Decision-Making to Reduce Manufacturing Greenhouse Gas Emissions

by

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Abstract

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The manufacturing sector is a significant contributor to environmental damage and resource use, which has potential long-term implications if resources are overused and our air, water, and soil are altered irreversibly. To alleviate these impacts, the manufacturing research community has primarily focused on reducing the environmental impacts of specific manufacturing processes and systems within a factory; however there are opportunities for environmental impact reductions that emerge from a supply chain perspective. For example, researchers have recognized that by taking advantage of regional differences when locating facilities there is the opportunity to alleviate global water scarcity and reduce the human health effects of pollution. We add to this body of work by focusing on the opportunity to take advantage of regional variability to reduce supply chain GHG emissions.

Through the development of targeted environmental return-on-investment (ROI) metrics and hybrid life-cycle assessment techniques, we enable the minimization of global greenhouse gas emissions through informed supply chain design. Founded on the premise that GHG emissions are a global problem that can benefit from global optimization, we focus on the tradeoffs between transportation emissions and electricity emissions.

A three-pronged approach to management and reduction of GHG emissions in manufacturing is presented: (1) metric design for environmental decision-making (2) comprehensive, repeatable, and efficient life-cycle assessment using a hybrid approach (3) optimization of the system to take advantage of regional tradeoffs. This approach is demonstrated through a generic case study of automotive manufacturing and a case study of SolFocus Inc. concentrated solar photovoltaic panels.

The case-studies show that 30-40% of GHG emissions in the supply chain are from electricity and transportation and can be reduced by up to 50% through changes in supplier location. Furthermore, regional variability in electricity emissions means that local manufacturing is not always optimal. Finally, the incorporation of ROI metrics for the SolFocus system presented the most rapid path to global reductions in GHG emissions. Installation of solar technology in Australia results in a savings of nearly 20 kg-CO_{2eq} for every kg-CO_{2eq} emitted during production; whereas the savings from installation in Spain, Northern California, or Arizona is 7-8 kg-CO_{2eq}.

This dissertation presents the following new contributions to the field (1) a method for global GHG reductions, separate from product re-design, through optimization of supply

chain layout based on transportation and electricity GHG emissions tradeoffs; (2) development of effective and targeted ROI environmental metrics to guide decisions that promote the fastest route to reduce environmental impacts in manufacturing; (3) validation of the feasibility of using of iterative financial hybrid LCA to ensure a comprehensive LCA and guide regional input-output electricity estimates and tradeoffs in key areas; (4) demonstration and development of the greenhouse gas ROI metric, iterative hybrid LCA methodology, and supply chain layout decision-making for concentrator solar PV

We note that these supply chain efforts must occur in conjunction with efforts on sustainable product design such as design for remanufacture, improved use-phase efficiencies, or utilization of new materials.

To my father.

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Chapter 1

Introduction

Manufacturing research in the past century went through a series of revolutions that increased the scope of critical activities to be measured, controlled, and optimized to stabilize costs, quality, and production time. A century ago, F.W. Taylor [1] focused his efforts on individual tasks in a factory to make them simple and efficient. Gilbreth [2] connected these individual tasks and discovered the non-value added time between them that could be optimized. Toyota continued to discover non-value added opportunities for optimization through holistic waste reduction efforts, continuous improvement, and employee engagement [3]. Then, in the 1970s and 1980s, the sphere of focus expanded beyond the factory to the supply chain, and further cost savings from inventory control and just in time manufacturing were discovered [4].

We are now examining the environmental impacts of manufacturing, but much less has been done to extend these studies to supply chain impacts. Manufacturing researchers have investigated the resource consumption and health risks associated with specific manufacturing processes [5, 6, 7, 8, 9] and factory operations [10, 11, 12]. These studies have been vital to sustainable manufacturing research and provide insight on the impacts of specific processes and factories. However, the development of a global economy where resource scarcity and resource consumption are not limited by borders has impaired our ability to see the environmental effects of manufacturing across supply chains. There is inherent risk in these unknown and unmanaged environmental impacts.

The supply chain can account for up to 80% of total greenhouse gas (GHG) emissions [13]. Expanding our toolkit of methods to reduce environmental impacts into the supply chain opens up a wealth of environmental management and reduction opportunities that are external to product design and manufacturing design. Supply chain decisions influence environmental impacts in multiple ways, including regional energy mix variations, resource availability (materials, water, transport, infrastructure), labor (cost, societal requirements), policy (regulatory, political), climate variability, and available technologies.

