Dana Fradon, *The New Yorker* May 17, 1976
Credit: Dana Fradon/The New Yorker Collection/The Cartoon Bank

Chapter 2 : Quantitative and Qualitative Methods Supporting Life Cycle Assessment

In this chapter, we introduce basic quantitative skills needed to perform successful work in LCA. The material is intended to build good habits in critically thinking about, assessing, and documenting your work in the field of LCA (or, for that matter, any type of systems analysis problem). First we describe good habits with respect to data acquisition and documentation. Next we describe skills in building and estimating simple models. These skills are not restricted to use in LCA and should be broadly useful for business, engineering, and policy modeling tasks. As this book is intended to be used across a wide set of disciplines and levels of education, we write as if aimed at undergraduates who may not be familiar with many of these concepts. This chapter may be a cursory review for many students. Regardless, improving basic skills will make your LCA work even more effective.

Learning Objectives for the Chapter

At the end of this chapter, you should be able to:

1. Apply appropriate skills for qualitative and quantitative analysis.

2. Document values and data sources in support of research methods.

3. Improve your ability to perform back of the envelope estimation methods.

4. Approach any quantitative question by means of describing the method, providing the answer, and describing what is relevant or interesting about the answer.

Basic Qualitative and Quantitative Skills

To be proficient in any type of systems analysis, you need to have sharp analytical skills associated with your ability to do research, and much of this chapter is similar to what one might learn in a research methods course. While the skills presented here are generally useful (and hopefully will serve you well outside of the domain of LCA) we use examples relevant to LCA to emphasize and motivate their purpose.

Much of LCA involves doing "good research" and communicating the results clearly. That is why so many people with graduate degrees are able to learn LCA quickly – because they already have the base of skills needed to be successful, and just need to learn the new domain knowledge. Amongst the most important skills are those associated with your quantitative and qualitative abilities.

Quantitative skills are those associated with your ability to create numerical manipulations and results, i.e., using and applying math and statistics. **Qualitative skills** are those related to your ability to think and write about your work beyond numbers, and to describe the relevance of your results. While this textbook is more heavily geared towards improving your quantitative skills, there are many examples and places of emphasis throughout the text that are intended to develop your qualitative skills. You will need to be proficient at both to successfully appreciate and perform LCA work.

Identifying your own weaknesses in these two areas now can help you improve them while you are also learning new material relevant to the domain. Your quantitative skills are relatively easy to assess – e.g., if you can correctly answer a technical or numerical question by applying an equation or building a model, you can "pass the test" for that quantitative skill. Qualitative skills are not as easy to evaluate and so must be assessed in different ways, e.g., your ability to synthesize or summarize results or see the big picture could be assessed by using a rubric that captures the degree to which you put your findings into context.

In the remainder of this chapter, we'll first review some of the key quantitative types of skills that are important (and which are at the core of life cycle studies) and then discuss how to mix qualitative and quantitative skills to produce quality LCA work. One of the most important skills is identifying appropriate data to use in support of analyses.

Working with Data Sources

Most data are quantitative, i.e., you are provided a spreadsheet of numerical values for some process or activity and you manipulate the data in some quantitative way (e.g., by finding an average, sorting it, etc.). But data can also be qualitative – you may have a description of a process that discusses how a machine assembles inputs, or you may generally know that a machine is relatively old (without knowing an exact date of manufacture). Being able to work with both types of data is useful when performing LCA.

As we seek to build a framework for building quantitative models, inevitably one of the challenges will be to find data (and in LCA, finding appropriate data will be a recurring challenge). But more generally we need to build skills in acquiring and documenting the data we find. As we undertake this task, it is important to understand the difference between primary and secondary sources. A **primary source** of data comes directly from the entity collecting the data and/or analyzing it to find a result. It is thus generally a definitive source of information, which is why you want to find it. A **secondary source** is one that cites or reuses the information from the primary source. Such sources may use the information in different ways inconsistent with the primary source's stated goals and intentions, and may incorporate biases. It is thus good practice to seek the primary source of the information and not merely a source that makes use of it. Finding (and reading, if necessary) the primary source also allows you to gain appreciation for the full context that reported the result. This context may include the sponsor of the study, any time or data constraints, and perhaps caveats on when or how the result should be used.

In today's Internet search-enabled world, secondary sources are far more prominent. Search engines are optimized to find often linked to and repeated sources, not necessarily primary sources. As an example, the total annual emissions of greenhouse gases in the US are prepared in a study and reported every year by the US Environmental Protection Agency (EPA). The EPA spends a substantial amount of time - with the assistance of government contractors - each year refining the methods and estimates of emissions to be reported. Given their official capacity and the work done, the reporting of this annual estimate (i.e., 'the number') is a primary source. This number, which is always for a prior period and is therefore a few years old, gets noticed and reported on by hundreds of journalists and media outlets, and thousands of web pages or links are created as a result. A web search for "annual US GHG emissions" turns up millions of hits. The top few may be links to the latest EPA report or the website that links to the report. The web search may also point to archived EPA reports of historical emissions published in previous years. But there is only a single primary source for each year's emissions estimate – the original study by EPA.

The vast majority of the web search results lead to studies 're-reporting' the original published EPA value. It is possible that the primary source is not even in the top 10 of the ordered websites of a web search. This phenomenon is important because when looking for data sources, it is easy to find secondary sources, but there is often a bit of additional work needed to track backwards to find and cite the primary source. It is the primary source that one should use in any model building and documentation efforts (even if you found it via finding a secondary source first). A primary source of data is typically from a credible source, and citing "US EPA" instead of "USA Today" certainly improves the credibility of your work. Backtracking to find these primary sources can be tricky because often newspaper articles will simply write "EPA today reported that the 2011 emissions of greenhouse gases in the United States were 7 billon metric tons" without giving full references within the article. Blogs on the other hand tend to be slightly more academic in nature and may cite sources or link to websites (and of course they still might link to a secondary source). If your secondary sources do not link to the EPA report directly, you need to do some additional searching to try to find the primary source. It will help your search that you know the numerical value that will be found in the primary source (but of course you should confirm that the secondary source used the correct and most up to date value). With some practice you will become adept at quickly locating primary sources.

The relevant contextual information that may appear in the official EPA source includes things like how the estimate was created, what year it is for, what the year-over-year change was, and which activities were included. All of that contextual information is important. A more frequently reported estimate of US GHG emissions (only a few months old when reported) comes from the US Department of Energy, but only includes fossil fuel combustion activities, which are far easier to track because power plants annually report their fuel use to the Department. If you were looking for a total inventory of US greenhouse gas emissions, the EPA source is the definitive source.

After finding appropriate data, it is essential to reference the source adequately. It is assumed that you are generally familiar with the basics of creating footnote or endnote references or bibliographical references to be used in a report. You can see short bibliographical reference lists at the end of each of the chapters of this textbook. Primary data sources should be completely referenced, just as if you were excerpting something from a book. That means you need to give the full bibliographic reference as well as point to the place inside the source where you found the data. That might be the page number if you borrow something from the middle of a report, or a specific Table or Figure within a government report. For example, if you needed data about the electricity consumption per square foot for a commercial building, the US Department of Energy's Energy Information Administration 2003 Commercial Buildings Energy Consumption Survey (CBECS) suggests the answer is 14.1 kWh/square foot (for non-mall buildings). The summary reports for this survey are hundreds of pages in length. The specific value of 14.1 kWh/sf is found (on page 1) of Table C14. By referencing this source specifically, you allow others to reproduce your study quickly. You also are allowing others (who may stumble upon your own work when looking for something else) to use your work as a secondary source. The full primary source reference for the CBECS data point could look like this:

> US Dept. of Energy, 2003 Commercial Buildings Energy Consumption Survey (CBECS), Table C14. "Electricity Consumption and Expenditure Intensities for Non-Mall Buildings, 2003", 2006, http://www.eia.gov/consumption/commercial/data/2003/pdf/c14.pdf, last accessed July 5, 2013.

