important to understanding the total variability in the final LCI results.

In the final LCI report, practitioners should provide a worksheet, or other means of clearly conveying data quality, for each of the key LCI data sources. Ultimately, internal and external users should be able to conduct their own quality assessment of key data sources and assumptions based on the information provided in the final report.

Practitioners conducting external studies should also distribute their LCI results for peer review. If an LCI is peer reviewed, the results of this evaluation should be included in the final LCI. Obtaining general agreement from peer reviewers or colleagues about the quality of the LCI data and the assumptions and calculations used will lend significant credibility to the analysis.

CHAPTER 4
APPLYING SENSITIVITY AND UNCERTAINTY ANALYSIS TECHNIQUES TO LCI DATA

At the beginning of an LCI, sensitivity and, to a lesser extent, uncertainty analysis techniques may provide a useful screening tool to approximate variability among available data sources before the data are actually collected. During LCI data quality assessment, sensitivity and uncertainty analysis techniques may be employed to pinpoint data values, or sets of values, that contribute significantly to the LCI totals, thus providing practitioners with information to help determine where to emphasize quality assessment and improvement efforts. Practitioners will likely want to consult a statistician in the appropriate application of these techniques.

Sensitivity analysis can be performed on all types of LCIs: internal, external, comparative, and noncomparative. Sensitivity analysis is typically used to determine the effect of changes in a model's input parameters on the model's results (Morgan and Henrion, 1990; Clemen, 1991). Three methods for conducting sensitivity analysis are discussed in this chapter, each requiring the generation of a mathematical model to determine the relative importance of system input parameters. LCA practitioners can use these methods to determine the importance of individual LCI input parameters (e.g., raw materials, energy, and water inputs; and various waste stream outputs) or combined parameters on overall LCI results.

KEY POINTS

- During LCI data quality assessment, sensitivity and uncertainty analysis techniques may be employed to pinpoint data values, or set of values, that contribute significantly to the LCI totals.
- LCI data found to be both highly sensitive and uncertain are prime candidates to carefully assess, and if necessary, improve data quality.
- Sensitivity analysis may be used to indicate how LCI totals are affected by changes in LCI parameters.
- Uncertainty analysis may be used to determine how various sources of uncertainty in LCI parameters affect LCI totals.

Uncertainty analysis is used to measure the degree to which uncertainty in individual parameters contributes to the total uncertainty in model results (Morgan and Henrion, 1990; Vesely and Rasmuson, 1984; and Finkel, 1990). Uncertainty analysis involves developing probability distributions or ranges and applying different mathematical methods to determine possible combinations of parameters with a high level

of uncertainty. In general, as the scope of an LCI broadens, the level of uncertainty in LCI data and the overall LCI results increases.

LCI input parameters found to be both highly sensitive and uncertain are prime candidates to carefully assess, and if necessary, improve data quality. It should be noted that when results are sensitive to a particular input parameter and the values of that input parameter are highly variable, data quality is not necessarily a problem. It does, however, indicate a need to estimate the distribution of output values and incorporate this range into LCI results.

4.1 SENSITIVITY ANALYSIS TECHNIQUES

Sensitivity analysis indicates how final results are affected by changes in individual or combinations of input parameters. In the context of LCI, the application of sensitivity analysis may be useful in the following situations:

- the analyst does not have a high degree of confidence in an important data source,
- the production system being assessed is highly variable, or
- data for a particular element are missing or deficient (Arthur D. Little, 1993b).

Sensitivity analysis is typically performed in a series of steps. Individual parameters are varied one at a time while all other parameters are held constant. The impact on model results caused by varying an individual parameter reveals the importance, or sensitivity, of that parameter to model results (Clemen, 1991; Morgan and Henrion, 1990). Analysts typically use the following techniques to depict model sensitivity: one-way analyses of individual parameters to model results, "tornado graphs" for one-way analyses, and simple ratios that depict the sensitivity between parameters in the same model or in different models (Clemen, 1991; Franklin Associates, Ltd., 1993; and North, 1990). These techniques highlight the relative importance of model parameters and may help identify places where additional data collection or compensation efforts are needed to improve the quality of LCI results (Watson and Buede, 1987). Each of these techniques is described briefly below.

When interpreting the results of a sensitivity analysis it is important to consider the number of data values upon which model parameters are based, since any given parameter value could represent an individual data point or the average of many data points. In

general, averages of many data points produce results with lower variability and higher reliability than individual data values (Franklin Associates, Ltd., 1993). Thus, when interpreting sensitivity analysis results, analysts should refer back to the original data source and worksheets from which the data value was derived.

4.1.1 Single System (One-Way) Sensitivity Analyses

Single system, or one-way, sensitivity analysis is useful for evaluating the importance of individual parameters to model results. The sensitivity of individual parameters relative to the system total is determined by calculating the amount individual parameters would need to change in order for model results to be altered by a given percentage. For example, a 10 percent change in the system total may be chosen as a general threshold above which changes in model results are considered to be "significant." Practitioners may want to consult a statistician and/or process engineer to help determine appropriate threshold level for specific system.

Table 4-1 summarizes a hypothetical one-way sensitivity analysis on energy use and solid waste generation of a generic pulp mill product. The sensitivity of individual parameters is calculated as the amount each parameter needs to change (while all other parameters are held constant) in order for final results to be changed by a given percentage. In this example, to change total energy consumption by 10 percent or 5.7 million Btu, raw materials energy would need to change by 380 percent (5.7/1.5 x 100). To change total solid waste generation by 10% or 164 lbs, raw materials solid waste generation would need to change by 13,644 percent (164/1.2 x 100). The smaller the percentage change of an individual parameter needed to change the total by a given percentage, the more sensitive the total is to that parameter. Table 4-1 shows that, for energy consumption, product manufacture is the most sensitive parameter and consumer use/disposal the least sensitive parameter. For solid waste generation, consumer use/disposal is the most sensitive parameter and transportation the least sensitive parameter.

4.1.2 Tornado Diagrams

Tornado diagrams are another method to illustrate model sensitivities. Tornado diagrams, typically created as bar graphs, indicate the degree to which model outputs vary due to predicted changes in individual parameters (Clemen, 1991). Instead of determining the change in individual parameters needed to change model results by a given percentage

TABLE 4-1. HYPOTHETICAL SENSITIVITY ANALYSIS WORKSHEET

Calculation of the percentage by which parameter values must change for the total to be changed by 10%

	Energy (mil Btu)	10% Sensitivity
Raw Materials	1.5	378
Pulp Mill	18.0	32
Product Manufacture	28.0	20
Packaging, etc.	6.6	86
Transportation	2.5	227
Consumer Use/Disposal	0.1	5,670
Total	56.7	

Example: To change the system energy results by 10% (5.7 mil Btu) product manufacture energy consumption must change by 20% (5.6 mil Btu).

	Solid Waste (lbs)	10% Sensitivity
Raw Materials	1.2	13,644
Pulp Mill	442.0	37
Product Manufacture	155.0	106
Packaging, etc.	84.0	195
Transportation	0.1	163,730
Consumer Use/Disposal	955.0	17
Total	1,637.0	

Example: To change the system solid waste results by 10% (164 lbs), consumer use/disposal generation of solid waste must change by 17% (162 lbs).

Source: Modified from Franklin Associates, Ltd., 1993.

(as described in the previous section), tornado diagrams illustrate the change in model results for given levels of change in individual parameters.

In the tornado diagram shown in Figure 4-1, the top bar, which is always the longest, represents the most sensitive parameter (i.e., the parameter that has the greatest relative impact on model results), and the bottom bar, which is always the shortest, represents the least sensitive parameter (i.e., the parameter that has the smallest relative impact on model results). The bars on the diagram are created by developing a model of the system or problem under evaluation. Then high and low values are selected for each parameter while all other parameters are held constant. The lengths of the bars represent the extent to which air releases change relative to given changes in LCI parameters. In this example, a 0- to 10-percent change in virgin materials has the greatest effect on total air releases and is thus considered the most sensitive parameter.

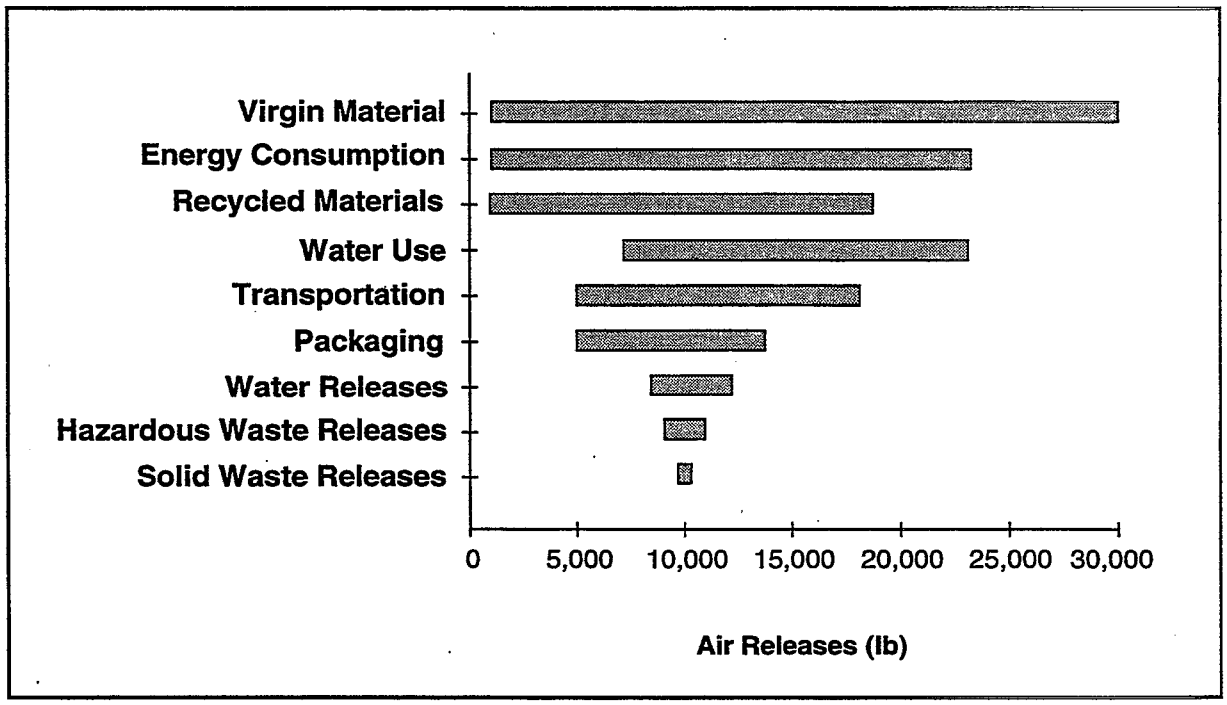

Figure 4-1. Sensitivity of Air Releases for Product X

Table 4-2 presents a hypothetical data worksheet for constructing a tornado diagram of air releases associated with given input parameters for product X. To keep the analysis simple, low and high input parameter values were set at 1 and 10 percent of the individual parameter values. In practice, process engineers and industry experts may need to be consulted to help determine appropriate low and high input parameter values.

TABLE 4-2. HYPOTHETICAL TORNADO DIAGRAM WORKSHEET FOR PRODUCT X

Model Parameters	Range of Change in Parameter Values[a]	Range of Change in Air Releases (lbs)
Virgin Material	1 - 10%	1,000 - 30,000
Energy Consumption	1 - 10%	1,000 - 24,000
Recycled Materials	1 - 10%	1,000 - 19,000
Water Use	1 - 10%	7,500 - 24,000
Transportation	1 - 10%	5,500 - 18,500
Packaging	1 - 10%	5,000 - 14,000
Water Releases	1 - 10%	8,500 - 12,500
Hazardous Waste Releases	1 - 10%	9,000 - 11,000
Solid Waste Releases	1 - 10%	9,750 - 10,075

Example: A 1- to 10-percent change in water usage will result in a 7,500- to 24,000-lb change in air releases.