In recent years, novel supply chain design methods have emerged to reduce environmental impacts by taking advantage of regional variations. For example, trade in virtual water has been proposed as an idea to alleviate regional water scarcity by manufacturing water-intensive goods (like agricultural products) in regions with plentiful water supply [14]. Furthermore, the idea that the fate of pollution various by climate and geographic region has been utilized by researchers when discussing where to locate factories [15]. We propose an addition to this body of work that focuses on the 30-40% of supply chain GHG emissions that are from electricity and transportation, and we take advantage of the fact that GHG emissions have the same impact regardless of where they are emitted [16] so emissions in one location can be traded for emissions elsewhere. Further work on regionalized supply chain tradeoffs could one day provide a harmonized approach to reducing environmental impacts across supply chains.

We present a three-pronged approach for manufacturing supply-chain analysis: (1) metric design for environmental decision-making (2) comprehensive, repeatable, and efficient life-cycle assessment using a hybrid approach (3) optimization of the system to take advantage of regional tradeoffs. The structure of this approach is reflected in the structure of this dissertation, which starts by providing background on Life-Cycle Assessment methodologies and environmental supply-chain analysis, and then expands from this baseline of knowledge into each of the three areas: metrics, LCA, and decision making. Finally, this three-pronged approach is demonstrated through case studies of automotive manufacturing and concentrated solar photovoltaic manufacturing.

Chapter 2

Literature Review

2.1 Life-Cycle Assessment

Environmental life-cycle assessment (LCA) is a powerful tool to measure the environmental impacts associated with a process, product, or service. LCA is generally described as a systematic analysis of the material flows associated with every stage of a product's existence throughout materials extraction, manufacturing, distribution, use, and end-of-life; however, in practice any number of these stages might be omitted in what is called a "gate to gate," "cradle to gate," or "gate to cradle" analysis.

The ISO 14040 series of standards define LCA guidelines and establish four stages to an LCA: (1) goal and scope definition (2) inventory assessment (3) impact assessment (4) interpretation of results [17].

The first, and arguably the most important, component of any environmental assessment is to determine the goal of the study. This step requires agreement on the ultimate purpose of the work being completed, the level of detail needed for the intended application and audience, and the requirements for data quality.

With the goal in mind, the scope (or system boundary) of the study can be assessed. A boundary is defined by the pre-determined set of activities to be analyzed within the product's life-cycle. The boundary can be set to include just about anything the practitioner decides to include; such as the full life-cycle, all manufacturing operations, a factory, a machine-tool, or a geographic region. We argue that for certain environmental metrics it is useful to determine the total impact associated with a product or service globally. This is the case for GHG emissions as they contribute to global climate change regardless of emissions location, and insight can be gained from a global perspective. However, a global assessment is not necessarily appropriate for a metric such as water, where environmental damage is relative to regional water scarcity. For the case of water a "gate-to-gate", or region specific, analysis might be most appropriate. Additionally, for comparative studies, only those areas of the life cycle that are different between the two items need to be measured. For example, given a goal of comparing the lifetime GHG of one laptop to another, it is not critical to determine transportation emissions from the store to the consumer if it is the same for each laptop.

A fundamental problem with boundary selection as defined by ISO is the introduction of “cutoff criteria”. ISO allows a practitioner to decide to completely leave an environmental flow out of the analysis if the mass or energy of the flow is shown to be small relative to all other flows. There is, unfortunately, no theoretical reason that a small mass or energy flow would have a small environmental impact, making this method particularly prone to error. Additionally, although a single flow may appear to be insignificant, the sum of these ignored flows could be significant and their exclusion would lead to a false conclusion [18].

Another critical part of the “scope” step is determining exactly what functional unit will be used. The functional unit is the normalization factor for the assessment. In some cases the normalization factor can be simple, such as emissions per computer manufactured. Or, it can be more complicated, such as emissions per computer manufactured per year of use. The choice of functional unit is critical for decision-making as will be discussed again in Chapter 3.