What is unfortunately common is to see very loose or abbreviated referencing of data sources, such as "DOE CBECS". Such casual referencing is problematic for many reasons. The DOE has done at least four CBECS surveys, roughly four years apart, since 1992, for which they have made the results available online. If one finds a single data point on the Energy Information Administration's website and uses it in a study, that data point might come from any of these four surveys, which span 20 years of time, from any of the thousands of pages of data summaries. With only a reference to "CBECS", one would have no way of knowing how recent, relevant, or useful is your data point.

Beyond the examples above, one might be interested in the population of a country, the average salary of workers, or other fundamental data. You are likely (and encouraged) to find and report **multiple primary sources**. These multiple sources could come from independent agencies or groups who sought to find answers to the same or very similar questions. A rule of thumb is to seek and report results from at least three such sources if possible. In the best case, the primary sources yield the same (or nearly equal) data. In reality, they will likely disagree to a small or large extent. There may be very easy explanations for why they differ, such as using different assumptions or methods. By noting and representing that you have found multiple data points, and summarizing reasons for the differences, you gain the ability to judge whether to simply use an assumption based on the three sources, or need to use a range or an average. The practice of seeking multiple sources will sometimes even uncover errors in original studies or data reports, or at the least make you realize that a primary source found is not appropriate to use in your own work given differences in how the result was made.

> "When we look up a number in more than one place, we may get several different answers, and then we have to exercise care. The moral is not that several answers are worse than one, but that whatever answer we get from one source might be different if we got it from another source. Thus we should consider both the definition of the number and its unreliability." -- Mosteller (1977)

If you end up with several values, it may be useful to summarize them in a table. If you had been trying to find the total US greenhouse gas emissions as above, you might summarize it like in Figure 2-1. Additional rows could be added for other primary or secondary sources. A benefit of organizing these summary tables is that it allows the audience to better understand your underlying data sources as well as potential issues with applying them.

Value (million metric tons CO_2)	Source	Type of Source	Comments
6,702	US EPA, Inventory Of U.S. Greenhouse Gas Emissions And Sinks: 1990-2011	Primary	Value is for 2011.
5,471	US DOE, U.S. Energy-Related Carbon Dioxide Emissions, 2011	Primary	Value is for 2011. Only counts energy-related emissions.
6,702.3	Environmental News Network, US Greenhouse Gas Emissions are Down, April 21, 2013	Secondary	Specifically references EPA.

Figure 2-1: Summary of Sources for US Greenhouse Emissions

A final note about seeking data sources pertains to the use of statistical abstracts. Such references exist for many countries, states and organizations like universities. These abstracts are valuable reference materials that are loaded with many types of summary data. They are typically organized by sections or chapter of related data. For example, the *Statistical Abstract of the United States* (2011) has sections on agriculture, manufacturing, energy, and transportation (all of which are potentially relevant for LCA studies). Each of the sections contains a series of data tables. The Agriculture section has, amongst other interesting facts, data on the number of farms and area of cropland planted for many types of crops. The Table (Number 823) of farms and cropland has a footnote showing the primary source of the data, in this case the 2007 Census of Agriculture. Such abstracts may also have other footnotes that need to be considered when using them as a source, such as noting the units of presentation (e.g., dollar values in millions), or the boundaries considered.

This example is intended to reinforce two important facts of using statistical abstracts. First, it is important to realize that while generally statistical abstracts may be a convenient "go to" reference source, they are not a primary source. The best practice is to use statistical abstracts as links to primary sources – and then go read the primary source. Re-publication of data sometimes leads to errors, or omissions of important footnotes like units or assumptions used. Second, despite the "2012" in the title of the abstract, it is generally not true that all data within is from the year 2012. Generally though, any data contained within is the most recent available. Abstracts for states and other organizations are organized in similar ways and with similar source referencing. Finally, it is worth noting that in the age of Google, statistical abstracts are no longer the valuable key reference sources that they once were. Nonetheless, they are still a great first "one stop" place to look for information, especially if doing research in a library with an actual book.

Accuracy vs. Precision

We seek primary sources (and multiple primary sources) because we want to get credible values to use. Depending on the kind of model we are building, we may simply need a reasonable estimate, or we may need a value as exact as possible. This raises the issue of whether we are seeking accuracy or precision in our search for sources and/or our model building efforts. While the words accuracy and precision are perhaps synonyms to lay audiences, the "accuracy versus precision" dialogue is a long-standing one in science. We are often asked to clarify our goals more clearly in terms of what we are seeking – accuracy or precision (or both)—in our system of measurement.

The **accuracy** of a measurement system is the degree to which measurements made are close to the actual value (of course, as measured by some always correct system or entity). The **precision** of a measurement system is the degree to which repeated measurements give the same results. Precision is thus also referred to as repeatability or reproducibility.

In addition to physical measurement systems, these features are relevant to computational methods on data, such as statistical transformations, Microsoft ® Excel ®[1] models, etc. Figure 2-2 summarizes the concepts of accuracy and precision within the context of aiming at a target, but could be analogously used to consider our measurements of a value.

[1] Microsoft and Excel are registered trademarks of Microsoft Corporation. In the rest of the book, just "Microsoft Excel" will be used.

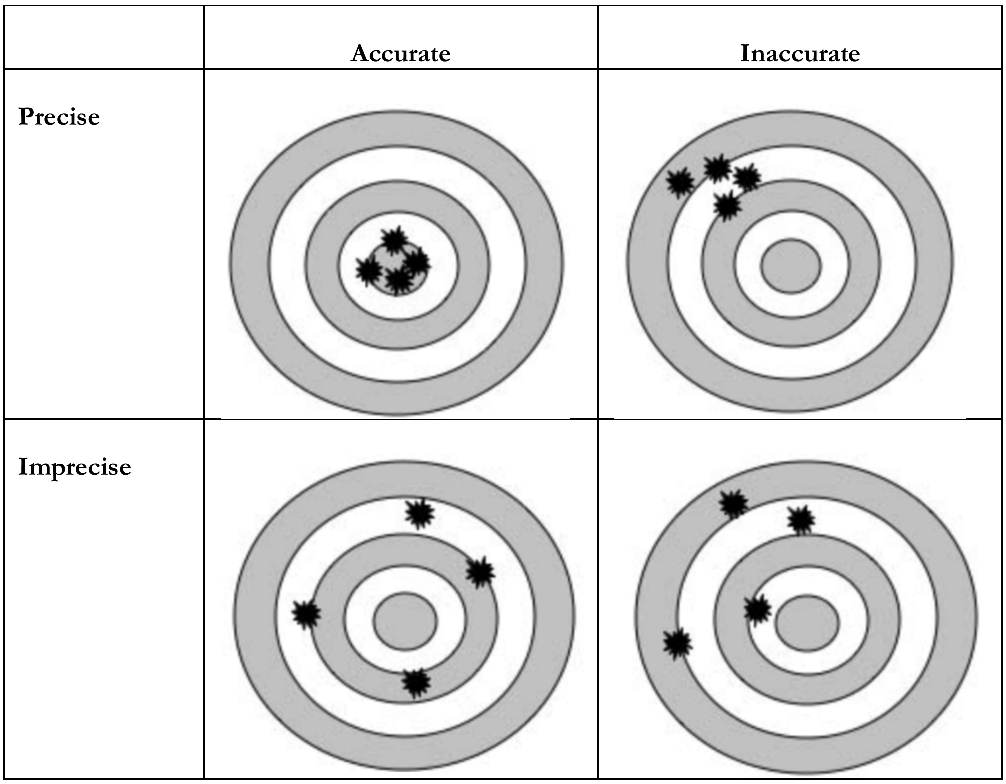

Figure 2-2: Comparison of accuracy and precision. Source: NOAA 2012

Systems can thus be accurate but not precise, precise but not accurate, or neither, or both. Systems are considered valid when they are both accurate and precise. With respect to our CBECS example above, the survey used could provide an inaccurate (but precise) result if mall and non-mall buildings are included in an estimate of retail building effects. It could produce an imprecise (but accurate) result if samples from different geospatial regions do not align with the actual geospatial mix of buildings. Performing mathematical or statistical operations (e.g., averages) on imprecise values may not lead to a value that is credible to use in your work.