[a] Note that the range of change of 1 - 10% was chosen for purposes of example only. In practice, a range of reasonable values would be more appropriate.

Table 4-2 shows how 0- to 10-percent changes in input parameter values affect air releases. The larger the range of change in air releases, the greater effect the input parameter will have on the final LCI results.

Although the tornado graph is a relatively simple sensitivity analysis technique, it requires developing a mathematical model to evaluate the relationship between model inputs and outputs. Practitioners analyze numerous parameters and information sources when building an LCI. The pertinent information typically is entered into a computer and a model of the major input/output processes is developed. Practitioners may want to consult a statistician for assistance in

- designing the mathematical model,
- identifying important model input parameters, and
- analyzing and interpreting sensitivity analysis results.

The tornado diagram technique is most applicable to an evaluation of the sensitivity in single systems. If a comparative LCA is conducted, this approach can be applied to each model independently, and the results of each tornado diagram can be compared to determine the most sensitive input parameters in each system.

4.1.3 Ratio Sensitivity Analysis

Sensitivity in model parameters can also be expressed as a ratio (North, 1990; Morgan and Henrion, 1990). This method is a comparative analysis and is applicable only to comparative LCAs. Rather than varying individual parameters one at a time to determine the effect on model results, two systems or processes can be compared according to an identified criterion (e.g., total emissions, where the process with the lowest emissions is ranked higher). A ratio is calculated to determine the percentage a parameter would need to change to reverse the rankings.

Table 4-3 provides an example of energy consumption data for two different production and delivery processes. Energy usage is broken down by the different components of the process: packaging processes, distribution of the product to the retail sector, and final disposition of the product. Based on a "least emissions" criterion, the two processes are ranked by total energy usage. System 1 uses approximately 16.8 million Btu, and System 2 uses approximately 13 million Btu. Thus, System 2 is ranked higher (less energy consumption) than System 1. The sensitivity is expressed as the ratio of the difference in total energy consumption (16.8 - 13.2 = 3.60 million Btu) over the amount of energy consumed by each process component. For example, for the "distribution to retail" component of System 1, the percent error is 3.60/1.03 = 3.49 or approximately 350 percent. This indicates that energy consumption in the retail component of System 1 would have to change or be in error by approximately 350 percent to reverse the rankings of the two systems. Given that the data are unlikely to be in error to this order of magnitude, the "distribution to retail" component of System 1 would not be considered important (or sensitive) to the overall results. However, if a 5- or 10-percent error in the data could reverse the rankings of the two systems, this would indicate where data quality resources may best be focused.

TABLE 4-3. ENERGY SENSITIVITY ANALYSIS ON TWO PRODUCTION SYSTEMS

System Components	Energy Consumption (million Btu)		Percent Error Needed to Reverse Total Ranking
System #1			
Component 1	4.200		86
Component 2	6.300		57
Component 3	0.555		649
Component 4	0.921		391
Component 5	1.300		277
Subtotal		13.276	
Primary Packaging		1.200	3 00
Secondary Packaging			
Corrugated	0.200		1,800
Stretch Wrap	0.050		7,200
Subtotal		0.250	
Filling and Packaging		0.985	365
Distribution to Retail		1 .030	350
Disposition		0.042	8,571
Total		16.783	21
System #2			
Component 1	3.600		100
Component 2	3.200		113
Component 3	0.640		563
Component 4	1.350		267
Subtotal		8.790	
Primary Packaging		2.300	156
Secondary Packaging			
Corrugated	0.260		1,385
Stretch Wrap	0.032		11,250
Subtotal		0.292	
Filling and Packaging		0.752	479
Distribution to Retail		0.996	361
Disposition		0.056	6,429
Total		13.186	27

Source: Franklin Associates, 1992.

Although straightforward, the ratio sensitivity analysis approach has some limitations. First, it is applicable only to comparative LCIs. If a single product or process was under evaluation, a second system would be needed to use for comparison. However, it is not clear whether an existing LCI would be suitable for use in this situation. Also, the percent-error calculation evaluates process components separately when in actuality each component is part of a complex industrial system. Therefore, calculating a simple ratio or percentage of error may fail to show the interrelationships between the many components of an industrial process.

4.2 UNCERTAINTY ANALYSIS

Uncertainty analysis is used to determine how various sources of uncertainty in parameter inputs—such as incomplete information, variability, or the structure and simplifying assumptions used in the creation of a model—influence the uncertainty in model results. The basic principle of uncertainty analysis is to assign probabilities to uncertain parameters and then use statistical or mathematical techniques to determine the uncertainty in model outputs. In general, probabilities are assigned based on past empirical data or expert or subjective judgment (Keeney and Raiffa, 1976).

Uncertainty analysis may be used to better understand the importance of a data source or model and for determining whether to acquire additional information (Morgan and Henrion, 1990). Uncertainty analysis techniques may also be used to determine where data quality resources could best be focused and to determine the total uncertainty in the final LCI results. As a cautionary note, it should be recognized that the use of expert or subjective judgment in uncertainty analysis leads to a larger "garbage in, garbage out" issue. That is, very elegant uncertainty distributions may be developed, but they consist of entirely pseudo-information of unknown accuracy.

4.2.1 Sources of Uncertainty

The process of determining sources of uncertainty involves asking a carefully stated question for which the answer is uncertain and itemizing all the sources of uncertainty that could contribute to the answer (Finkel, 1990). Sources of uncertainty that are useful to consider when collecting and analyzing data include (1) random error in measurement and sampling methods, (2) systematic error in measurement and sampling methods, (3) natural variability, and (4) approximation in modeling.

Random Error

The most commonly studied and best understood cause of uncertainty is random error in direct measurements of a quantity. Random error results from imperfections in the measuring instrument and observational technique (Morgan and Henrion, 1990). Taking repeated measurements can help reduce the effects of uncertainty caused by random error.

To estimate random error, an analyst must have the following:

- primary or secondary statistically sampled data,
- a complete description of the data collection method, and
- nonaggregated data.

With all three of the prerequisites, the process of describing uncertainty is relatively straightforward because standard statistical measures (e.g., standard deviation, confidence intervals) can be used. Probability sampling is necessary to quantify sampling error. Replicated measurements are needed to quantify measurement error. Although such an approach may not be amenable to nonparametric samples, it does provides a powerful tool for describing uncertainty associated with statistically sampled data.

Systematic Error

Unlike random error, systematic error results from an inherent flaw or bias in the data collection or measurement process (Finkel, 1990). Systematic error may be caused, for example, by improper calibration of measurement instruments or by the continuous misreading of a measurement instrument due to such factors as poor training or the angle at which the gauge is read. In a survey, systematic error occurs when questions are phrased so that an unintended response is consistently obtained. Or, the sampling frame may systematically exclude members of one segment of the population.

Systematic error can be reduced by careful design of the data collection plan. Some degree of systematic error will still exist, however, no matter how carefully the plan is designed. For systematic error that cannot by eliminated, and is large enough to be of concern, subjective probability distributions can be assigned to the possible effects of the systematic error. For example, utilization of blocks and spikes can allow estimation of the bias, and statistical compensation.

In assigning a subjective probability distribution to a series of possible effects, an analyst may use expert opinion to assign numerical probabilities to the occurrence of an event, which represents the frequency with which the event would occur in repeated trials (Kennedy, 1991). Expert opinion is the likely method for developing these subjective probability distributions. Once the distribution has been developed, methods for propagating and analyzing the effects of uncertainty can be employed.

Natural Variability

Variability refers to the natural fluctuation in variables over time or space. Examples include the salinity of sea water, phosphate concentrations in waste water, and the heights of 20-year-old Americans. Assessing the uncertainty caused by natural variability of a quantity can be simple provided that enough data are available on the quantity to form a frequency distribution. Unlike a probability distribution, which provides a probability of obtaining a specific value for a variable, a frequency distribution expresses the number of times a variable takes on a specific value. Thus it shows which values have occurred more often. A relative frequency distribution expresses the percentage of time a variable has taken a specific value.

If LCI data are aggregated, it may be impossible to construct a frequency distribution. However, if a frequency distribution is available and is considered to be appropriate for assessing uncertainty, the uncertainty about a quantity can be represented by a probability distribution with the same parameters as the frequency distribution. Analysts may also assign ranges with defined boundaries to each uncertain variable. Uncertainty analysis methods (described in Section 4.2.3) can then be used to analyze the effects of parameter uncertainty.

Approximation in Modeling

Uncertainty resulting from approximation may be assessed in the industrial process model used to generate final results or in a primary or secondary modeled data source used as an input to the LCI. Uncertainty from approximation occurs when models are used or created. Designing a model that truly represents the process or system of concern is virtually impossible. Therefore, certain approximations and assumptions must be made.

Specific sources of uncertainty in a model include (1) model structure, (2) abnormal conditions, (3) excluded variables, and (4) surrogate variables (Finkel, 1990). A lack of independence between input variables is an additional source of uncertainty. Inappropriate model structure can lead to results that do not represent the process being modeled. Abnormal conditions may prevent generalizing a model of the system of interest. Model verification and validation can help pinpoint areas where uncertainties may be reduced by denoting why the model structure is inappropriate or by describing any abnormal conditions that may exist. Excluding variables can increase the uncertainty associated with a model because one or more variables that have a strong influence on the outcome may be inadvertently leftout or dropped to increase computational efficiency. For LCI data, sensitivity analysis or expert opinion could be used to determine which variable(s) might be considered for exclusion from the model. Using surrogate variables, or proxies (discussed in Chapter 5), can also add uncertainty because they do not measure the exact quantity of interest.

4.2.2 Qualitative Measures for Controlling Data Errors and Uncertainty

Determining data error may be done with the statistical techniques just discussed as well as through more qualitative means. The following qualitative, proactive measures should help practitioners reduce errors and uncertainty in LCI results:

- careful planning and execution of the LCI data development process,
- formal and informal reviews of the LCI data development process,
- focusing data quality efforts on data values that have the greatest influence on LCI results, and
- ensuring that sample sizes for key data values are as large as possible, thus increasing the reliability of the estimates and decreasing variability (Arthur D. Little, 1993b).

In the planning and execution of the LCI data development process, each step in the process must be performed carefully to maintain consistency with the study goals and scope, to minimize errors, and to ensure that final results represent the system of interest. For example, DQGs should be defined in a manner that fosters the use of representative data, the study scope and boundary settings should include all relevant life-cycle inputs and outputs of the system of interest, key assumptions should be substantiated and clearly documented, the data collection questionnaires should be designed to obtain the appropriate data values, and so on.

To help ensure that final results are representative, formal and informal review of the data and the data development process can be conducted. Formal review can include development of data quality worksheets and submission of the data collection plan and final worksheets to a peer-review panel. In addition to formal review, informal reviews by analysts, peers, industry experts, and consultants may take place in each of the data development steps and may help to minimize errors that could undermine results. For example, a reviewer may discover that in the development of process input/output charts, an important aspect of the process was inadvertently excluded. Thus, even if high quality data are used, the final results may not be representative—these types of omissions may be avoided through a carefully planned LCI review process.