With the goal and scope determined, it is then time to do the life-cycle inventory (LCI). The LCI stage is generally the most time-consuming phase, because detailed data collection is required across a range of processes to obtain a complete picture of environmental interactions, emissions, and resource use [17]. Where necessary, sensitivity analysis may be used at this stage to refine the system boundary, allocation principles, and the inventory procedures. Life-cycle inventories can be obtained using one of three general methodologies: process LCI, input-output LCI, or a hybrid combination of process and input-output LCI. These methodologies will be discussed further in section 2.1.1.

Once data has been collected via the chosen LCI methodology, the LCA practitioner has a large set of emissions and consumption values that can be aggregated into more meaningful values through an impact assessment. Using chosen impact categories and characterization models, the various interactions with the environment classified as having the same type of impact can be aggregated into an equivalent set of emissions. Impact characterization for GHGs will be discussed in section 2.1.2.

Finally, the interpretation stage utilizes the LCA practitioner’s judgment to summarize the results and analyze the limitations and data quality of the assessment for further iteration, research, decision-making, and reporting.

2.1.1 LCI Methodologies

Practitioners debate the “best” methodology to complete a product, company, or system LCI; however, at its most basic, every LCI is a combination of primary (measured) and secondary data (data directly from a database or research document, extrapolated data, or modeled data). The difference between each methodology is in the steps taken to collect the data, where there are essentially two possible approaches: (1) start with primary data as much as possible and fill in data gaps using secondary data (2) start with secondary data to evaluate hot spots and then collect primary data to refine the results where necessary. We will refer to the first approach as “bottom-up” LCI and the second approach as “top-down” LCI. A risk with bottom-up LCI is that the practitioner may spend time collecting primary data for components of the analysis that turn out to be insignificant. A risk of top-down LCI is that the practitioner could reach a false conclusion based on incomplete or mis-applied secondary data and fail to do further analysis. The differences between these approaches is important and will be explored further in this section.

Process LCI

Process LCI is the traditional method for inventory assessment and is often referred to as the SETAC-EPA method because of the role played by SETAC [19] and EPA in this method's development [20]. Process LCI consists of methodically analyzing material and energy flows at every stage of the life-cycle to understand precise consumption and emission values. The results are aggregated into single metrics of impact such as eutrophication, toxicity, and GHG emissions. This method in practice is time consuming, limited in scope to a handful of products or processes, and not efficiently scalable [20].

An inherent requirement of any process LCI is the drawing of a boundary on the analysis. Flows within this boundary may be omitted if they meet a cut-off criterion. These decisions are often made based on the mass, energy, or assumed environmental impact of the ignored flow. ISO 14044 explicitly states, "The deletion of life cycle stages, processes, inputs or outputs is only permitted if it does not significantly change the overall conclusions of the study" [21]. Of course, it is impossible to know if something will significantly alter the results if it has not been measured yet, a fundamental flaw in the process LCI approach.

Multiple software tools and databases exist on the market to assist researchers in conducting process LCI (such as GaBi [22], Ecoinvent [23], and SimaPro [24]). These tools contain data from previous researchers on the environmental impact of materials and processes that are then combined by the user to form a system. The use of both primary and secondary data to create a process LCI is supported by ISO 14044, which states, "in practice, all data may include a mixture of measured, calculated or estimated data." In some cases, the secondary data provided by these databases is from an input-output analysis, which technically makes the result a "hybrid" result, however, the spirit of the analysis is still process-based and therefore we would call it a bottom-up LCI.

For situations where the desired analysis boundary is finite, as it is for regional water consumption, a process approach is appropriate. However, when a comprehensive supply chain analysis is desired, process LCI has a boundary definition problem. This is because a supply chain is inherently infinite (every step of the supply chain creates additional demands), and every component of a system simply cannot be accounted for by the LCI practitioner given time and cost constraints.

There is a common misconception that process LCI is the more accurate of the methodologies (compared with pure IO or hybrid analysis). However, there have been multiple studies demonstrating the strength of input-output analysis when used in conjunction with process LCI to be more comprehensive, accurate, and efficient than process LCI alone [13, 18, 25, 26, 27]. This is because hybrid LCI methodologies combine the full picture analysis of IO-LCA with the specificity of process LCI. We are not aware of any research attempting to disprove the strength of a hybrid approach.

Computational aspects of process LCI:
Process LCI is typically modeled using process flow diagrams. A process flow diagram shows the flow of materials and energy between various stages of a manufacturing system and the environment. This enables practitioners to use mass and energy balances to ensure that

the net flows in equal the net flows out of the system. This is a well understood method for describing life-cycle stages and is a required step of many LCA standards.