When a measurement system is popular and needs to be known to be accurate and precise, typically a standard is made for all parties to agree upon how to test and formalize the features of the system (e.g., how to perform the test many times and assess the results). Standards will be discussed more in Chapter 4.

Uncertainty and Variability

As we seek to find multiple sources for our data needs, inevitably we will come across situations where the data do not agree to the extent that we would hope. This will lead us to situations of dealing with uncertainty and variability of our data. While the ways in which we work with and model uncertain and variable data are similar, we first separately define each condition. These simple definitions will be used here, with further detail in later chapters as needed. **Variability** exists because of heterogeneity or diversity of a system. It may be, for example, that the energy used to manufacture an item differs between the morning and afternoon shift in a factory. **Uncertainty** exists because we either are unable to precisely measure a value, or lack full information, or are ignorant of some state. It is possible that if we did additional research or improved our measurement methods, we could reduce the uncertainty and narrow in on a most likely outcome or value. Variability, on the other hand, is not likely to be reducible – it may exist purely due to natural or other factors outside of our control.

Management of Significant Figures

Beyond thinking that we have created a way of accurately and precisely measuring a quantity, we also want to ensure that we appropriately represent the result of our measurement. Many of us learned of the importance of managing the use of **significant figures (or digits)** in middle school. Two important lessons learned that merit mention in this context relate to leading and trailing zeros and reporting the results of mathematical operations. Remember that trailing zeros are always significant and indicate the level of precision of the measurement. Leading zeros (after a decimal point), however, are not significant. This means that a value like 0.00037 still has only two significant digits because scientific notation would refer to it as 3.7E-04 and the first component of the notation (3.7) represents all of the significant digits. Also take care not to introduce extra digits in the process of adding, subtracting, multiplying, or dividing significant figures. That means, for example, not perpetuating a result from a calculator or spreadsheet that multiplies two 2-digit numbers and reporting 4 digits. The management of significant digits means reporting only 2 digits from such a result, even if it means rounding off to achieve the second digit.

Recall that the basis for such directives is that our measurement devices are calibrated to a fixed number of digits. A graduated cylinder used to measure liquids in a laboratory usually shows values in 1 ml increments (e.g., 10, 11, or 12 ml). We then attempt to estimate the level of the liquid to the nearest 10^{th} of an increment. As an example, when measuring a liquid we would report values like 10.2 ml – with three significant figures - which expresses our subjective view that the height of the liquid is approximately $2/10^{th}$s of the way between the 10 and 11 ml lines. Given our faith in the measurement system, we are quite sure of the first 2 digits to the left of the decimal point (e.g., 10), and less sure of the digit to the right of the decimal point as it is our own estimate given the uncertainty of the measurement device, and thus is the least significant figure.

When counting significant figures, think about scientific notation. • All nonzero digits are significant • Zeroes between nonzero digits are significant • Trailing zeroes that are also to the right of a decimal point in a number are significant
Digits do not increase with calculations. • When adding and subtracting, the result is rounded off to have the same number of decimal places as the measurement with the least decimal places. • When multiplying and dividing, the result is rounded off to have the same number of significant figures as in the component with the least number of significant figures.

Figure 2-3: Summary of Rules of Thumb for Managing Significant Figures

Inevitably, our raw measurements will be used in additional calculations. For example our graduated cylinder observation of volume can then be used to find mass, molarity, etc. If those subsequent calculations are presented with five significant figures (since that's what the calculator output reads), such results overstate the accuracy of the calculations based on the original data, and by implication understate their uncertainty. Figure 2-3 summarizes rules for managing significant figures. We will circle back to discussing data acquisition in the context of life cycle assessment in a later chapter.

Going back to our CBECS example, the published average electricity use of 14.1 kWh/square foot is a ratio with three significant figures. That published value represents an average of many buildings included in the survey. The buildings would give a wide range of electricity consumption values in the numerator. However, the three significant figures reported are likely because some relatively small buildings led to a value with only three significant figures. If not concerned about managing significant figures, DOE could have reported a value of 14.1234 kWh/sf. This result would have led to negligible modeling errors, but would have added extraneous digits for no reason.

One of the main motivations for managing the number of significant digits is in considering how to present model results of an LCA. As many LCAs are done in support of a comparison of two alternatives, an inevitable task is comparing the quantitative results of the two. For such a comparison to be valid, it is important not to report more significant figures in the result than were present in the initial measured values. A common output of an LCA, given the need to maintain assumptions between the modeling of various alternatives, is that the alternatives would have very similar effects across at least one metric. Consider a hypothetical result where the energy use Alternative A is found to be 7.56 kWh and for Alternative B is 7.57 kWh. Would one really expect a decision maker to prioritize one over the other because of a 0.01 kWh reduction in energy use, which is a 0.1% difference, or a savings worth less than 0.1 cents at current US electricity prices? Aside from the fact that it is a trivial amount, it is likely outside of the range of measurement available.

In LCA, we do not have the same 'measurement device' issues used to motivate a middle school introduction to significant digits. Instead, the challenge lies in understanding the uncertainty of the 'measurement process' or the 'method' used to generate the numerical values needed for a study. So while we do not worry about the number of digits on a graduated cylinder, we need to consider that the methods are uncertain.

In the absence of further guidance, what would we recommend? Returning to our discussion above an LCA practitioner should seek to minimize the use of significant digits. We generally recommend reporting no more than 2 or 3 digits (if for no other reason than consideration of uncertainty). In the example of the previous paragraph that would mean comparing two alternatives with identical energy use – i.e., 7.6 kWh. The comparison would thus have the appropriate outcome – that the alternatives are equivalent.

Ranges

If you are able to find multiple primary sources, it is typically more useful to fully represent all information you have than to simply choose a single point as a representation. If you use a single value, you are making a conscious statement that one particular value is the most correct and the others are irrelevant. In reality, you may have more than one value being potentially correct or useful, e.g., because you found multiple credible primary sources. By using **ranges**, you can represent multiple data points, or a small set or subset of data. While individual data points are represented by a single number (e.g., 5), a range is created by encapsulating your multiple data points, and may be represented with parentheses, such as (0,5) or (0-5). A range represented as such could mean "a number somewhere from 0 to 5".

The values used as the *limits of a range* may be created with various methods. Often used parameters of ranges are the minimum and maximum values of a dataset. In an energy technology domain, you might want to represent a range of efficiency values of an electricity generation technology, such as (30%, 50%).

If you have a large amount of data, then it might be more suitable to use the *5th and 95th percentile values* as your stated range. While this may sound like an underhanded way of ignoring data, it can be appropriate to represent the underlying data if you believe some of the values are not representative or are overly extreme. Using the same technology efficiency example, you may find data on efficiencies of all coal-fired or gas-fired power plants in the US, and decide that the lowest efficiency values (in the 10-20% range) are far outside of the usual practice because they represent the efficiencies of plants that are used very infrequently or are using extremely out of date technology. There could be similarly problematic values at the high end of the full range of data if the efficiency for a newer plant has be estimated by the manufacturer, but the plant has not been in service long enough to measure the true efficiency. Using these percentile limits in the ranges can help to slightly constrain the potential values in the data.

Ranges can be used to represent *upper and lower bounds*. Bounding analysis is useful when you do not actually have data but have a firm (perhaps even qualitative) belief that a value is unlikely to be beyond a certain quantity. A bounding analysis of energy technology might lead you to conclude that given other technologies, it is unlikely that an efficiency value could be less than 20% or greater than 90%. Using a range in this way constrains your data to values that you feel are the most realistic or representative.