Focusing data quality efforts on data values that have the greatest influence on LCI results refers back to the issues of large versus small data values (see Section 2.3) and sensitivity (see Sections 3.4 and 4.1). Large data values generally contribute proportionately more to final LCI results and the quality of those results than do smaller data values. Therefore efforts to reduce errors and uncertainty in larger data values can provide a proportionately greater improvement on overall data quality. Data values found to be highly sensitive to a specific LCI parameter, and contribute significantly to the value of that parameter, are also a good candidates for focusing data quality efforts. By improving the quality of highly sensitive data values, the quality of overall parameter values may also be improved.

Regarding sample size and variability; practitioners should consider two important factors:

- Outliers in the data set, both large and small, have the greatest influence on the total variance and uncertainty of the data.
- A smaller total number of data values means less reliability in results (Franklin Associates, Ltd., 1993).

These two factors highlight the importance of achieving maximum sample sizes for key data inputs and carefully evaluating outliers to ensure that they are legitimate values.

4.2.3 Quantitative Methods of Uncertainty Analysis

Uncertainty analysis involves determining how the uncertainties involved with input parameters affect the uncertainty of model results. There are a variety of methods for analyzing uncertainty. This section describes three possible methods to analyze uncertainty including uncertainty propagation, the Gaussian approximation method, and Monte Carlo simulation.

Uncertainty Propagation

Any measured value has associated with it some degree of uncertainty for which bounds must be determined in order for this uncertainty to be meaningful (EPA, 1987). When such a measured value is used in a calculation, its associated uncertainty results in an uncertainty in the computed value. Thus, one is then faced with determining uncertainty bounds on the computed value based on uncertainty associated with input values.

The manner in which uncertainties propagate in a calculation depends on the functional relationship between the input variables and the type of error (random or systematic) involved (EPA, 1978). Uncertainty propagation formulas for random and systematic errors are listed in Table 4-4 for four basic arithmetic operations. The formulas provide confidence intervals for functions of two independent variables. From these confidence intervals, bounds may be placed on the degree of uncertainty associated with a final calculated value that has been propagated from the two independent input variables. In the context of LCI, these functions may be useful for identifying the level of uncertainty associated with calculated data values and/or the final results of the LCI computation model. For a more complete discussion of uncertainty propagation and the application of uncertainty propagation formulas, refer to EPA (1978).

The Gaussian Approximation Method

The Gaussian method takes into account both sensitivity and uncertainty. Like sensitivity analysis, low and high values representing plausible ranges or probability distributions are selected for individual parameters while all other variables are held constant to determine the relative uncertainty associated with each variable and with overall results. Once a mathematical model for the system of interest has been developed, rates of change in the model results are calculated based on unit changes in a model parameter; holding all other variables constant. The model results are then evaluated against theoretical values to provide initial "best guess" values for model parameters.

TABLE 4-4. UNCERTAINTY PROPAGATION FORMULAS FOR RANDOM AND SYSTEMATIC ERRORS

Operation	Uncertainty Propagation Formula
Random Error	
Addition, $x_1 + x_2$	$A + B +/- \sqrt{a^2 + b^2}$
Subtraction, $x_1 - x_2$	$A + B +/- \sqrt{a^2 + b^2}$
Multiplication, $x_1 x_2$	$A + B +/- \sqrt{B^2 a^2 + b^2}$
Division, x_1/x_2	$A/B) +/- \sqrt{\frac{a^2}{B^2} + \frac{A^2}{B^2} b^2}$

NOTE: A +/- a and B +/- b are confidence intervals for x_1 and x_2. The formulas give confidence intervals for the various mathematical operations performed with x_1 and x_2. The formulas are valid only when A and B are statistically independent.

Systematic Error		
	Lower Bound	**Upper Bound**
Addition	$A + B - (a + b)$	$A + B + (a + b)$
Subtraction	$A - B - (a + b)$	$A - B + (a + b)$
Multiplication	$AB + sgn(AB)ab - (a\|B\| + b\|A\|)$	$AB+sgn(AB)ab+(a\|B\| + b\|A\|)$
Division	$\frac{A}{B} - \frac{a\|B\| + b\|A\|}{B^2 + sgn(AB)b\|B\|}$	$\frac{A}{B} - \frac{a\|B\| + b\|A\|}{B^2 - sgn(AB)b\|B\|}$

NOTE: A +/- a and B +/- b are error bounds for x_1 and x_2. The formulas give upper and lower bounds for the four basic mathematical operations performed with x_1 and x_2. The formulas are valid only when x_1 and x_2 are functionally independent variables.

NOTE: These equations involve strong assumptions regarding the shape of the underlying distributions, as well as their independence. Refer to EPA (1978) for a complete discussion of these issues.
Source: EPA, 1978.

Following the evaluation of the model results, each best guess value is squared and multiplied by the variance of the input model parameters. If the individual parameters are independent of each other, the quantities calculated above may be summed to produce an estimate of the variance of the model results. If the individual parameters are not independent of each other, the calculation can be used to estimate the covariance of each pair of explanatory variables.

The Gaussian method allows for the assignment of ranges or probability distributions for uncertain model inputs to assess the composite uncertainty in model outputs. This method can also reveal which sensitive variables are also uncertain. If parameters identified as most important (or sensitive) to LCI results are also highly uncertain, practitioners should focus data quality resources on these parameters. "When a decision must be made about whether to expend resources to acquire additional information, in general, the greater the uncertainty, the greater the expected value of additional information" (Morgan and Henrion, 1990).

The formulas for these calculations and a detailed discussion of the Gaussian method are beyond the scope of this document. The reader should consult a statistician or refer to Morgan and Henrion (1990) for a more complete discussion of the Gaussian method.

Monte Carlo Simulation

Monte Carlo simulation involves simulating a system by randomly selecting values for each explanatory variable in a model (as described in the Gaussian-approximation section) then plugging the values into a functional equation and producing a simulated output value. Monte Carlo simulation requires the following steps:

- model the data generating process,
- employ the generating process and an estimator to create several estimates, and
- use these simulated data to estimate the population distribution properties, assuming that the model is at least approximately correct (Kennedy, 1991).

For a more complete description of these steps refer to Kennedy (1991). Through the use of computers, this process is repeated hundreds or thousands of times to generate a simulated distribution for the output variable (Morgan and Henrion, 1990).

The random selection of the explanatory variables is typically based on frequency distributions or Bayesian methods. The simulated values are usually assumed to be independent of each other because this allows for easier statistical analysis.

CHAPTER 5
COMPENSATING FOR MISSING DATA AND DATA DEFICIENCIES

This chapter addresses missing data (actual missing values) and data deficiencies, such as weaknesses in measurement techniques, and describes mathematical techniques used to compensate for missing data and data deficiencies encountered during the LCI data development process.

While the methods described are suitable for addressing many problems with LCI data, they vary in complexity and may require consultation with experts or the use of advanced statistical techniques. The methods described in this chapter have not been tested in LCI applications. It is recommended that practitioners consult experts from the applicable methodological field before applying these techniques.

KEY POINTS

- Data compensation methods may be employed to address missing data or data that does not satisfy the defined DQGs.
- Imputation and weighting are two data compensation methods that potentially apply to typical LCI data.
- It is critical that practitioners clearly communicate the effect of data compensation methods on LCI results.

5.1 MISSING DATA AND DATA DEFICIENCIES

Practitioners must frequently compensate for missing or deficient data to complete the LCI (Arthur D. Little, 1993b). Three general types of missing data are:

- data that may not be available for a given industry, facility, product, or process;
- data that may be available for a product but not for all the components of the process used in making that product; and
- data derived from a survey that may be missing due to nonresponse by facilities receiving the survey (unit nonresponse) or nonresponse to specific items on a questionnaire (item nonresponse) (Lepkowski, Landis, and Stehouwer, 1987).

Data can be missing for other reasons. For example, a data set with values on air emissions may have a previously determined threshold level below which values are marked with a code instead of the actual value. Other values may be missing on the basis of a second variable—that is, if information for a variable is not available, values for

other variables that are dependent on the initial variable may also be indeterminable (Azen, Guilder, and Hill, 1989).

Unlike missing data, data deficiencies are associated with the methods involved in collecting, synthesizing, analyzing, and describing data. Some causes of data deficiencies are faulty sampling design, data collection methods, aggregation techniques, description of variables in data sets, and measurement methods (Plewa et al., 1988). For example, if data were collected on electricity usage for all firms within an industry, but the reported data were rounded up to the nearest 100 kWh before any analysis, measures such as the sum, sample mean, and sample standard deviation would be biased.

5.2 ADJUSTING FOR MISSING DATA AND DATA DEFICIENCIES

As discussed in section 3.4.2, once key data sources have been identified and assessed against applicable DQIs and data values have been evaluated for their impact on LCI results, the practitioner can determine if the data source, and corresponding data values from that source, meet the defined DQGs. If the obtained data quality results meet the DQGs, then the practitioner proceeds with the study and documents the data quality results. If DQGs are not met (i.e., data are missing or deficient) practitioners have several options:

- collect additional, better quality data which satisfies the DQGs,
- redefine the DQGs,
- revisit and possibly redefine the goals and scope of the LCI,
- proceed with the LCI and clearly communicate any limitations that should be placed on the results,
- abandon the LCI, or
- apply data compensation methods to address problems with the data.

A number of different factors contribute to whether the practitioner should undertake compensation efforts. Such factors include:

- importance of the data relative to other missing or deficient data points;
- ease or feasibility of data compensation (this is not discussed); and
- resource constraints (time, money, and technical knowledge).

In using data compensation techniques, as with all other aspects of LCI, it is critical that practitioners clearly communicate the effect of these techniques on LCI results.

Various methods have been introduced to adjust and analyze data sets that have missing values or other deficiencies. Imputation and weighting are two compensation methods that potentially apply to typical LCI data. The methods have different strengths and weaknesses in terms of ease of use, cost, the need for a statistician, and potential effects. In using these techniques, as with other aspects of LCI, it is critical that practitioners clearly communicate the effect of data compensation methods on LCI results.

5.2.1 Imputation

Imputation is a general method used to adjust for item nonresponse and for many other varieties of missing data. Simply stated, imputation is the procedure of replacing a missing value with a value considered to be a reasonable proxy or substitute (Lepkowski, Landis, and Stehouwer, 1987). A range of proxies exists, from an ad hoc value developed from prior experience or logical deduction, to a predicted value from an empirically derived model.

Imputation includes a broad spectrum of techniques involving proxies, logical deductions, and statistically based procedures, or a combination of methods. The following imputation techniques are examined in this section:

- logical proxies,
- deductive imputation,
- mean imputation overall,
- random imputation overall,
- mean imputation within classes,
- random imputation within classes,
- hot-deck imputation,
- predicted regression imputation, and
- random regression imputation.

The imputation methods discussed below may be applicable to LCI data. However, clearly denoting any imputed data and explaining the uncertainty involved with the use of these methods is very important. While these methods "compensate" for data problems, they do not enhance data quality or replace missing data with more applicable (or detailed) facility data. In many cases, it will be necessary and appropriate to consult with a statistician on the application of these methods and the uncertainty that they introduce to the LCI process.

Logical Proxies

One way to fill in missing data is to find a "reasonable" substitute for the missing information. Logically developed proxies are one viable substitute for missing data, especially when there are no data on a given component of the process or product of interest. For example, if no data exist on water releases for a specific facility within an industry, certain facilities in the industry for which the data do exist could be evaluated for use as a proxy for the facility of concern. Similarly, if data were missing for an entire industry, an analyst could use data for the industry determined to be most similar to that industry as a proxy. Expert opinion is sometimes required to determine the validity of the proxy.