However, the flow of materials and energy can also be modeled in matrix form as discussed by Hendrickson et al. [28] and Heijungs and Suh [29] (equation 2.1), where each column of H describes the flows into and out of a system, B describes the environmental flows as a consequence of H, f is the external demand on this system given by the commodity or service being analyzed, and g is the final vector of environmental impacts.

$$g = BH^{-1}f \tag{2.1}$$

Creating the H matrix for a process LCI is something of an iterative process. For example, a column of H might be established showing that 1 unit of Furniture requires 4 kg wood, 10 screws, and releases 0.3 kg of scrap to the environment (Figure 2.1). Then three more columns are needed to demonstrate the inputs to screws, and wood, and the process continues. At some point, the LCA practitioner must draw a boundary on the analysis; this is called the cutoff. A cutoff occurs when an output flow references a needed input that does not then have a column describing its inputs.

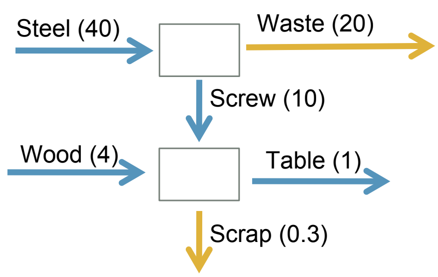

	Table	Screw	Wood	Steel	
Table	1	0	0	0	
Screw	-10	1	0	0	H
Wood	-4	0	1	0	
Steel	0	-4	0	1	
Scrap	0.3	0	0	0	B
Waste	0	2	0	0	

Figure 2.1: Comparison of process flow diagram versus matrix representations of LCA

Figure 2.1 draws a comparison between the process flow and matrix representations. Note that each row of H and B must be in consistent units, but these could be literally any physical or energetic measure (e.g., kWh, kJ, kg, or \$).

Input-Output LCI

In contrast with process LCI, where an analysis of interrelated flows is built from the bottom-up, input-output LCI starts with a top-down model of the economy. Economic input-output tables [30] and industry-level environmental data are used to construct a database of environmental impact per dollar of sales from an industry [20, 29]. There is a large setup cost in creating the IO-LCI database; however, it is relatively straightforward to use once in place as financial data can be mapped to IO-LCI data directly. This method is more complete than process LCI because the economic input-output tables capture the interrelations of all economic sectors; however, input-output LCI has the problem of providing only aggregate industry level data [31, 32].

The use of input-output models to capture the interrelations of economic sectors was discovered by Leontief in the 1960s [33]. Researchers quickly recognized the usefulness of Leontief's input-output models for environmental analysis [34], and most of the work in the 1970s and 1980s was focused on energy input-output models for environmental analysis and policy decisions [35, 36, 37, 38, 39, 40]. In the 1990s this work was broadly adopted and expanded to incorporate environmental metrics beyond energy [28, 41, 42, 43, 44].

Computation aspects of IO LCI:
Environmental input-output assessment requires the following data:

- Z: input-output matrix showing total purchases between commodities and services.
- y: total final or household level demand for each commodity and service throughout the economy.
- f: demand for each commodity and service by the company, product, or service being studied in the LCA
- x: total demand for each commodity and service in the economy.
- B: flows to and from the environment per unit of each good and service

The Z matrix can be normalized so each element represents the dollars of input required from one sector for every dollar of output from another sector. This is given by equation 4.4, where A_{ij} represents sector j's direct demand for sector i per dollar output from sector j.

$$A = Z(diag(x))^{-1} \tag{2.2}$$

Direct demand from the company, product, or service being studied to each sector is If, first-tier supplier demand is Af, second-tier supplier demand is A^2f and so on. The total demand generated throughout the economy as a result of a company buying products and services is $(I - A)^{-1}f$. As shown in equation 2.3, T_{ij} represents sector j's cumulative demand for sector i throughout the economy per dollar output from sector j.

$$T = (I - A)^{-1} = I + A + A^2 + A^3 + ... \tag{2.3}$$

Through these equations, Leontief discovered the notion of circularity, which is indicated along the diagonal of T, where demand for a sector generates additional demand for that sector in the economy. For example, demand for computers generates demand for aluminum, which generates demand for machinery, which in turn generates demand for computers.