Finally, ranges can be used to represent *best or worst case* scenarios. The limit values chosen for the stated ranges are thus subjectively chosen although perhaps by building on some range limits derived from some of the other methods above. For example, you might decide that a "best case value" for efficiency is 100% and "worst case" value is 0% (despite potentially being unrealistic). Best and worst case limits are typically most useful when modeling economic parameters, e.g., representing the highest salary you might need to pay a worker or the lowest interest rate you might be able to get for a bank loan. Best and worst cases, by their nature, are themselves unlikely. It is not very probable that all of your worst parameters will occur, just as it is improbable that all best parameters will occur. Thus you might consider the best-worst ranges as a type of bounding analysis.

Another way of implementing a range is by using *statistical information* from the data, such as the variance, standard error, or standard deviation. You may recall from past statistics courses that the variance is the average of the squared differences from the mean, and the standard deviation (how much you expect one of the data points to be different from the mean) is the square root of the variance. The standard error (the "precision of the average", or how much you might expect a mean of a subsample to be different from the mean of the entire sample) is the standard deviation divided by the square root of the number of samples of data. Either of these values if available can be used to construct confidence intervals to give some sense of the range of the underlying data. A related statistical metric is the relative standard error (RSE), which is defined as the standard error divided by the mean and multiplied by 100, which gives a percentage-like range variable. Another way to think about the RSE is as a metric representing the standard error relative to the mean estimate on a scale from zero to 100. As the RSE increases, we would tend to believe our mean estimate is less precise when referring to the true value in the population being studied. Of course when found in this way, the range will be symmetric around the mean.

A 95-percent confidence range is calculated for a given survey (mean) estimate from the RSE via a three-step process. First, divide the RSE by 100 and multiply by the mean presented by the survey to get the standard error. Second, multiply the standard error by 1.96 to generate the confidence error (recall from statistics that the value 1.96 comes from the shape and structure of an arbitrarily assumed normal distribution and its 0.975 quantile). Finally, add and subtract the confidence error to the survey estimate from the second step to create the 95% confidence range. Note that a 95% confidence range is not the same as a 5^{th}-95^{th} percentile range. A 95% confidence range represents the middle 95% of a normal distribution, or a 2.5^{th}-97.5^{th} percentile range, leaving only 2.5% of the distribution at the top and bottom. A 5^{th}- 95^{th} percentile range leaves 5% on the top and bottom.

Example 2-1:

Question: Develop a 95% confidence interval for the 2003 CBECS estimate of US commercial building electricity consumption per square foot (14.1 kWh/sf) given the RSE (3.2).

Answer: Given the RSE definition provided above, the standard error is (3.2/100)*14.1 = 0.45 kWh/square foot, and the confidence error is 0.88 kWh/square foot. Thus, the 95% confidence interval would be 14.1 +- 0.88 kWh/square foot. Note that this range seems to contradict the 25^{th}-75^{th} percentile range of 3.6-17.1 provided directly by the survey (it is a much tighter distribution around the mean of 14.1). However the confidence interval is representing something different –how confident we should be that the average electricity use of all of the buildings surveyed (as if we re-did the survey multiple times) would be approximately 14.1, not trying to represent the underlying range of actual electricity use of the buildings! If you are making a model that needs to represent the range of electricity use, the provided 25^{th}-75^{th} percentile values are likely much more useful.

Source: US Dept. of Energy, 2003 Commercial Buildings Energy Consumption Survey (CBECS), RSE Tables for Consumption and Expenditures for Non-Mall Buildings, http://www.eia.gov/consumption/commercial/data/2003/pdf/c1rse-c38rse.pdf, page 94.

A main benefit of using ranges instead of single point estimates is that the range boundaries can be used throughout a model. For example one can propagate the minimum values of ranges through all calculations to ensure a minimum potential result, or the maximum values to get a maximum potential result. One word of caution when using ranges as suggested above is to maintain the qualitative sense of the range boundaries. If you are envisioning a best-worst kind of model, then the "minimum" value chosen in your range boundary should consistently represent the worst case possible. This is important because you may have a parameter in your model that is very high but represents a worst case, for example, a loss factor from a production process. In a best-worst range type of model, you want to have all of your best and worst values ordered in this way so that your final output range represents the worst and best case outputs given all of the worst possible variable values, and all possible best values.

Units and Unit Conversions

In quantitative analysis, it is critical to maintain awareness of the **unit of analysis**. That might mean noting grams or kilograms, short tons or metric tons (a.k.a. tonnes). While conversions can be simple, such as multiplying or dividing by 1000 in SI units, this is an area where many errors occur, especially when done manually. It is easy to make errors by not thinking out the impacts and accidentally multiply instead of divide, or vice versa. Thus a good practice is to ask yourself whether the resulting conversion makes sense. This is also known as applying a **reasonableness test**, or a sanity check. Some refer to it as a "sniff test", suggesting that you might be able to check whether the number smells right. To convert from kilograms to grams, we multiply by 1000 - the result should be bigger because we should have many more grams than we do kilograms. If we accidentally divide by 1000 (an error the authors themselves have made many times in the rush of getting a quick answer) the number gets smaller and the sniff test would tell us it must be an error.

In the context of finding sources for data, simple changes of unit scales, such as grams to kilograms, don't require extensive referencing. When performing simple unit conversions like this, it is typical that instead of seeking external data sources you would simply document the step used (e.g., you would state that you "converted to kilograms").

There are however more complex unit conversions that change the entire basis of comparison (not just kg to g). If you are changing more than just the scale, such as switching from British Thermal Units (BTU) to megajoules (MJ), this is referred to as performing physical or energy **unit conversions**. A unit conversion factor is just a mathematical relation between the same underlying phenomena but with different measurement scales, such as English and SI (metric) units. For example you may find a data source expressing emissions in pounds but need to report it in kilograms (or metric tons). This type of conversion does not require much documentation either, e.g., you could write that you "assumed 2.2 pounds per kilogram". Such conversions still need to be done and managed correctly. In 1999, NASA famously lost the Mars Climate Orbiter after a nine-month mission when navigation engineers gave commands in metric units to the spacecraft, whose software engineers had programmed to it to operate with English units, causing the vehicle to overshoot the planet.

If you do not know the conversion factors needed, then you will need to search for sources of your conversion factors using the same methods discussed above. If you were to do a search for unit conversions with the many tools and handbooks available, you will certainly find slightly different values in various sources, although most of these differences are simply due to rounding off or reducing digits. One source may say 2.2 pounds per kg, another 2.20462, and yet another 2.205. Practically speaking any of these unit conversions will lead to the same result (they would be at most 0.2% apart) and quantity aside, in the big picture they are all the same number, i.e., 2.2. The existence of multiple conversion factors is the reason why to state the one you used. Without stating the actual conversion factor used, someone else may not be able to reproduce your study results (or may assume an alternative unit conversion factor and not understand why your results are different). Given the scientific and engineering basis of unit conversion factors, you do not typically need to cite specific 'sources' for them, just the numbers used.

As you build your models, your calculations will become increasingly complex. You can double-check your calculations by tracing your units. As a simple example, assume you have towboat transit time data for a stretch of river between two locks. You know the transit time in minutes (140), and the distance between locks in miles (6.1). Equation 2-1 shows how to calculate the towboat speed in kilometers/hour, which could later allow you to calculate power load and emissions rates. Getting the speed units wrong, despite being a trivial conversion, could have disastrous effects on your overall model results. Tracing the units confirms that you have used all of the necessary conversion factors, and used them appropriately and in the right order.

$$x\,\frac{km}{hour} = \frac{6.1\ miles\ between\ locks}{140\ minutes\ transit\ time} \times \frac{1\ kilometer}{0.621\ mile} \times \frac{60\ minutes}{1\ hour} = 4.2\ km/hr \qquad (2\text{-}1)$$

We end by briefly discussing the need to manage units in calculations. Note that when solving Equation 2-1, a calculator would report the speed as 4.2098 km/hr, a level of accuracy that would be impossible to achieve (and silly to present). The reason to document the units is so that when we are using them in calculations that we do the mathematical operations correctly, i.e., adding kg to kg, not kg to g. The 'Hillsville' graphic from *The New Yorker* (presented at the beginning of this chapter) is another reminder of adding units.