Deductive Imputation

Deductive imputation involves examining patterns in the data to determine and draw conclusions about missing data values. Suppose an analyst is examining a raw material used in a specific product. In making the product, a coproduct and waste releases are created. Portions of the raw material are transformed into the product, the coproduct, and the waste releases. Now suppose that the analyst has a data set for an industry that used 500,000 kg of the raw material, 400,000 kg of which became part of the product and 37,000 kg of which went into solid waste. Using deductive imputation—taking the total amount of inputs and subtracting all the known amounts of outputs—the analyst could deduce that 63,000 kg of the material went into the coproduct.

In the above example the analyst would need to consider whether a mass-balance equation would suitably represent the process. In order to use this method, some distinguishable pattern in the data or the process must exist, such that there is a high

likelihood that the calculated value is equal or very close to the correct value (Kalton and Kasprzyk, 1982).

Mean Imputation

The mean imputation overall method involves taking the mean of the known data values and substituting this mean for each of the missing data values (Kalton and Kasprzyk, 1982). For example, if a data set contained 500 reported values and 100 missing values for the amount of a chemical released into a waste stream, an analyst could calculate the average of the 500 known values and substitute this value for the 100 missing values. Analyses could then be performed using all 600 data points.

This method should be used with caution given that the variability in the unknown missing values is not taken into account (Rubin, 1987). Because the sample mean is used for the missing data points, the sample variance and standard deviation will most likely be significantly understated. The results also may be biased to the extent that missing values consistently differ from secured values.

Similar items in a sample can be grouped into imputation classes, determined by evaluating the subjects and by expert opinion. They can also be determined by similarities in other variables (Cox, 1981; Kalton and Kasprzyk, 1982). For each imputation class, the mean of the respondents' values is calculated. Each calculated mean is used to replace the missing data in its own class. As in the mean imputation overall method, using the sample mean as a replacement may result in biased statistics in the analysis.

Referring back to the chemical example, an analyst may determine from an examination of the data or expert opinion that the amount of the chemical released varies significantly from one industry to another. Industry classifications can be the foundation for the imputation classes. The mean imputation procedure could then be used within each class and the classes analyzed separately.

Random Imputation

In contrast to the mean imputation overall method, the random imputation method accounts for some of the variability in the unknown data values (Rubin, 1987). Each missing value is replaced with a data value selected at random from the respondent data. Using the chemical release example mentioned in the previous section, each of the 500 known values could be assigned a probability of 1/500 (e.g., by using a random number

generator, or random digit table). One value is then chosen as the 501st data value. The value should not be removed from possible further selection as this complicates the analysis. The procedure is continued until all 100 missing values have been imputed.

Random imputation within classes combines the random imputation overall methodology with the formation of imputation classes. After forming imputation classes, the analyst replaces missing values with values selected at random from the respondents' values within the class being imputed (Kalton and Kasprzyk, 1982). As in the case of comparing the random and mean imputation overall methodologies, random imputation within classes accounts for some of the increase in variability that is not accounted for by the mean methodology.

Hot-Deck Imputation

Hot-deck imputation is a variation of cold-deck imputation, which must first be understood to describe the hot-deck imputation procedure. Cold-deck imputation uses values from a prior distribution to replace missing values in the data set of concern. This requires a data set similar to the one for which values are being imputed. The imputed values can be selected using randomization or systematic methods. In addition, the data are often divided into imputation classes (Chapman, 1976). Cold-deck procedures are no longer common due to the criticism that current data were not being used for imputation procedures (Chapman, 1976; Cox, 1981). Therefore, cold-deck procedures are not recommended for application to LCI data.

Unlike cold-deck methods, hot-deck imputation uses only the data set for which the missing values are being imputed. As in the cold-deck procedure, imputation classes need to be formed. An initial value (or cold-deck) based on current data or expert opinion is derived for the variable of concern. The records are then analyzed sequentially. If the first data value is present, it replaces the cold-deck value. If not, the cold-deck value is used to replace the missing value. This procedure is repeated until all of the missing data values have been filled in.

Hot-deck procedures could be used in conjunction with published data that have missing values. For example, if an analyst was using a database to determine energy usage for transportation in a given industry, and the values for the 6th, 27th, and 65th facilities in a specific imputation class were missing, these values would be replaced by the 5th, 26th, and 64th values in that class, respectively. However, using expert opinion and logical proxies may produce more accurate values for the missing data.

Regression Imputation

Regression imputation includes predicted imputation and random imputation. In the predicted method, a regression model is developed in which changes in an independent variable that is missing values are characterized by changes in other existing independent variables. These existing independent variables are obtained from subjects/units for which all values have been reported (Kalton and Kasprzyk, 1982).

The predicted regression imputation method can be useful if the relationship between the variables is not easily determined by inspection or expert opinion. For instance, suppose changes in the amounts of any of ten inputs change the amount of a certain release. One must not only determine how a change in one of the inputs affects the release amount but also how all possible simultaneous changes of two or more inputs affect the release amount. A statistician is required to develop an appropriate regression model.

The random regression imputation method is an extension of the predicted regression imputation; the entire predicted method is used but each imputed value has a residual (random) term added to it to account for the difference between values predicted by the regression model and values that are measured or observed.

The random term, or residual, is the difference between the observed and predicted value of the dependent variable for specific values of the independent variables. Residuals provide insight into the predictive error of the model (i.e., the difference between values predicted by the model and observed values). Because a regression model is used to predict values for missing data, a residual cannot be calculated. Rather, a residual is chosen based on deductive or more complex statistical methods. Refer to Kalton and Kasprzyk (1982) for further information on random regression imputation.

5.2.2 Weighting Methods

One method commonly used to compensate for unit nonresponse in surveys is the development of weights to inflate the responses of units that do respond. The various weighting methods correspond to the statistical sampling methods used in choosing the survey participants. Weighting methods can also be used to compensate for item nonresponse in analyses of individual parameters by computing an analysis weight for each item, if, that is affected by nonresponse.

An example of a weighting method could involve surveying 20 companies on energy usage. If only 8 companies respond, the analyst examines other information about the companies to see which responding companies are most similar to each nonresponding company. If one responding company is most similar to 2 nonresponding companies while another is most similar to 3 nonrespondents, these responding companies would be assigned weights of 3 and 4, respectively. The weights are calculated by summing 1 (for the responding company) to the number of nonresponding companies deemed to be most similar to the responding company. Each responding company that was not considered to be most similar to one or more of the nonresponding companies would receive a weight of 1. The sum of the responding companies' weights should then equal 20 (Rubin, 1987). Because of the complex statistical methods involved, the estimation procedures associated with this or any other weighting method are beyond the scope of this document. The interested reader is referred to Little and Rubin (1987).

The use of weighting methods by an LCI analyst would be rare, as very little of the primary data are gathered using large-scale surveys of companies or facilities. However, if a secondary data source such as a database contains data obtained through sampling methods, to gather data, determining the validity of any weighting methods used in assembling the database may be important. This requires consulting a statistician and obtaining a description of both the sampling and weighting methods.

APPENDIX A

DATA QUALITY INDICATORS

A.1 ACCEPTABILITY

Acceptability refers to the degree to which the data source has been peer reviewed, evaluated against a standard, or checked for errors through expert judgment. Acceptability also refers to the extent to which the model has been checked to determine if it represents what it is supposed to represent, (e.g., emissions from a facility's high-density polyethylene production line). The acceptability DQI encompasses the concepts and procedures of both verification/validation and quality assurance/quality control (QA/QC).

Data that are peer reviewed and found to be of adequate quality are generally considered to be acceptable. Peer review of a primary data source generally requires the consensus of process engineers and others knowledgeable in the production system of interest. Peer review of a secondary data source may show that the source was not officially validated or verified although it is regarded by colleagues in the field as a fairly accurate data source. For example, although the TRI data base has not been validated or verified, it is an accepted source of air, water, and waste emissions data for those industries subject to the reporting requirements. For an LCI, using the TRI data base may be more acceptable than using a data base that has not at least received similar acceptance. Peer review can also be applied to assumptions and calculations used to interpolate, extrapolate, or back-calculate data suitable for an LCI.

Acceptability is also expressed by the degree to which a data source has been evaluated against an accepted method or standard, and/or checked for errors. This means that an "acceptable" model should be both verified and validated. A model can be validated by consulting an expert familiar with the process or product being modeled. Model verification involves comparing the model output with actual facility data or a reference value. If the model output is similar to the known value(s) then the model is likely to generate relatively accurate results (Lewis and Orav, 1989). If a model is validated but not verified, or verified but not validated, the accuracy of the results could be questioned.

Validation/verification techniques are most easily applied to primary data generated through the use of a model. The applicability of these techniques is less clear for model-based secondary data. Unless the model and appropriate documentation can be obtained, only qualitative verification/validation techniques can be employed. Expert judgment can determine if the model results are representative of the industry or facility under

evaluation and the natural variability in the model. Similarly, the model can be compared against known facility input/output values.

In cases where the data or model can be subjected to standard methods of statistical analysis (e.g., primary data collected through sampling or generated pursuant to a statistical protocol), QA/QC is the preferred analytical technique under this DQI. EPA has developed QA/QC methodology requiring that certain objectives or goals be set, that DQIs (such as precision, bias, and representativeness) be used to evaluate the objective, and that the data are collected pursuant to sound statistical procedures.

A.2 BIAS

Bias refers to the level of systematic error that causes the values of a data set to be consistently higher or lower than the corresponding "true" parameter values. These "true" parameter values serve as baseline, or reference, values against which LCI data can be compared. Although the discussion of bias in this section assumes that these reference values exist for LCI data, in many cases, they are not known.

Bias can be created by, among other things, a weakness in the data collection methodology (e.g., improper sampling, uncalibrated measurement equipment, or consistently rounding up values). As indicated in Table A-1, bias can be measured by taking the difference between the average measured value ($\bar{X}$) and the reference value of a standard material (T) (EPA, 1984; EPA, 1991). In the Table A-1 example, bias is -0.5. This means that the average measured value is .5 units lower than the reference value (T). An alternative index of bias is the percent bias, which indicates the percent difference of the averaged measured value from the reference value. In the Table A-1 example, the percent bias is 1 percent (EPA, 1984).

The bias DQI can also be applied to data generated through modeling. For example, in modeling air emissions, model bias can be evaluated if there is a reference air-emission level or concentration against which the model results can be compared. Similarly, the bias DQI can be applied to statistically based data provided in the published literature if a reference value is given or known by the analyst. The bias DQI may also be useful for analyzing whether measurement devices used to collect primary LCI data exhibit systematic error, as compared against an existing reference value (i.e., the measured values are consistently higher or lower than the reference values). Measurement of bias in primary data necessarily involves the use of reference values. Thus, the bias

TABLE A-1. SAMPLE DATA TO CALCULATE BIAS

Measurements	X_i	$X_i - \bar{X}$	$(X_i - \bar{X})^2$
1	48	-1.5	2.25
2	55	5.5	30.25
3	50	0.5	0.25
4	45	-4.5	20.25

Average $\bar{X} = (X_1 + X_2 + X_3 + X_4) \div n$
$= (48 + 55 + 50 + 45) \div 4$
$= 49.5$

Bias $= \bar{X} - T$ (T = reference sample value)
$= 49.5 - 50$
$= -0.5$

Percent Bias $= \frac{\bar{X} - T}{T} \times 100$

$= \frac{49.5 - 50}{50} \times 100$

$= 1.0\%$

Source: EPA, 1984.

DQI becomes of limited value for evaluating primary data in cases where reference values are unavailable.

The bias DQI is more difficult to apply to modeled or nonmeasured secondary data. If the data are modeled, bias can be evaluated in one of two ways: the model can be assessed against a standard value to determine if the results are consistently higher or lower than the standard, or expert judgment can be used to make the determination. However, reference materials are not likely to be available to assess the bias in secondary data.