Finally, the total environmental interventions associated with spend in the economy are given in equation 2.4. We can also break out contributions by industry sector based on equation 2.5. Harmonization of these equations for IO-LCA with those presented for process LCA simply requires this conversion: $(I - A) = H$.

$$g = BTf \tag{2.4}$$

$$G = B * diag(Tf) \tag{2.5}$$

Hybrid LCI

While process LCI can provide a detailed analysis of specific process flows, IO-LCI is able to quickly capture the interrelations between all sectors of the economy [45, 13, 26]. The scope of process LCI is limited by time and data; whereas the specificity of IO-LCI is limited by the granularity of the IO table. Given that each method has its particular strengths and weaknesses, the hybrid approach combines the two methods to minimize the weaknesses of each and take advantage of their strengths [46, 20, 31, 40, 47, 48, 49, 50].

Suh and Huppes [51] define three types of hybrid analysis: tiered hybrid, IO hybrid, and integrated hybrid. A tiered hybrid methodology uses process data for upstream use-phase and end-of-life calculations, and supplements the downstream calculations with IO data. In a tiered hybrid methodology it is unnecessary to combine the process and IO data in a single matrix, although it is possible. The IO hybrid methodology essentially disaggregates an existing category in the IO matrix into multiple more specific categories – the resulting table is then used as it would be in the tiered hybrid approach. Integrated hybrid LCI establishes a matrix representation of all system flows and utilizes the IO portion of the matrix to complete process LCA cutoffs.

Each of these mathematical representations of Hybrid LCI can be thought of in one of two ways: either process data is augmented with IO data to provide a comprehensive analysis, or IO data is modified by process data to provide specificity. The former of these is a bottom-up approach to hybrid and the second is a top-down approach.

We utilize the top-down approach, where IO data is used to determine critical components of a product's supply chain, which are then further scrutinized for supply chain decision making. The hybrid methodology is ideal for the goal of this dissertation to ensure a comprehensive supply chain analysis including GHG emissions associated with both transportation and electricity in a supply chain. We will utilize regionally modified IO data for electricity emissions estimates, and process LCA data for transportation GHG estimates. Further details will be given in Chapter 4.

Table 2.1: Global warming potential of GHG common gases.

Gas	20 Year GWP	100 Year GWP	500 Year GWP
CO_2	1	1	1
CH_4	62	23	7
N_2O	275	296	156
SF_6	15100	22200	32400
$HFCs$	40-9400	12-12000	4-10000
$PFCs$	3900-8000	5700-11900	8900-18000

2.1.2 Greenhouse Gas Emissions Impact Assessment

Because we are focused on GHG emissions, some discussion of the impact assessment phase of a GHG LCA is necessary. Here environmental flows quantified in the inventory phase are sorted into different environmental concerns and then characterized into a single "equivalency" metric.

There are numerous emissions that are classified as greenhouse gases, including: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), hydrofluorocarbons ($HFCs$), and perfluorocarbons ($PFCs$). Each of these gases has a different ability to absorb and trap heat in the atmosphere. To capture this variation, researchers have determined the global warming potential (GWP) of each GHG relative to CO_2. All GHG emissions can then be aggregated and reported in terms of their net GWP; units are often given in pounds, tons, or kilograms of CO_{2eq}. Table 2.1 shows conversion factors for the six major categories of GHG emissions as given by the IPCC [16].

In technical terms, "The GWP has been defined as the ratio of the time-integrated radiative forcing from the instantaneous release of 1 kg of a trace substance relative to that of 1 kg of a reference gas" [16]. In mathematical terms, this GWP calculation is as shown in equation 2.6, where a_x is the radiative efficiency per unit mass of the gas in question, a_r is the radiative efficiency of the reference gas, and $x(t)$ and $r(t)$ are the decay functions in time for the gas in question and the reference gas, respectively. The reference gas in this case is CO_2; therefore, CO_2 has a GWP or CO_{2eq} of 1. The time-horizon used throughout this dissertation is 100 years, although as shown in Table 2.1, 20 and 500 year time-horizons have also been defined.

$$GWP(x) = \frac{\int_0^{TH} a_x * x(t) * dt}{\int_0^{TH} a_r * r(t) * dt} \tag{2.6}$$

As an aside, there are two other terms that are often confused for carbon-dioxide equivalents in the literature. One is carbon-equivalents, which is fundamentally the same as carbon-dioxide equivalents, except the weight needs to be scaled up from carbon to carbon-dioxide to be equivalent to results reported in carbon-dioxide equivalents (i.e., multiply carbon equivalents by 44/12 to get carbon-dioxide equivalents). The other term to be aware of is given by CO_{2e}, and represents a volumetric (rather than weight based) description of GHG emissions in parts per million.