Energy-Specific Considerations

An important underlying concept for energy conversion processes is **efficiency**, which measures how much of the input energy can be converted to output energy (represented as output/input). You may recall from a physics course that **energy** is a measure of the amount of work done or generated, with units such as joules, BTU, or kilowatt-hours. On the other hand, **power** is the rate at which energy is used or transformed, with units such as watts or joules/second. Electricity generation processes often are assessed in terms of their efficiency. Thus a power plant that outputs 50 units of energy from 100 units of fuel input is 50% efficient. But moving between different energy sources with different units, e.g., fuel in BTU and electricity in kWh, can be more complicated than they appear.

One should not treat efficiency as a unit conversion factor. While engineering reference manuals give the unit conversion factor '1 kWh = 3,413 BTU', supplying 3,413 BTU of coal in a steam turbine <u>will not</u> produce 1 kWh of electricity. No energy system is 100% efficient. This is because of the many intermediate processes in the plant. An important thermodynamic concept specific to the modeling of fuel use pertains to the **heating value** of the fuel, which refers to the energy released from combusting the fuel[2], with units such as kJ/kg or BTU/lb.

The effect of a thermodynamic process that converts a fuel input to a quantity of electricity is represented as a **heat rate**. In describing the conversion of fossil energy from a fuel in a power plant, the heat rate for a typical coal–fired plant may be 10,000 BTU (of coal input) to generate 1 kWh (electricity output). The reason that the power plant heat rate is not the same as the unit conversion factor 1 kWh = 3,413 BTU is because converting coal to electricity requires burning the coal, then using the produced heat to turn water into steam, and then using the pressurized steam to spin a turbine which is connected to a generator. Losses exist throughout all of these steps, and thus, far more than the 3,413 BTU of fuel is needed to generate 1 kWh of electricity. The overall efficiency of this power plant is 1 kWh per 10,000 BTU, or, given the unit conversion factor for a kilowatt-hour, 3,413 BTU / 10,000 BTU = 34%. Natural gas plants can have efficiencies of about 50%. While not comprised of burning fuels, solar PV cells are about 10% efficient. It may be surprising to you to learn that in the 21st century we rely on such inefficient methods to make our electricity! The point of this example is that a power plant's efficiency is not a unit conversion factor. Unit conversion factors are mathematical conversions. Power plant efficiencies are thermodynamic metrics. Be sure to keep these concepts separate. For all of the reasons mentioned above, it is important to document all conversion factors, rates, or efficiencies used, as others might make different assumptions.

The quantity of energy used locally for a specific task is typically referred to as **site energy**, such as the electricity we use for recharging a laptop or mobile phone. However, site uses of energy typically lead to an even greater use of energy elsewhere, such as at a power plant. As noted above, the energy conversion performance of a coal-fired power plant, as well as losses from the power grid, means that for every 3 units of energy in the coal burned at a plant we can use only about 1 unit of energy at our electrical outlet. That amount of original energy needed, such as at a power plant, is referred to as **primary or source energy**.

As a final note, 'converting' between energy and power is not appropriate for LCA analyses, but is often done to provide examples or benchmarks to lay audiences. For example, 300 kWh of electricity may be referred to as the quantity such that a 30-Watt light bulb is used for 10,000 hours (a bit more than a complete year).

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[2] Of particular importance is which heating value is used. The difference between the lower heating value (LHV) and the higher heating value (HHV) is whether the energy used to vaporize liquid water in the combustion process is included or not. While the difference between HHV and LHV is typically only 10%, you can argue that the HHV is a more inclusive metric, consistent with the system and life cycle perspectives of LCA. Regardless, this is another example of why all relevant assumptions need to be explicit in energy analysis.

Use of Emissions or Resource Use Factors

Many production processes have releases to the environment, such as the various types of pollutants mentioned in Chapter 1. For many analyses, an **emissions factor** is needed to represent the units of emissions released as a function of some level of activity. We will discuss specific data sources for emissions factors in later chapters, but most emissions factors can be found using the same type of methods needed to find primary data sources or unit conversions. Emissions factors may be sourced from government databases or reports (e.g., the US EPA's AP-42 database) or technical specifications of a piece of equipment and as such should be explicitly cited if used. Given the potential for discrepancies in emissions factors, you should look for multiple sources of emissions factors and represent them with a range of values.

Beyond finding sources, knowledge of existing physical quantities and chemical processes can be used to find emissions factors. Equation 2-2 can be used to generate a CO_2 emissions factor for a combusted fuel based on its carbon content (as found by laboratory experiments) and an assumed oxidation rate of carbon (the percent of carbon that is converted into CO_2 during combustion):

CO_2 emissions from burning fuel (kg / MMBTU) =

Carbon Content Coefficient (kg C / MMBTU) * Fraction Oxidized * (44/12) (2-2)

where the 44/12 parameter in Equation 2-2 is the ratio of the molecular weight of CO_2 to the molecular weight of carbon, and MMBTU stands for million BTU.

If we were doing a preliminary analysis and only needed an approximate emissions factor, we could assume the fraction oxidized is 1 (100% or complete oxidation). In reality, the fraction oxidized could be closer to 0.9 than 1 for some fuels. For an example of coal with a carbon content of 25 kg C per MMBTU, and assuming perfect oxidation, the emissions factor would be 92 kg CO_2 / MMBTU.

Various emissions factors can be developed through similar methods by knowing contents of elements (such as for SO_2), however, other emissions factors are a function of the choice of combustion and emissions control technologies used (such as for nitrogen oxide or particulate matter emissions)

In LCA, we will also discover resource use factors, such as material input factors, that are used and developed in similar ways as emissions factors. The main difference is that resource use factors are made as a function of input rather than output.

Estimations vs. Calculations

> "It is the mark of an instructed mind to rest satisfied with the degree of precision which the nature of the subject permits and not to seek an exactness where only an approximation of the truth is possible." - Aristotle

> "God created the world in 4004 BC on the 23rd of October." – Archbishop James Ussher of Ireland, The Annals of the Old Testament, in 1650 AD

> ".. at nine o'clock in the morning." –John Lightfoot of Cambridge, in 1644 AD

Most courses and textbooks teach you how to apply known equations and methods to derive answers that are exact and consistent (and selfishly, easy to grade). These generally are activities oriented towards teaching **calculation methods**. Similarly, methods as described above can assist in finding and documenting data needed to support calculations. A simple example of a calculation method is applying a conversion factor (e.g., pounds to kilograms). More complex calculation methods may involve solving for distance traveled given an equation relating distance to velocity and time. As solving LCA problems seldom requires you to learn a completely new calculation method, we presume you have had sufficient exposure to doing calculations.

But what if all else fails and you cannot find a primary source or a needed unit conversion? What if we are unable to locate an appropriate calculation method? An alternative method must be found that assists in finding a quantitative answer, and which preserves a scientific method, but is flexible enough to be useful without all needed data or equations. Such an alternative could involve conducting a survey of experts or non-experts, or guessing the answer. It is this idea of "guessing" the answer that is the topic of this section. Here we assume that there is a time-critical aspect to the situation, and that you require a relative guess in lieu of investing a substantial more amount of time looking for a source, conducting a complete survey, etc.

Estimation methods use a mix of qualitative and quantitative approaches to yield a "ball-park", or "back of the envelope", or order of magnitude assessment of an answer. These are not to be confused with the types of estimation done in statistical analyses that are purely quantitative in nature (e.g., estimating parameters of a regression equation). With estimation methods, we seek an approximately right answer that is adequate for our purpose – thus the concept that we are merely looking for an order of magnitude result, or one that we could do in the limited space of an envelope. The quotations at the beginning of this section are given here to represent the spectrum of the exact versus approximate methods being contrasted.