The bias DQI also can be used to evaluate assumptions and calculations used to manipulate LCI data. Again, either expert judgment can be used to assess whether an assumption is biased, or the output of a calculation can be assessed against a reference value (if one exists).

It should be noted that measures of bias themselves do not reveal much about the significance of the bias. It is left up to the data analyst to determine the importance of bias measures. For example, a bias measure of -0.5 indicates the difference between the average measured value and the reference value. However, this measure does not provide any insight into how significant a -0.5 (or 1 percent) bias is. There is no *a priori* rule of thumb to help guide interpretation of bias. Practitioners should use expert judgment or consult a statistician to help determine the significance of bias measures.

A.3 COMPARABILITY

Comparability is the degree to which different methods, data sets, or decisions agree or can be represented as similar or equivalent (EPA, 1991c). Practitioners should discuss how comparability criteria are satisfied so that variations between the data sources are clear to users of the material.

Primary sampled data should be comparable with other measured data for similar samples. More specifically, samples should be collected in a comparable manner from comparable media and by comparable methods. This is achieved by using standard data collection and analytical techniques (EPA, 1991; EPA, 1990a). If the primary data are judgment samples, however, bias and comparability become closely related, diminishing the value of comparability as a DQI (Franklin Associates, Ltd., 1993).

A more complicated matter is the use of comparability for secondary data sources, where, for a particular LCI parameter, an analyst can combine more than one data source. In this situation, it is preferred that the data sources be comparable, but this may be difficult to discern or achieve. For example, the TRI data base contains air, water, and waste release data for industries in SIC code 20 through 39 that manufacture, produce, or use greater than 25,000 pounds of any of 300 listed chemicals. Due to the reporting threshold, the TRI data base may not contain certain facility emissions needed in an LCI. If this is the case, an analyst may need to combine the TRI data with other data sources to adequately reflect industry air, water, and waste emissions. To be comparable, the additional data sources would need to be collected and reported in a similar manner. In this example, the additional data would preferably be facility-specific emissions data (versus industry, national, or other aggregate data).

A.4 COMPLETENESS

Completeness routinely is expressed as the percentage of obtained data to needed data (Mickler and Medlarz, 1987; EPA, 1990b; and EPA, 1991). The level of desired completeness is largely determined by the goal of the study or data collection effort.

The completeness DQI is applicable to LCI data that are statistically based, modeled, or nonmeasured. The completeness DQI can be used to evaluate whether the information or measurement procedures provide all the data values necessary. In other words, this DQI could be used to identify whether there are missing data or data deficiencies. For example, if an LCI requires air emissions data for a sample of, say, 10 facilities in an industry but the information source includes data for only eight sampled facilities, the data source would be considered 80 percent complete.

The completeness DQI can also be used to evaluate any assumptions and calculations used to manipulate secondary data. Secondary data sources may only provide aggregated data, such as total energy consumption by fuel type (e.g., coal, nuclear, or other), which must be interpolated, extrapolated, or back-calculated to develop a facility-specific number suitable for an LCI. Although a data source could be determined to be complete, the requisite assumptions employed by the analyst may be incomplete. Thus, when interpolating, extrapolating, or back-calculating data, considering the completeness of assumptions is important. Incomplete or deficient assumptions will lead to inaccurate calculations used to derive LCI data values.

A.5 DESCRIPTION OF THE DATA COLLECTION METHOD AND LIMITATIONS

This DQI applies to both primary and secondary data sources that are statistically based or nonmeasured. In both cases, a description of the data collection method provides additional information to help an analyst assess data quality using the other DQIs.

With regard to statistically based data, data quality can be more easily assessed if detail is provided about the sampling procedure used to obtain the data. This sort of information includes:

- a description of the sampling plan,
- a discussion of how the sample was developed,

- a discussion of how the sample size was determined,
- an identification of exactly what was measured, and
- an identification of the instruments used to collect the samples.

If the data were generated through the use of a survey, the data source can include the list of questions. Reviewing the questionnaire can help the analyst determine whether the data reflect the questions asked and whether the data are suitable for the LCI. Without this kind of information, determining the accuracy or overall quality of the data source is difficult, if not impossible.

With respect to a nonmeasured data source, it is equally important from a data quality perspective that the source contain a discussion of why and how the data were collected. For example, the source can indicate whether the data were gathered to fulfill a legal reporting requirement generated by using proxies or generated by using expert opinion. If the data were generated due to a legal reporting requirement, the applicable regulations could be assessed to determine the extent of coverage. Depending on the goals and scope of the LCI, the data may be totally or partially suitable for the analysis. Determining that the data are, among other things, nonrepresentative or that they contain an undercoverage bias can reduce the usefulness of the data base. For data generated with proxies, knowing the basis for the proxy or the level of difference in the comparison provides an indication of whether the estimates are biased. Similarly, if the data were based on expert opinion, knowing the assumptions and calculations used to generate the data is helpful.

A discussion of model limitations provides an indication of the variability (or precision) in the data set. With respect to statistical data, the data source can identify the precision of the measurement instruments and the completeness of the data set (the number of samples collected versus the number needed). If a survey is employed, the data source can indicate, among other things, coverage of the sampling source and the level or degree of nonresponse. With a statistical sample or a survey, the source can show whether there were missing values, or data deficiencies and for which problems there was compensation.

With regard to nonmeasured data, the data source also can show the sources of variation in the data set. This can include a discussion of data deficiencies (e.g., companies who were required to report but reported the data incorrectly), limitations in

any proxies used, or the lack of procedures to ensure that data were properly input to the data base or spreadsheets.

A.6 PRECISION

Precision refers to the closeness, expressed numerically if possible, of estimates to one another or the variability in a set of values or measurements compared to their mean. As shown in Figure A-1, precision and bias are closely related. Precise data can be heavily biased, and unbiased data can be largely imprecise. The goal is to obtain data that are both precise and unbiased (i.e., accurate).

The sample standard deviation and the coefficient of variation (CV) (i.e., the standard deviation divided by the mean) are indicators of precision. Their calculation is shown is Table A-2. To increase the confidence in the generality of results, the sample should have as little variability as possible (Franklin Associates, Ltd., 1993). Thus, the lower the standard deviation and CV, the higher the precision (EPA, 1984; EPA, 1990b; and EPA, 1991).

Precision can be used to evaluate measurement methods used to collect primary environmental data. For any measurement method, sources of variation include sample collection, handling, shipping, storage, preparation, and analysis. Generally, precision is measured by comparing individual repeated measurements against the sample mean ($\bar{X}$) of measurements on the same unit, or a reference value if available, and calculating the coefficient of variation (CV) by dividing the standard deviation in the sample data by the sample mean, or reference value. The higher the CV, the higher the dispersion of sample measures relative to the sample mean, and generally, the lower the quality of the measurement tool. Based on the sample data provided in Table A-2, the standard deviation is 4.2 and the CV is approximately 0.085 (EPA, 1984). Comparing these values against the mean provides an indication of the degree of variability in the data. Once again, it is recommended that data analysts use expert judgment or consult a statistician to determine the significant of CV measures.

The application of the precision DQI is less clear for secondary data that are modeled or nonmeasured. With respect to modeled data, the precision DQI may possibly be applied if three pieces of information are provided:

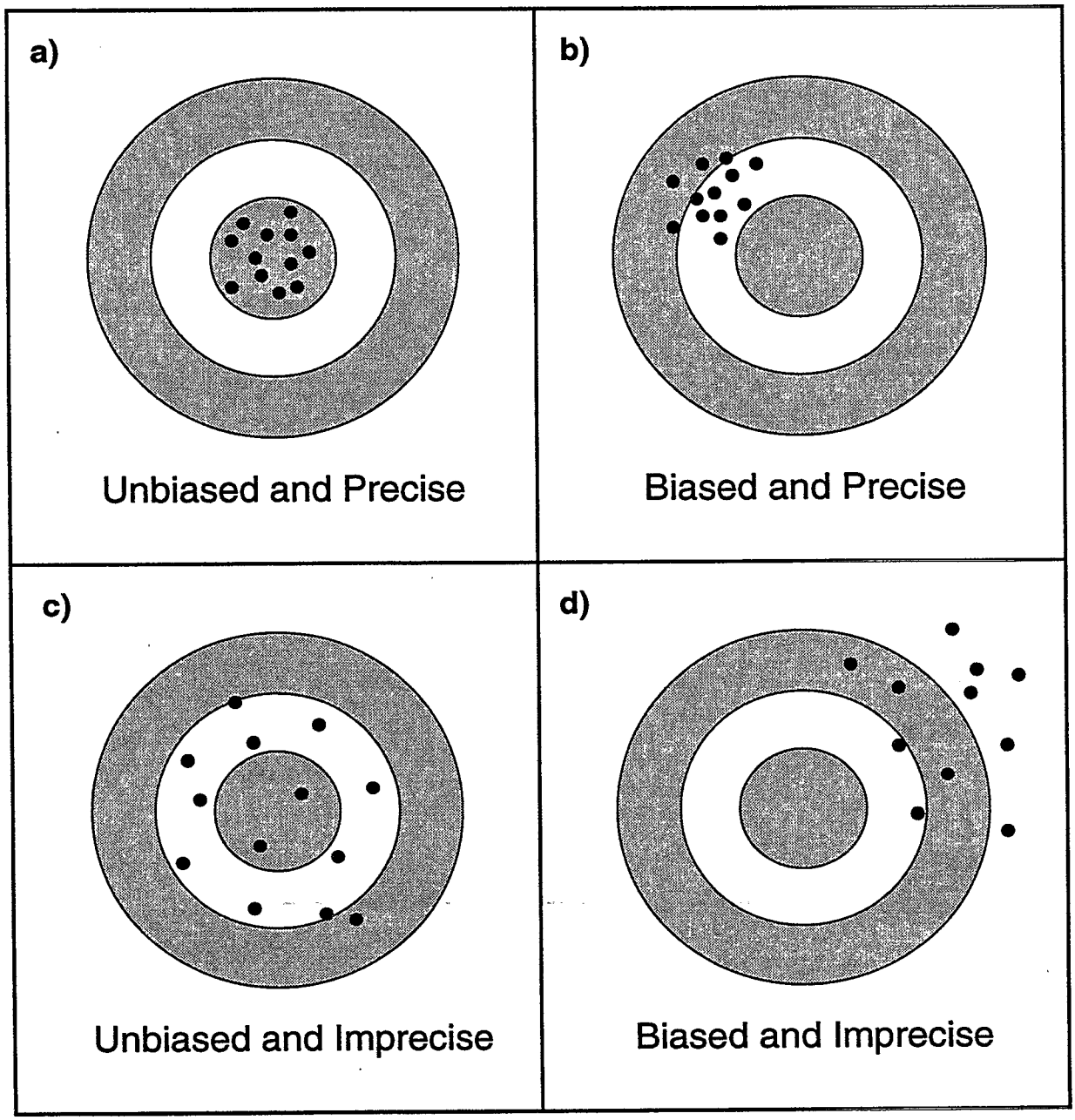

Figure A-1. Relationship Between Precision and Bias

TABLE A-2. SAMPLE DATA TO CALCULATE PRECISION

Measurements	X_i	$X_i - \bar{X}$	$(X_i - \bar{X})^2$
1	48	-1.5	2.25
2	55	5.5	30.25
3	50	0.5	0.25
4	45	-4.5	20.25

$$\text{Average } \bar{X} = (X_1 + X_2 + X_3 + X_4) \div n = (48 + 55 + 50 + 45) \div 4 = 49.5$$

$$\text{Variance } S^2 = \sum_{i=1}^{4} (X_i - \bar{X})^2 \div (n - 1) = (2.25 + 30.25 + 0.25 + 20.25) \div 3$$

$$S^2 = \frac{53}{3} = 17.67$$

$$S = 4.2$$

$$CV = \frac{S}{\bar{X}} = \frac{4.2}{49.5} = 0.085$$

Source: EPA, 1984.

- the full data set,
- the model documentation, and
- a reference value.

If this information is unavailable, model precision may possibly be determined based on expert opinion. An expert or group of experts can be consulted to determine the degree of variability in the data and whether the variation is acceptable.

The application of the precision DQI to nonmeasured data such as the TRI data base or a DOE total energy consumption value is even less clear than for modeled data. A possible application of the precision DQI to these data would be evaluating the data in a time series and determining if the year-to-year variation is reasonable. For example, the

TRI data base can be evaluated to obtain lead releases from several years for a particular company or group of companies. Expert opinion can be used to determine whether the year-to-year change is reasonable. An expert can determine that the change in releases is disproportionate based on known production processes and emission controls. This approach can provide an indication of the "precision" of the estimates reported by industry.

For secondary data that require manipulation in order to develop a value(s) suitable for an LCI, the precision DQI can be used to assess the adequacy of the calculation. The results of a calculation can be measured against the mean, standard deviation and the CV for the data. As indicated above, this information would reveal the variability in the data. If this information is unavailable, a more likely scenario would be to assess the precision of the calculation based on expert opinion. Clearly, if expert opinion is the choice, an expert different from the one who developed it should review the calculation.

A.7 LEVEL OF REFERENCE

To adequately review the quality of a data source used in an LCI, an analyst must have a complete reference for the source. Practitioners should clearly indicate what data sources were used, who developed the sources, and when they were published. An adequate reference enables an analyst to go directly to the source to gain a better understanding of its quality and how it was used in the LCI.

For primary data sources, references provide information on where the data were obtained. For example, references on a primary data source on facility air emissions might include information on where, when, and how the data were obtained (e.g., actual measures, process back-calculations, engineering estimates).

Referencing secondary data sources presents a challenge. Although it is relatively easy to reference an immediate source, it is not always easy to determine the origin of the data in the secondary source or how it was obtained. For example, secondary energy data can be obtained from the Energy Information Administration (EIA). While this may be a reputable source, the practitioner has only limited insight into where and how those data were generated, and thus limited confidence in whether those data accurately represent the

production system of interest. Practitioners should attempt to obtain and document as much information as possible on secondary data sources.

A.8 REPRESENTATIVENESS

Representativeness refers to the degree to which the data describe what an analyst is attempting to describe (EPA, 1991; and Mickler and Medlarz, 1987). This DQI can be used in a variety of ways. From a traditional QA/QC perspective, the representativeness DQI is used to determine if the sampling program design accurately depicts the system of interest. This DQI is best met by ensuring that sampling locations are selected properly and the appropriate number of samples is collected (Barth et al., 1989).

With respect to LCI data, the representativeness DQI can be used to determine the degree to which primary data represent or depict the parameter of interest. For example, if primary air emissions data are collected, the representativeness DQI can be used to determine the degree to which the data represent what is being measured, such as peak or average air emissions.

The representativeness DQI may be more difficult to apply to secondary data. For example, if an LCI required hazardous waste release data for a specific waste stream, the TRI data base—a nonmeasured data source—could be searched to determine if it contained the data for the industry of interest. If the TRI data base contained the hazardous waste release data, the data source would on the surface appear to be representative. However, superficial appearance is not enough to ensure representativeness. Typical TRI data are for generic waste streams, but these data are not necessarily representative of the specific waste stream data needed for an LCI that is often linked to a specific product or process. Therefore, practitioners should carefully evaluate secondary data sources to ensure that they accurately represent what is desired in the LCI.

Understanding the distinction between the representativeness and completeness DQIs is important. Continuing with the TRI example, if the data base contains the type of hazardous waste releases generated by the selected industry, the data source would be considered representative. However, it is possible that the data base would not contain information for all of the facilities studied. In this case, the data source is representative but not complete.

Applying the representativeness DQI to assumptions and calculations is possible and is just as, or even more, important as the completeness DQI. For example, an LCI for antifreeze might have a complete set of emissions data for antifreeze using ethylene glycol. However, this emissions data cannot be fit to antifreeze using propylene glycol. Constructing an LCI for propylene glycol antifreeze using the emissions data for ethylene glycol would be misrepresentative.

In addition, data derived through a back-calculation may be representative of what the analyst wants to obtain. However, if an analyst's assumptions are incomplete, no matter how representative the data are, they still may not reflect the actual value needed in an LCI. Take the example given under the completeness DQI for an extrapolated energy value. If an analyst assumes that a facility uses coal-based electricity when it in fact uses nuclear-based electricity, the data derived can represent the perceived need for the LCI: coal-based electricity data values. However, because the analyst's assumption regarding the use of nuclear fuel was incorrect, the data would not reflect the actual value needed in the LCI.

APPENDIX B

BIBLIOGRAPHY

RESEARCH METHODOLOGY

A number of data bases were searched extensively for literature on data quality. These databases are:

American Statistics Index (ASI): 1/1/74 to 3/1/92

Economic Literature Index: 1/1/69 to 3/31/92

Embase (Excerpta Medica): 1974 to 1992

Energy Science and Technology: 1974 to 1992

Enviroline: 1/1/70 to 5/31/92

Environmental Bibliography: 1/1/74 to 3/31/92

Health Planning and Administration: 1/1/75 to 7/1/92

Mathsci: 1/1/40 to 6/30/92

Medline: 1/1/85 to 7/1/92

National Technical Information Service (NTIS): 1964 to 1992

Pollution Abstracts: 1/1/70 to 5/31/92

Toxline: 1/1/65 to 5/31/92

Water Resources Abstracts: 1/1/68 to 5/1/92

Different combinations of the following key words were used in performing the literature search:

assessment, available data, data deficiency/deficiencies, data gap(s), data indicator(s), data quality, environmental impact assessment, extrapolation, full fuel cycle, hazard ranking, hot decking, imputation, missing data, quality assurance, quality control, risk assessment, sensitivity analysis, uncertainty/uncertainty analysis.

This bibliography includes references not used in this report but of use to anyone interested in data quality assessment methodologies.

BIBLIOGRAPHY

Albridge, Kim M., Jim Standish, and James F. Fries. 1988. "Hierarchical Time-Oriented Approaches to Missing Data Inference." *Computers and Biomedical Research* 21:349-366.

Alexander, Greg R., Mark E. Tompkins, and Donald A. Cornely. 1990. "Gestational Age Reporting and Preterm Delivery." *Public Health Report* 105(3):267-275.

Anderson, Carl L. 1987. "The Production Process: Inputs and Wastes." *Journal of Environmental Economics and Management* 14:1-12.

Anderson, D. W. 1983. "Development of Product-Specific Output Projections Using an Input-Output Model." *Empirical Economics* 8:1-8.

Arthur D. Little, Inc. 1993a. Technical Review of the Draft Guidance Document "Assessing Data Quality for Life Cycle Assessment." Prepared for the U.S. Environmental Protection Agency, Office of Solid Waste, Washington, D.C.

Arthur D. Little, Inc. 1993b. "Case Studies and Document Review: Assessing Data Quality for Life Cycle Assessment." Prepared for the Research Triangle Institute, Center for Economics Research, Research Triangle Park, NC.

Azen, Stanley P., Michael Van Guilder, and Mary Ann Hill. 1989. "Estimation of Parameters and Missing Values Under A Regression Model With Non-Normally Distributed and Non-Randomly Incomplete Data." *Statistics In Medicine* 8:217-228.

Bailey, Paul E. 1990-91. "Life-Cycle Costing and Pollution Prevention." *Pollution Prevention Review* Winter:27-39.

Barth, D.S. et al. 1989. *Soil Sampling Quality Assurance Users' Guide, Second Edition.* U.S. Environmental Protection Agency report 600/8-89/046, PB89-189864. Las Vegas, Nevada: University of Nevada.

Bérubé, M., and S. Bisson. 1991. *Lifecycle Studies: A Literature Review and Critical Analysis.* Ministère De L'Environment Du Québec.

Bogen, Kenneth T., and Robert C. Spear. 1990. "Uncertainty and Variability in Environmental Risk Assessment: A Framework for Analysis." In *New Risks*, L. A. Cox, Jr., and P.F. Ricci, eds., pp. 389-401. New York: Plenum Press.

Boustead, I., and G. F. Hancock. *Handbook of Industrial Energy Analysis.* New York: John Wiley and Sons.

Brodzinsky, Richard, and Hanwant B. Singh. 1983. *Volatile Organic Chemicals in the*

Atmosphere: An Assessment of Available Data. Research Triangle Park, NC: EPA Office of Research and Development, Environmental Sciences Research Laboratory.

Bunn, Derek W. 1984. *Applied Decision Analysis.* New York: McGraw-Hill Book Company.

Bunnett, Joseph F. 1985. "Errors in Publications." *Accounts of Chemical Research* 18(10).

Byrd, Daniel M., and Elizabeth T. Barfield. 1989. "Uncertainty in the Estimation of Benzene Risks: Application of an Uncertainty Taxonomy to Risk Assessments Based on an Epidemiology Study of Rubber Hydrochloride Workers." *Environmental Health Perspective* 82:283-287.

Calabrese, Edward J. 1982. "The Role of Exposure Data in Standard Setting." *Toxic Substances Journal* 4:12-22.

Center for Policy Alternatives. 1990. "Update on Diapers." Revised. September.

Chapman, David W. 1976. "A Survey of Nonresponse Imputation Procedures." Prepared for the Proceedings of the Section of Social Statistics. Westat, Inc.

Checkoway, Harvey, David A. Savitz, and Nicholas J. Heyer. 1991. "Assessing the Effects of Nondifferential Misclassification of Exposures in Occupational Studies." *Appl. Occup. Environ. Hyg.* 6(6):528-533.

Clemen, R.T. 1991. *Making Hard Decisions: An Introduction to Decision Analysis.* Boston: PWS-Kent Publishing Company.

Commission on Geosciences, Environment, and Resources. 1990. *Tracking Toxic Substances at Industrial Facilities: Engineering Mass Balance Versus Materials Accounting.* Washington: National Academy Press.

Conn, Judith M., Kung-Jong Lui, and Daniel L. McGee. 1989. "A Model-Based Approach to the Imputation of Missing Data: Home Injury Incidences." *Statistics In Medicine* 8:263-266.

Cook, Thomas D. 1990. "The Generalization of Casual Connections: Multiple Theories in Search of Clear Practice." In *Research Methodology: Strengthening of Non-Experimental Data*, Lee Sechrest, Edward Perrin, and John Bunker, eds., pp. 9-18. Washington, DC: U.S. Department of Health and Human Services, Agency for Health Care Policy and Research.

Cooper, Lee G., Jan De Leeuw, and Aram G. Sogomonian. 1991. "An Imputation Method for Dealing with Missing Data in Regression." *Applied Stochastic Models and Data Analysis* 7:213-235.

Cordray, David S. 1990. "Strengthening Casual Interpretations of Nonexperimental Data: The Role of Meta-Analysis." In *Research Methodology: Strengthening of Non-Experimental Data*, Lee Sechrest, Edward Perrin, and John Bunker, eds., pp. 151-172. Washington, DC: U.S. Department of Health and Human Services, Agency for Health Care Policy and Research.

Council for Solid Waste Solutions. 1990. *Resource and Environmental Profile Analysis of Polyethylene and Unbleached Paper Grocery Sacks.* Final report. Prepared by Franklin Associates, Ltd. June.

Council for Solid Waste Solutions. 1991. *Resource and Environmental Profile Analysis of High-Density Polyethylene and Bleached Paperboard Gable Milk Containers.* Final report. Prepared by Franklin Associates, Ltd.