Estimation methods are sometimes referred to as educated guessing or opportunistic problem solving. As you will see, the intent is to create educated guesses that do not sound like guesses. The references at the end of this chapter from Koomey, Harte (both focused on environmental issues), Weinstein and Adam, and Mahajan are popular book-length resources and are highly recommended reading if you find this topic interesting.

Estimation methods succeed by using a structured approach of creating and documenting assumptions relevant to the question rather than simply plugging in known values into an equation. In this context, you need to adjust your expectations (and those of your audience) to reflect the fact that you are not seeking a calculated value. You may be simply trying to correctly represent the sign and/or the order of magnitude of the result. "Getting the sign right" is fairly straightforward but still often difficult. Approximating the order of magnitude means generating a value where only one significant figure is needed and the "power of 10" behind it gives a sense of how large or small it is (i.e., is the value in the millions or billions?).

If you come from a "hard science" discipline such as chemistry or physics, the thought of generating an answer without an equation may sound like blasphemy. But recall the premise of estimation methods – that you do not have access to, are unable to acquire, or unfamiliar with the data and equations needed for a calculated result. We are not suggesting you need to use estimations to find the force of gravity, the number of molecules per mole, etc. Many students may have encountered these methods in the form of classroom exercises known as "Fermi Problems". Furthermore, such estimation challenges are being used more and more frequently as on-the-spot job interview questions for those entering technical fields.

While the mainstream references mentioned above give many examples of applying estimation methods, other references are useful for learning the underlying methods. Mosteller (1977) lists several building block-type methods that can be used and intermixed to assist in performing estimation. You are likely familiar with many or all of them, but may not have considered their value in improving you estimation skills:

- **Rules of thumb** – Even a relative novice has various numbers and knowledge in hand that can help to estimate other values. For example, if performing a financial analysis it is useful to know the "rule of 72" that defines when an invested amount will double in value. Likewise, you may know of various multipliers used in a domain to account for waste, excess, or other issues (e.g., contingency or fudge factors). The popular Moore's Law for increases in integrated circuit densities over time is an example. Any of these can be a useful contributor to a good estimation. Also realize that one person's rule of thumb may be another's conversion factor.

- **Proxies or similarity** – Proxy values in estimation are values we know in place of one we do not know. Of course the needed assumption is that the two values are expected to be similar. If we are trying to estimate the total BTU of energy contained in a barrel of diesel fuel, but only had memorized data for gasoline, we could use the BTU/gallon of gasoline as a proxy for diesel fuel (in reality the values are quite close, as might be expected since they are both refined petroleum products). Beyond just straight substitution of values via proxy, we can use similarity methods to reuse datasets from other purposes to help us. For example if we wanted to know estimates of leakage rates for natural gas pipelines in the US, we might use available data from Canada which has similar technologies and environmental protection policies.

- **Small linear models** – Even if we do not have a known equation to apply to an estimation, we can create small linear models to help us. If we seek the total emissions of a facility over the course of a year, we could use a small linear model (e.g., of the form y = mx + b) that estimates such a value (y) by multiplying emissions per workday (m) by number of work days (x). In a sense we are creating shortcut equations for our needs.

  Of course, these small linear models could be even more complicated, for example by having the output of one equation feed into another. In the example above, we could have a separate linear model to first estimate emissions per day (perhaps by multiplying fuel use by some factor). Another way of using such models is to incorporate growth rates, e.g., by having b as some guess of a value in a previous year, and mx the product of an estimated growth rate and the number of years since.

- **Factoring** – Factoring is similar to the small linear models mentioned above, except in purely multiplicative terms. Factoring seeks to mimic a chain of unitized conversions (e.g., in writing out all of the unitized numerators and denominators for converting from days in a year to seconds in a year, which looks similar to Equation 2-1). As above, the goal here is to estimate the individual terms and then multiply them together to get the right value with the right units. The factors in the equation used may be comprised of constants, probabilities, or separately modeled values.

- **Bounding** – Upper and lower bounds were discussed in the context of creating ranges for analysis purposes, but can also be used in estimations. Here, we can use bounds to help set the appropriate order of magnitude for a portion of the analysis and then use some sort of scaling or adjustment factor to generate a reasonable answer. For example if we were trying to estimate how much electricity we could generate via solar PV panels, using the entire land mass of the world would give us an upper bound of production. We could then scale down such a number by a guess at the fraction of land that is highly urbanized or otherwise not fit for installation.

- **Segmentation or decomposition** – In this type of analysis, we break up a single part into multiple but distinct subparts, and then separately estimate a value for each subpart and then report a total. If we were trying to estimate fossil-based carbon dioxide emissions for the US, we could estimate carbon dioxide emissions separately for fossil fueled power plants, transportation, and other industries. Each of these subparts may require its own unique estimation method (e.g., a guess at kg of CO_2 per kWh, per vehicle mile traveled, etc.) that are added together to yield the original unknown total emissions of CO_2.

- **Triangulation** – Using triangulation means that we experiment in parallel with multiple methods to estimate the same value, and then assess whether to use one of the resulting values or to generate an average or other combination of them. Triangulation is especially useful when you are quite uncertain of what you are estimating, or when the methods you are otherwise choosing have many guesses in them. You can then control whether to be satisfied with one of your results, or to use a range. Of course if your various parallel estimates are quite similar you could just choose a consensus value.

While Mosteller summarized these specific building blocks, you should not feel limited by them. Various other kinds of mathematical functions, convolutions, and principles could be brought to bear to aid in your estimation efforts. Beyond these building blocks, you should try to create ranges (since you are estimating unknown quantities) by assuming ranges of constants in your methods or by using ranges created from triangulation. Do not assume that you can never "look up" a value needed within the scope of your estimation. There may be some underlying factor that could greatly help you find the unknown value you seek, such as the population of a country, the total quantity of energy used, etc. You can use these to help you reach your goal, but be sure to cite your sources for them. It might be useful to avoid using these reference source values while you are first learning how to do estimation, and then incorporate them when you are more experienced.

As expressed by several of the building block descriptions, a key part of good estimations is using a "divide and conquer" method. This means you recursively decompose a high-level unknown value as an expression of multiple unknown values and estimate each of them separately. A final recommendation is that you should be creative and also to consider "outside the box" approaches that leverage personal knowledge or experience. That may mean using special rules of thumb or values that you already know, or attempting methods that you have good experience in already. Now that we have reviewed the building blocks, Example 2-2 shows how to apply them in order to create a simple estimate.

Example 2-2: Estimating US petroleum consumption per day for transportation

Question: Given that the total miles driven for all vehicles in the US is about 3 trillion miles per year, how many gallons of petroleum are used per day in the US for transportation?

Answer: If we assume an average fuel economy figure of about 20 miles per gallon we can estimate that 150 billion gallons (3 trillion miles / 20 miles per gallon) of fuel are consumed per year. That is about 400 million gallons per day.

You might also develop estimations to serve a specific purpose of explaining a result to be presented to a general audience. In these cases, you might want to find a useful visual or mental reference that the audience has, and place a result in that context. Example 2-3 shows how you might explain a concentration of 1 ppb (1 part per billion).

Example 2-3: Envisioning a one part per billion concentration

Question: How many golf balls would it take to encircle the Earth?

Answer: Assume that the diameter of a golf ball is approximately 1.5 inches, and that the circumference of the Earth is about 25,000 miles (roughly 10x the distance to travel coast to coast in the United States). We can convert 25,000 miles to 1.6 x 10^9 inches. Thus there would be 1.6 x 10^9 inches / 1.5 inches, or ~1 billion golf balls encircling the Earth.

Thus, if trying to explain the magnitude of a 1 part per billion (ppb) concentration, think about there being one red golf ball along the equator that has 1 billion white balls lined up!

Acknowledgment to "Guesstimation" book reference for motivating this example.