Council of State Governments, Lexington, Kentucky, and U.S. Environmental Protection Agency. 1982. *CSG/Tellus Packaging Study*, Volume I. Prepared by Tellus Institute.

Cox, Brenda G. 1981. "Imputation Procedures to Replace Missing Responses to Data Items." Prepared in the Annual Meetings of North Central Sociological Association. Cleveland, Ohio. April.

Cox, David C., and Paul Baybutt. 1981. "Methods for Uncertainty Analysis: A Comparative Survey." *Society for Risk Analysis* 1(4):251-258.

"Diaper Decisions." *Consumer Reports.* August 1991. pp. 551-556.

Denison, Richard. 1992. *Toward a Code of Ethical Conduct for LCAs.* Washington DC: Environmental Defense Fund.

Eddy, David M. 1990. "The Role of Meta-Analysis." In *Research Methodology: Strengthening of Non-Experimental Data*, Lee Sechrest, Edward Perrin, and John Bunker, eds., pp. 173-176. Washington, DC: U.S. Department of Health and Human Services, Agency for Health Care Policy and Research.

Ekvall, Thomas. 1992. "Life-cycle Analyses of Corrugated Cardboard: A comparative analysis of two existing studies." Unpublished draft report.

Ellis, Hugh. 1992. "Acid Rain: Operations Research Joins the Battle to Control Serious Ecological Threat." *OR/MS Today* June:26-28.

Energy Information Administration. 1992a. *Annual Energy Outlook with Projections to 2010.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1992b. *Assumptions for the* Annual Energy Outlook 1992. Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1992c. *Monthly Energy Review*. Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1992d. *Supplement to the Annual Energy Outlook 1992.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1991a. *An Assessment of the Quality of Selected EIA Data Series.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1991b. *Manufacturing Energy Consumption Survey: Consumption of Energy 1988.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1991c. *Manufacturing Fuel-Switching Capability 1988.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1991d. *New Releases*. Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1990. *Energy Consumption and Conservation Potential: Supporting Analysis for the National Energy Strategy.* Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1989. *An Assessment of the Quality of Selected EIA Data Series*. Washington, DC: U.S. Government Printing Office.

Energy Information Administration. 1987. *An Assessment of the Quality of Selected EIA Data Series*. Washington, DC: U.S. Government Printing Office.

Esmen, Nurtan A. 1991. "Analysis of Strategies for Reconstructing Exposures." *Appl. Occup. Environ. Hyg.* 6(6):488-494.

Finkel, Adam M. 1990. *Confronting Uncertainty in Risk Management: A Guide for Decision-Makers.* Washington, DC: Center For Risk Management.

Finn, John T. 1976. "Measures of Ecosystem Structure and Function Derived from Analysis of Flows." *Journal of Theoretical Biology* 56:363-380.

Ford, Judith S. 1991. *AEERL Quality Assurance Procedures Manual for Contractors and Financial Assistance Recipients.* Draft. Washington, DC: EPA Office of Research and Development.

Forsund, Finn R. "Input-Output Models, National Economic Models, and the Environment." *Handbook of Natural Resource and Energy Economics.* Vol. 1, A.V. Kneese and J. L. Sweeney, eds., pp. 325-339.

Franklin Associates, Ltd. 1993. "Data Quality Case Studies." Prepared for Research Triangle Institute. Prairie Village, Kansas.

Franklin Associates, Ltd. 1992. "Example Information on Sensitivity Analysis for Two Production Systems." Prairie Village, Kansas.

Franklin Associates, Ltd. 1991. *Resource and Environmental Analysis of High-Density Polyethylene and Bleached Paperboard Gable Milk Containers.* Prairie Village, Kansas.

Franklin Associates, Ltd. 1989. *Comparative Energy and Environmental Impacts for Soft Drink Delivery Systems.* Prairie Village, Kansas.

French, Simon. 1989. *Readings in Decision Analysis.* New York, NY: Chapman and Hall.

Funtowicz, S.O., and J.R. Ravetz. 1990. *Uncertainty and Quality in Science for Policy.* The Netherlands: Kluwer Academic Publishers.

Funtowicz, S.O., and J.R. Ravetz. 1987. "The Arithmetic of Scientific Uncertainty." *Physics Bulletin* 38:412-414.

Funtowicz, S.O., and J.R. Ravetz. 1986. "Policy-Related Research: A Notational Scheme for the Expression of Quantitative Technical Information." *Journal of Operational Research Society* 37(3):243-247.

Funtowicz, S.O., and J.R. Ravetz. 1984. "Uncertainties and Ignorance in Policy Analysis." *Risk Analysis* 4(3):219-220.

Funtowicz, S.O., S.M. Macgill, and J.R. Ravetz. 1989. "The Management of Uncertainties in Radiological Data." *J. Radiol. Prot.* 9(4):257-261.

Funtowicz, S.O., S.M. Macgill, and J. R. Ravetz. 1988. "Mapping Uncertainties of Radiological Hazards." *Atom.* Nov:15-16.

Galloway, James N., J. David Thornton, Stephen A. Norton, Herbert L. Volchok, and Ronald N. McLean. 1982. "Trace Metals in Atmospheric Deposition: A Review and Assessment." *Atmospheric Environment* 16(7):1677-1700.

Hämäläinen, Raimo P. 1992. "Politics & Policy: Decision Analysis Makes Its Way Into Environmental Policy in Finland." *OR/MS Today* June:40-43.

Henrion, Max, and Baruch Fischoff. 1986. "Assessing Uncertainty in Physical Constants." *American Journal of Physics* 54(9):791-798.

Hocking, Martin B. 1991. "Paper vs. Polystyrene: A Complex Choice." *Science* 251:504-505.

Hope, C.W., and S. Owens. 1986. "Research Policy and Review 10: Frameworks for Studying Energy and the Environment." *Environment and Planning* 18:851-864.

Hui, Siu L., and James O. Berger. 1983. "Empirical Bayes Estimation of Rates in Longitudinal Studies." *Journal of the American Statistical Association* 78(384):753-760.

Hunt, Robert G., and William E. Franklin. 1975. "Resource and Environmental Profile Analysis . . . of Beer Containers." *Chemtech* August:474-481.

Iman, Ronald L. 1990. "Methods Use in Probabilistic Risk Assessment for Uncertainty and Sensitivity Analysis." In *New Risks*, L.A. Cox Jr. and P.F. Ricci, eds. New York: Plenum Press.

Iman, Ronald L. 1987. "A Matrix-Based Approach to Uncertainty and Sensitivity Analysis for Fault Trees. *Risk Analysis* 7(1):21-33.

Iman, Ronald L., and Jon C. Helton. 1988. "An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models." *Risk Analysis* 8(1):71-90.

James, David. 1985. "Environmental Economics, Industrial Process Models, and Regional-Residuals Management Models." *Handbook of Natural Resource and Energy Economics.* Vol. 1, A. V. Kneese and J. L. Sweeney, eds., pp. 271-319.

Johnson, Gary L., and Judith S. Ford. 1986. "Development of Data Quality Indicators for Toxic Air Pollution Measurements." In *Proceedings of the 1986 EPA/APCA Symposium on Measurement of Toxic Air Pollutants.* Research Triangle Park, NC: EPA Air and Energy Engineering Research Laboratory.

Kalton, Graham, and Daniel Kasprzyk. 1982. "Imputing for Missing Survey Responses." Prepared for the Proceedings of the Section on Survey Research Methods.

Keeney, Ralph L., and Raiffa, Howard. 1976. *Decisions with Multiple Objectives: Preferences and Value Trade Offs.* New York: John Wiley & Sons, Inc.

Kennedy, Peter. 1991. *A Guide to Econometrics.* Second Edition. The MIT Press: Cambridge, Massachuetts.

Kirk, Roger E. 1990. *Statistics: An Introduction.* Third Edition. Fort Worth: Holt, Rinehart, and Winston.

Kirkpatrick, Neil. 1991. Total Approach to Preserving the Environment." *Packaging Week* 7(25):19.

Kollig, Heinz P. 1987. "Criteria for Evaluating the Reliability of Literature Data on

Environmental Process Constants." *Toxicological and Environmental Chemistry* 17:287-311.

Kollig, Heinz P., and Brenda E. Kitchens. 1990. "Problems Associated with Published Environmental Fate Data." *Toxicological and Environmental Chemistry* 28:95-103.

Kollig, Heinz P., U.S. Environmental Protection Agency. 1992. Personal communication with Chris Lacke, Research Triangle Institute.

Lepkowski, James M., J. Richard Landis, and Sharon A. Stehouwer. 1987. "Strategies for the Analysis of Imputed Data From a Sample Survey: The National Medical Care Utilization and Expenditure Survey." *Medical Care* 25(8):705-716.

Lewis, P.A.W., and E.J. Orav. 1989. *Simulation Methodology for Statisticians, Operations Analysts, and Engineers: Volume I.* The Wadsworth and Brooks/Cole Statistics/ Probability Series.

Little, Roderick, J. A., and Donald B. Rubin. 1987. *Statistical Analysis with Missing Data.* New York: John Wiley and Sons, Inc.

Lübkert, Barbara, Yrjö Virtanen, Manfred Mühlberger, Jyrki Ingman, Bruno Vallance, and Sebastian Alber. 1991. "Life-Cycle Analysis Idea: An International Database for Ecoprofile Analysis, A Tool For Decision Makers." Working Paper. Laxenburg, Austria: International Institute for Applied Systems Analysis.

Macgill, S. M., and S. O. Funtowicz. 1988. "The 'Pedigree' of Radiation Estimates: An Exploratory Analysis in the Context of Exposures of Young People in Seascale as a Result of Sellafield Discharges." *J. Radiol. Prot.* 8(2):77-86.

Mann, Charles. 1990. "Meta-Analysis in the Breech." *Science* 249:476-480.
Marinelli, Janet. 1990. "Packaging." *Garbage*. May-June.

Marland, Greg, and Ralph M. Rotty. 1984. "Carbon Dioxide Emissions from Fossil Fuels: A Procedure for Estimation and Results for 1950-1982." *Tellus* 36B:232-261.

Massey, James T., and Keith L. Hoffman. 1989. "Monitoring Data Quality Through Comparisons Between Data Systems." *Statistics In Medicine* 8:367-377.

McNamee, P., and J. Celara. 1987. *Decision Analysis for the Professional with Supertree.* Redwood City: The Scientific Press.

Mekel, O.C.L., and G. Huppes. 1990. *Environmental Effects of Different Package Systems for Fresh Milk.* Printed in The Netherlands.

Mendenhall, William, and Robert J. Beaver. 1991. *Introduction to Probability and Statistics.* 8th Edition. Boston: P.W.S. Kent.

Mickler, Robert A., and Susan A. Medlarz. 1987. "The Role of Quality Assurance in National Acid Rain Research in the United States." *Environmental Technology Letters* 8:459-466.

Mill, Theodore, and Barbara T. Walton. 1987. "How Reliable Are Data-Base Data?" *Environmental Toxicology and Chemistry* 6:161-162.

Moore, David S., and George P. McCabe. 1989. *Introduction to the Practice of Statistics.* New York: W.H. Freeman and Co.

Morgan, M. Granger, and Max Henrion. 1990. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* New York: Cambridge University Press.

Morris, Peter A. 1974. "Decision Analysis Expert Use." *Management Science* 20(9):1233-1241.

National Academy of Science. 1988. *Final Report on Quality Assurance to the Environmental Protection Agency.* Washington, DC: National Academy Press.

Neptune, Dean, Eugene P. Brantly, Michael J. Messner, and Daniel I. Michael. 1990. "Quantitative Decision Making in Superfund: A Data Quality Objectives Case Study." *HMC* May/June:19-27.