Attributes of Good Assumptions

One of the key benefits of becoming proficient in estimation is that your skills in documenting the assumptions of your methods will improve. As application of estimation methods requires you to make explicit assumptions about the process used to arrive at your answer, it is worth discussing the attributes of good assumptions. You may have the impression that making assumptions is a bad thing. However, most research has at its core a structured set of assumptions that serve to refine and direct the underlying method. Your assumptions may refer specifically to the answer you are trying to find, as well as the measurement technologies used, the method, or the analysis. You might think of your assumptions as setting the "ground rules" or listing the relevant information that is believed to be true. You should make and write assumptions with the following attributes.

1. **Clarify and Simplify** - First, realize that the whole point of making an assumption is to help to clarify the analysis (or at the least to rule out special cases or complications). Assumptions ideally also serve to refine and simplify your analysis. It is not useful to have an assumption that makes things harder either for your analysis or for the audience to follow your process. For example, if you were trying to estimate the number of power plants in the US, you might first assume that you are only considering power plants greater than 50 MW in capacity. Or you might assume that you are only considering facilities that generate and sell electricity (which would ignore power plants used by companies to make their own power). By making these assumptions, you are ruling out a potentially significant number of facilities (leading to

an undercount of the actual), but you have laid out this fact explicitly at the beginning as opposed to doing it without mention.

It is possible that an assumption may be required in order to make any estimate at all. For example, you might need to assume that you are only estimating fossil-based power plants, because you have no idea of the capacities, scale, or processes used in making renewable electricity.

2. **Correct, credible and feasible** - If it is not obviously true (i.e., you are not stating something that is a well known fact), your audience should read an assumption and feel that it is valid - even if hard to believe or agree with. For example, you should not assume a conversion factor inconsistent with reality, such as there being only four days in a week or 20 hours in a day.

3. **Not a shortcut -** While assumptions help to narrow down and refine the space in which you are seeking an answer, they should not serve to merely carve out an overly simple path towards a trivial solution. Your audience should not be left with the impression that you ran out of time or interest in finding the answer and that you substituted a good analysis with a convenient analysis. For example, you might assume that you were only counting privately owned power plants. This is a narrowing of the boundaries of the problem, but does not sound like you are purposely trying to make the problem trivial.

4. **Unbiased** – Your assumptions should not incorporate a degree of connection to some unrelated factor. For example, in estimating the number of power plants you do not want to rely on a geospatial representation associated with the number of facilities that make ethanol, which are highly concentrated in areas where crops like corn grow.

Beyond listing them, it is good practice to explicitly write a justification for your assumptions. In the power plant example above, the justification for why you will only count relatively large (> 50 MW) facilities might be "because you believe that the number of plants with smaller capacities is minimal given the demands of the power grid". Since you're looking for an order of magnitude estimate, neglecting part of the solution space should have no practical effect. In the case of assuming only privately owned facilities, the justification might simply specify that you are not estimating all plants, just those that are privately owned. In Example 2-2, the 20 miles per gallon assumed fuel economy is appropriate for passenger vehicles, but not so much for trucks or buses that are pervasive. In that example, it would be useful to state and justify an assumption explicitly, such as "Assuming that most of the miles traveled are in passenger vehicles, which have a fuel economy of 20 miles per gallon, …"

Writing out the thought process behind your assumptions helps to develop your professional writing style, and it helps your audience to more comfortably follow and appreciate the analysis you have done. Furthermore, by becoming proficient at writing up the assumptions and process used to support back of the envelope calculations, you become generally proficient at documenting your methods. Hopefully you will leverage these writing skills in other tasks.

In the alternative where you do not state all of your assumptions, the readers are left to figure them out themselves, or to create their own assumptions based on your incomplete documentation. Needless to say either of those options raises the possibility that they make bad assumptions about your work.

Validating your Estimates

When you have to estimate a quantity, it is important that you attempt to ensure that the value you have estimated makes sense (see the discussion earlier in this chapter about reasonableness tests). Even though you have estimated a quantity that you were unable to find a good citation for originally, you should still be able to validate it by comparing it to other similar values.

As a learning experience, you might try to estimate a value with a known and available number that you know can be found but that you do not already know the answer to (e.g., the number of power plants in the US, or a value that you could look up in a statistical abstract). Doing so helps you to hone your skills with little risk, meaning that you can try various methods and directly observe which assumptions help you arrive at values closest to the 'real answer' and track the percentage error in each of your attempts before looking at the real answer. The goals in doing so are explicitly to learn from doing many estimates of various quantities (not just 5 attempts at the same unknown value) and to increasingly understand why your estimates differ from the real answers. You may not be making good assumptions, or you might be systematically always guessing too high or too low. It is not hard to become proficient after you have tried to estimate 5-10 different values on your own. When doing so, try to apply all of the building block methods proposed by Mosteller. Example 2-4 shows an example of a validation of an estimate found earlier in the chapter.

Example 2-4: Validating Result found in Example 2-2

In Example 2-2, we quickly estimated that the transportation sector consumes 400 million gallons per day of petroleum.

The US Energy Information Administration reports that about 7 billion barrels of crude oil and other petroleum products were consumed in 2011. About 1 billion barrels equivalent was for natural gas liquids not generally used in transportation. That means about 17 million barrels per day (about 850 million gallons per day at about 50 gallons per barrel) was consumed. That is roughly twice as high as our estimate in Example 2-2, but still in the same order of magnitude.

Let's think more about the reasons why we were off by a factor of two. First off, we attempted an estimate in one paragraph with two assumptions. The share of passenger vehicles in total miles driven is not 100%, and heavy trucks represent 10% of the miles traveled and about one-fourth of fuel consumed (because their fuel economies are approximately 5 mpg, not 20). Considering these deviations our original estimate, while simplistic, was useful.

Sources: US DOE, EIA, Annual Petroleum and Other Liquids Consumption Data http://www.eia.gov/dnav/pet/pet_cons_psup_dc_nus_mbbl_a.htm

US Department of Transportation, Highway Statistics 2011, Table VM-1.

Beyond validation of your own estimates, you might also want to do a reasonableness test on someone else's value. You will often find numbers presented in newspapers or magazines as well as scholarly journals that you are curious about or fail a quick sniff test. You can use the same estimation methods to validate those numbers. Just because something is published does not necessarily mean it has been extensively error-checked. Mistakes happen all the time and errata are sometimes (but not always) published to acknowledge them. Example 2-5 shows a validation of values published in mainstream media pertaining to EPA's proposed 2010 smog standard.

Example 2-5: Validating a comparative metric used in a policy discussion

Question: Validate the number of tennis balls in the following CBS News excerpt (2010) pertaining to the details of EPA's proposed 2010 smog standard.

> "The EPA proposal presents a range for the allowable concentration of ground-level ozone, the main ingredient in smog, from 60 parts per billion to 70 parts per billion. That's equivalent to 60 to 70 tennis balls in an Olympic-sized swimming pool full of a billion tennis balls."

Answer: Suppose your sniff test fails because you realize a billion tennis balls is a very large number of balls for this pool. A back of the envelope estimate suggests the approximate size of an Olympic pool is 50m x 25m * 2m = 2500 cubic meters. Similarly, assume a tennis ball occupies a 2.5 inch (70 mm or 0.07m) diameter cube so it thus has a volume of 0.00034 m^3. Such a pool holds only about 7 million tennis balls, almost three orders of magnitude less than the 1 billion suggested in the excerpt. Of course, we could further refine our assumptions such that the pool can be uniformly deeper, or that the tennis ball fully occupies that cube (to consider that adjacent tennis balls could fill in some of the voids when stacked) but none would fully account for the several orders of magnitude difference.

You cannot put a billion tennis balls in an Olympic-sized pool, thus the intended reference point for the lay audience was erroneous. It is likely an informal reference from the original EPA Fact Sheet was copied badly in the news article (e.g., "60-70 balls in a pool full of balls").

Thanks to Costa Samaras of Carnegie Mellon University for this example.

Now that we have built important general foundations for working with and manipulating data, we turn our attention to several concepts more specific to LCA.

Building Quantitative Models

Given all of the principles above, you should now be prepared to build the types of models needed for robust life cycle thinking. These models have inputs and outputs. The inputs are the various parameters, variables, assumptions, etc., and the output is the result of the equation or manipulation performed on the inputs. In a typical model, we have a single set of input values and a single output value. If we have ranges, we might have various sets of inputs and multiple output values. Beyond these typical models there are other types of models we might choose to build that are less straightforward.

A **breakeven analysis** solves for the input value that has a prescribed effect on a model. A classic example, and where the name 'breakeven' comes from is if you are building a profit or loss model, where your default model may suggest that profits are expected to be negative (i.e., the result is less than $0). A relevant breakeven analysis may assess the input value (e.g., price of electricity or number of units sold) needed to lead to a profit outcome, i.e., a $0 (or positive) value. It is what you need to 'break even', or make profit. This is simply back-solving to find the input required to meet the specified conditions of the result. Not all breakeven analyses need to be about monetary values, and do not need to be set against zero. Using the example of Equation 2-1, you could back-solve for the transit time for a towboat moving at a speed of 5 km/hr. While the math is generally easy for such analyses, common software like Microsoft Excel have built-in tools (Goal Seek) to automate them. Goal Seek is quite comprehensive in that it can solve for a breakeven value across a fairly complicated spreadsheet of values.

The final quantitative skill in this chapter shows how robust results are to changes in the parameters or inputs of your model. In a **sensitivity analysis**, you consider various model inputs individually, and assess the degree to which changing the value of those inputs has *meaningful* effects on the results (it is called a sensitivity analysis because you are seeing how 'sensitive' the output is to changes in the inputs). By meaningful, you are, for example, assessing whether the sign of the result changes from positive to negative, or whether it changes significantly, e.g., by an order of magnitude. If small changes in input values have a big effect on the output, you would say that your output is sensitive. If even large changes in the inputs have modest effect on the output, then the output is not sensitive. If any such results occur across the range of inputs used in the sensitivity analysis, then your qualitative analysis should support that finding by documenting those outcomes. Note that a sensitivity analysis changes each of your inputs independently (i.e., changing one while holding all other inputs constant). You perform a sensitivity analysis on all inputs separately and report when you identify that the output is sensitive to a given input. Again referring to the towboat example (Equation 2-1) we could model how the speed varies as the time in transit varies over a range of 20 minutes to more than 4 hours. Figure 2-4 shows the result of entering values for transit time in increments of 20 minutes into Equation 2-1. It suggests that the speed is not very sensitive to large transit times, but changes significantly for small transit times. We will show more examples of breakeven and sensitivity analyses in Chapter 3.

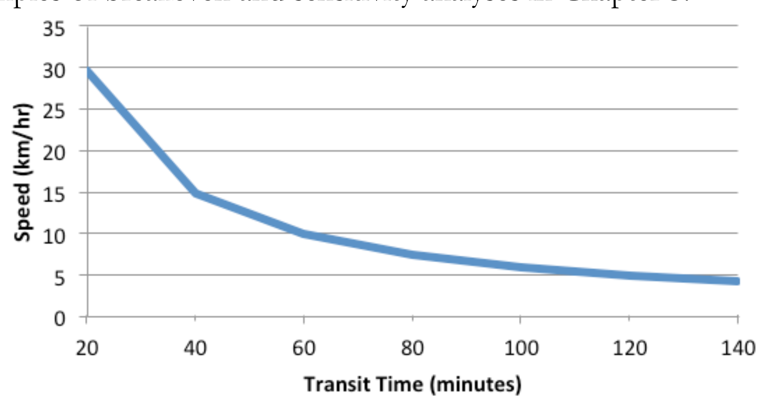

Figure 2-4: Sensitivity of Towboat Speed to Transit Time

A Three-step method for Quantitative and Qualitative Assessment

We conclude the chapter with suggestions on how to qualitatively and quantitatively answer questions. LCA is about life cycle *assessment*. While we have not yet demonstrated the method itself, it is important to develop assessment skills. If you are doing quantitative work (as you will need to do to successfully complete an LCA), a general guideline is that you should think of each task as having three parts:

(1) A description of the method used to complete the task,

(2) The result or output (quantitative or qualitative) of the task, and

(3) A critical assessment, validation, or thought related to the result.

The amount of time and/or text you develop to document each of these 3 steps varies based on the expectations and complexity of the task (and perhaps within the constraints of the size of a study).

In step one, you should describe any assumptions, data sources found, equations needed, or other information required to answer the question. In step two, you state the result, including units if necessary. In step three, you somehow comment on, validate, or otherwise reflect on the answer you found. This is an important step because it allows you to both check your work (see the example about unit conversions above) and to convince the reader that you have not only done good work but have also spent some time thinking about the implication of the result. For example, a simple unit conversion might be documented with the three-step method as follows:

> "Inputs of plastic were converted from kg to pounds (2.2 lbs. per 1 kg) yielding 100 kg of inputs. This value represents 20% of the mass flows into the system."

Each of the three expected steps is documented in those 2 sentences: the method (a basic unit conversion), the result (100 kg), and an assessment (20% of the total flows). If this were part of an assignment, you could envision the instructor deciding on how to give credit for each part of the question, e.g., 3 points for the method, 2 points for the result, and 2 points for the assessment. Such a rubric would emphasize the necessity of doing each part, and could also formalize the expectations of working in this manner and forming strong model building habits. For many types of problem solving—especially those related to LCA, where many answers are possible depending on how you go about modeling the problem—the emphasis may be on parts 1 and 3, relatively de-emphasizing the result found in part 2. In other domains, such as in a mathematics course, the result (part 2) may be the only significant part in terms of how you are assessed. Regardless, you probably still used a method (and may have briefly shown it by writing an equation and applying it), and hopefully tried to quickly check your result to ensure it passed a reasonableness test, even if you did not in detail write about each of those steps.

A way of remembering the importance of this three-step process is that your answer should never simply be a graph or a number. There is always a need to discuss the method you used to create it, as well as some reflection on the value. Regardless of the grading implications and distributions, hopefully you can see how this three-step process always exists – it is just a matter of translating the question or task presented to determine how much effort to make in each part, and how much documentation to provide as an answer. You will find that performing LCA constitutes assembling many small building block calculations and mini-models into an overall model. If you have mostly ignored how you came up with these building block results, it will be difficult to follow your overall work, and to follow how the overall result was achieved.

Chapter Summary

In LCA, any study will be composed of a collection of many of the techniques above. You'll be piecing together emissions factors and small, assumption-based estimates, generating new estimates, and summarizing your results.

People entering a field of science or engineering frequently state their being more comfortable with numbers or equations than they are with 'writing' as one reason for their choice of career. Perhaps unfortunately, communicating your method, process, and results via writing is an especially important skill in conducting life cycle assessment. However, the LCA framework can provide a strong foundation for technical practitioners to organize their writing and practice their communication skills.

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End of Chapter Questions

Objective 1: Apply appropriate skills for qualitative and quantitative analysis.

1. Find the fraction of the population that lives in cities versus rural areas in the US, or in your home state. Validate your findings as possible.

Objective 2: Document values and data sources in support of research methods.

2. Find and reference three primary sources for the amount of energy used in residences in the United States. Validate your findings as possible.

Objective 3: Improve your ability to perform back of the envelope estimation methods.

3. Estimate the number of hairs on your head.

4. Estimate the number of swimming pools in Los Angeles.

5. Estimate the total weight of the population in your home state.

Objective 4: Approach any quantitative question by means of describing the method, providing the answer, and describing what is relevant or interesting about the answer.

6. In terms of area, how much pizza is eaten by people in your country in one day? Give answer in terms of the number of football fields that would be covered.

7. How many gallons of beer are consumed each day in your country? Give answer in terms of how high it would fill a professional football stadium.

8. How many refrigerators are bought by people in your country each day? If stacked end-to-end, how long would it take to walk around them?