North, D. Warner. 1990. "Decision Analysis in Environmental Risk Management: Applications to Acid Deposition and Air Toxics." In *New Risks*, L.A. Cox Jr. and P.F. Ricci, eds. New York: Plenum Press.

Pacific Environmental Services, Inc. 1989. *Emission Factor Documentation for AP-42: Section 5.19 Synthetic Fibers.* Prepared for the U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Research Triangle Park, NC.

Plewa, Michael J., Roger A. Minear, Diane Ades-McInerney, and Elizabeth Wagner. 1988. *Refining the Degree of Hazard Ranking Methodology for Illinois Industrial Waste Streams.* Printed by the Authority of the State of Illinois 88/150.

Rogers, Everett M. 1987. "Methodology for Meta-Research." In *Organizational Communication: Abstracts, Analysis, and Overview*, Volume 10. Greenbaum, Howard H., Susan A. Hellweg, and Joseph W. Walter, eds, pp. 13-33. Beverly Hills, CA: Sage Publications.

Rothgeb, T. Michael, Charles A. Pittinger, and Celeste C. Kuta. 1991. "Environmental Quality of Consumer Products." *TAPPI* 28(3):64-69.

Rubin, Donald B. 1990. "Discussion." Paper presented at the 1990 U.S. Bureau of the Census Annual Research Conference Proceedings, Arlington, VA, March 18-21.

Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys.* New York: John Wiley and Sons, Inc.

Rubin, Donald B., and Nathaniel Schenker. 1991. "Multiple Imputation in Health-Care Databases: An Overview and Some Applications." *Statistics in Medicine* 10:585-598.

SAS Institute Inc. 1988. *SAS ® Procedures Guide, Release 6.03 Edition.* Cary, NC: SAS Institute Inc., 441 pp.

Schaffhauser, Anthony J., and Bruce Tonn. 1991. "Signaling Uncertainty and Quality of Cell Entries." Draft paper. Oak Ridge, TN: Oak Ridge National Laboratory.

Scientific Certification Systems, Inc. 1992. *Life Cycle Inventory and the Environmental Report Card.* Oakland, CA: Scientific Certification Systems, Inc.

Sechrest, Lee, and Maureen Hannah. 1990. "The Critical Importance of Nonexperimental Data." In *Research Methodology: Strengthening of Non-Experimental Data*, Lee Sechrest, Edward Perrin, and John Bunker, eds., pp. 1-7. Washington, DC: U.S. Department of Health and Human Services, Agency for Health Care Policy and Research.

Society of Environmental Toxicology and Chemistry. 1994. *Life-Cycle Assessment: A Conceptual Framework for Data Quality.* Pensacola, Florida: Society of Environmental Toxicology and Chemistry, and SETAC Foundation for Environmental Education, Inc.

Society of Environmental Toxicology and Chemistry. 1993a. *Guidelines for Life Cycle Assessment: A 'Code of Practice'.* Draft paper. Pensacola, Florida: Society of Environmental Toxicology and Chemistry, and SETAC Foundation for Environmental Education, Inc.

Society of Environmental Toxicology and Chemistry. 1993b. *A Conceptual Framework for Life-Cycle Impact Assessment.* Pensacola, Florida: Society of Environmental Toxicology and Chemistry, and SETAC Foundation for Environmental Education, Inc.

Society of Environmental Toxicology and Chemistry. 1992. *Guidelines for Conduct of LCA Peer Review.* Working paper. Pensacola, Florida: Society of Environmental Toxicology and Chemistry, and SETAC Foundation for Environmental Education, Inc.

Society of Environmental Toxicology and Chemistry, and SETAC Foundation for

Environmental Education, Inc. 1991. *A Technical Framework for Life-Cycle Assessments.* Pensacola, FL: Society of Environmental Toxicology and Chemistry, and SETAC Foundation for Environmental Education, Inc.

Spetzler, Carl S., and Carl-Axel Staël von Holstein. 1975. "Probability Encoding in Decision Analysis." *Management Science* 22(3):340-358.

Stephanou, Harry E. 1987. "Perspectives on Imperfect Information Processing." *IEEE Transactions on Systems, Man, and Cybernetics* 17(5):780-798.

Stern, R. M. 1989. "Cancer Incidence Among Welders Due to Combined Exposures to ELF and Welding Fumes: A Study in Data Pooling." In *Risk Assessment in Setting National Priorities*, James J. Bonin and Donald E. Stevenson, eds., pp. 517-527. New York: Plenum Press.

Talcott, Frederick W. 1992. "Environmental Agenda: The Time Is Ripe for an Analytical Approach to Policy Problems." *OR/MS Today* June:18-24.

Taylor, Jeremy M. G., Muñoz, Sue M. Bass, Alfred J. Saah, Joan S. Chmiel, and Lawrence A. Kingsley. 1990. "Estimating The Distribution of Times From HIV Seroconversion to AIDS Using Multiple Imputation." *Statistics In Medicine* 9:505-514.

Thompson, Michael, and Michael Warburton. 1985. "Decision Making Under Contradictory Certainties: How To Save The Himalayas When You Can't Find Out What's Wrong with Them." *Journal of Applied Systems Analysis* 12:3-34.

Tierney, William M., and Clement J. McDonald. 1991. "Practice Databases and Their Uses in Clinical Research." *Statistics in Medicine* 10:541-557.

Tonn, Bruce, and Richard Goeltz. 1990. "An Experiment in Combining Estimates of Uncertainty." In *New Risks*, L. A. Cox, Jr. and P.F. Ricci, eds., pp. 403-412. New York: Plenum Press.

U.S. Department of Commerce. 1985. "Methodology for Characterization of Uncertainty in Exposure Assessments." PB85-240455. Prepared by Roy W. Whitmore, Research Triangle Institute, Research Triangle Park, NC.

U.S. Department of Health and Human Services. 1985. *Environmental Health: A Plan for Collecting and Coordinating Statistical and Epidemiologic Data.* Washington, DC: U.S. Government Printing Office.

U.S. Department of the Interior. 1992. *Mineral Commodity Summaries 1992.* Washington, DC: U.S. Government Printing Office.

U.S. Department of the Interior. 1989. *Minerals Yearbook.* Volume I. Washington, DC:

U.S. Government Printing Office.

U.S. Department of the Interior. 1985. *Mineral Facts and Problems*. Washington, DC: U.S. Government Printing Office.

U.S. Environmental Protection Agency. 1994a. *Life Cycle Assessment: Public Data Sources for the LCA Practitioner.* EPA, Office of Solid Waste, Washington, DC. Prepared by Battelle Memorial Instititue.

U.S. Environmental Protection Agency. 1994b. Life Cycle Impact Assessment: A Conceptual Framework, Key Issues, and Summary of Existing Methods. EPA, Office of Air Quality Planning and Standards, Research Triangle Park, NC. Prepared by Research Triangle Instititue.

U.S. Environmental Protection Agency. 1993a. *Life Cycle Design Guidance Manual* Final Report, EPA600/R-92/226. Office of Research and Development. Prepared by National Pollution Prevention Center, University of Michigan..

U.S. Environmental Protection Agency. 1993b. *Life-Cycle Assessment: Inventory Guidelines and Principles.* Final Report, EPA/600/R-92/245. Office of Research and Development. Prepared by Battelle, and Franklin Associates, Ltd.

U.S. Environmental Protection Agency. 1991. "AEERL Quality Assurance Procedures Manual for Contracts and Financial Aid Recipients." Draft Document. Washington, DC: EPA Office of Research and Development.

U.S. Environmental Protection Agency. 1990a. *Revised Hazard Ranking System: Qs and As.* Washington, DC: EPA Office of Emergency and Remedial Response.

U.S. Environmental Protection Agency. 1990b. *Guidance for Data Usability in Risk Assessment.* Interim Final Report. Washington, DC.

U.S. Environmental Protection Agency. 1990c. *Toxic Release Inventory: TRIS Overview.* Washington, DC: EPA Office of Toxic Substances.

U.S. Environmental Protection Agency. 1989a. *Report on Minimum Criteria to Assure Data Quality.* EPA/530-SW-90-021. Washington, DC: EPA Office of Solid Waste.

U.S. Environmental Protection Agency. 1989b. *Risk Assessment Guidance for Superfund, Volume I, Human Health Evaluation Manual (Part A).* EPA/540/1-89/002. Washington, DC.

U.S. Environmental Protection Agency. 1987. *Municipal Waste Combustion Study: Emission Data Base for Municipal Waste Combustors.* Final report. EPA/530/SW-87/012B. Prepared by P. Schindler, Midwest Research Institute.

U.S. Environmental Protection Agency. 1986a. *Development of Data Quality Objectives: Description of Stages I and II.* Washington, DC: EPA Quality Assurance Management Staff. [Obtain by calling (202) 260-5763]

U.S. Environmental Protection Agency. 1986b. *Proceedings of the 1986 EPA/APCA Symposium on Measurement of Toxic Air Pollutants.* Raleigh, NC: EPA Environmental Monitoring Systems Laboratory and the Air Pollution Control Association.

U.S. Environmental Protection Agency. 1984. *Calculation of Precision, Bias, and Method Detection Limit for Chemical and Physical Measurements.* Chapter 5. Quality Assurance Management and Special Studies Staff.

U.S. Environmental Protection Agency. 1978. *Source Assessment: Analysis of Uncertainty—Principles and Applications.* EPA-600/2-78-004u. Prepared by R. W. Serth, T. W. Hughes, R. E. Opferkuch, and E. C. Eimutis, Monsanto Research Corporation. Dayton, OH: EPA Office of Research and Development.

Vesely, W. E., and D. M. Rasmuson. 1984. "Uncertainties in Nuclear Probabilistic Risk Analyses." *Risk Analysis* 4(4):313-322.

Vigon, Bruce and Mary Ann Curran. 1993. "Life-cycle Improvements Analysis: Procedure Development and Demonstration." Paper presented at the 1993 IEEE Internation Symposium of Electronics and the Environment, Arlington, Virginia, May 10-12, 1993. Institute of Electrical and Electronics Engineers, Inc., Piscataway, NJ.

Vigon, Bruce and Allan A. Jensen. 1992. "Lifecycle Assessment Data Quality and Databases Practitioner Survey." Discussion paper presented at the Society of Environmental Toxicology and Chemistry Lifecycle Assessment Data Quality Workshop, Wintergreen, Virginia, October 4-9, 1992.

Watson, S.R., and D.M. Buede. 1987. *Decision Synthesis: The Principles and Practice of Decision Analysis.* Cambridge University Press.

Wei, Greg C. G., and Martin A. Tanner. 1991. "Applications of Multiple Imputation to the Analysis of Censored Regression Data." *Biometrics* 47:1297-1309.

Wilkinson, G. N. 1958. "Estimation of Missing Values for the Analysis of Incomplete Data." *Biometrics* 14:257-286.

Wolf, Katy, Azita Yazdani, and Pamela Yates. 1991. *Waste Minimization: Small Quantity Generators at Los Angeles International Airport.* Prepared by UCLA Engineering Research Center for Hazardous Substances Control for Alternative Technology Division, California Department of Toxic Substances Control, U.S. Environmental Protection Agency.

Yin, Robert K., and Karen A. Heald. 1975. "Using the Case Survey Method to Analyze Policy Studies." *Administrative Science Quarterly*. 20:371-381.

Youngren, Susan Hunter, and Robert G. Tardiff. 1991. "Reducing Uncertainty in Risk Assessment: Exposure Assessment." In *Risk Analysis*, C. Zervos ed., pp. 575-588. New York: Plenum Press.