The remainder of this dissertation uses the terms GWP, GHG, and CO_{2eq} interchangeably in reference to the 100-year time-horizon GWP aggregate of GHG emissions data.

2.1.3 Input-Output Databases

A critical component of hybrid LCA is the IO database and two input-output LCA databases currently exist for the United States: (1) Carnegie Mellon has data freely available on their website at eiolca.net [52] (2) the Comprehensive Environmental Data Archive (CEDA) is available for researchers from Professor Sangwon Suh, currently at the University of California at Santa Barbara [53] [54]. For this research, access was given to the core matrices that create CEDA 3.0, the 1998 version of the Comprehensive Environmental Data Archive. The whole of CEDA includes 480 commodities and service sectors of the United States economy and 1344 environmental flows of which 21 are known greenhouse gases. This made it possible to do the hybrid LCA data manipulation and substitutions that will be necessary throughout this dissertation. For more details on the methods used to derive CEDA as well as the available environmental interventions in the database, please see a paper on the database's development [53] or a user guide written for CEDA 3.0 [54].

Because the CEDA 3.0 database is from 1998, company-specific financials from later years are adjusted to 1998 using the United States producer price index (PPI) inflation factors [55].

2.2 Previous Work on Supply Chain Decision-Making

The detailed discussion on the drawbacks and strengths of each LCA approach led us to a hybrid LCA solution for supply chain analysis. We now introduce previous work on environmental supply chain optimization so the two areas can be brought together in later chapters. Note that these studies are all based on a process LCA approach.

Research on supply chain decision-making can be broadly categorized into two groups: (1) operational (day-to-day) decision-making (2) strategic (long-term) decision-making. Operational decision-making looks at production sizes, transfer sizes, changeover times, inventory levels, and scheduling. Strategic decision-making considers aspects of reuse, re-manufacturing, differences in providers, and supply chain layout. The focus of this dissertation is on supply chain layout. More specifically, we are interested in where to locate facilities and how the choice of location influences transportation and electricity emissions. There is likely further opportunity for GHG reduction by considering all aspects of supply chain tradeoffs in future work.

Economic methods for supply chain optimization have focused on modeling to understand appropriate cost reduction strategies given multiple goals of inventory reduction, responsiveness, customer satisfaction, production flexibility, and lead times [56]. Similar work has also been conducted for reverse logistic systems comprised of take-back, recycling, and remanufacturing [57]. Analysis methods have primarily considered minimizing transport distances, inventory levels, or lead times.

Previous environmental supply chain work has either simply highlighted that research is needed in this area, or investigated multi-objective metrics to reduce environmental impacts. Durham [58] highlighted the need for environmental management of the entire manufacturing cycle. O'Brien [59] argued that industry had to play a pivotal role in ensuring sustainable development in society. Zhou et al. [60] investigated ways to incorporate sustainability considerations into the economic decision-making process with the use of an analytic hierarchy process (AHP), where weighting factors were used to determine a single metric that was then minimized across the supply chain. Weaver et al. [61] discussed the potential re-structuring of paper producer locations based on recycling collection sites, virgin pulp producer locations, and customer locations. Westkamper et al. [62] argued the need for a sustainable manufacturing strategy and discussed several approaches for life-cycle management and its application in sustainable manufacturing. Daniel et al. [63] focused on supplier location relative to the way local weather and geographic conditions (humidity, rainfall, airflow) affect the fate and transport of emissions to the environment. Neto et al. [64] wrote about the possibility of using multi-objective programming to create an optimal supply chain and demonstrated the approach on the pulp and paper industry. Among the previous research reviewed here, Neto's is the closest to ours; however, it is not clear where his regionalized data comes from and he does not use a hybridized approach to ensure key parameters are included in the optimization. Finally, Lenzen and Wachsmann [65] demonstrated that there is a wide variability in the GHG emissions of wind turbine manufacturing depending on the manufacturing location, but they did not suggest the possibility for global optimization.

One of the most studied supply chain tradeoffs is that of virtual water [66, 67, 68, 69, 14]. Virtual water is the water required to manufacture a product and could also be called embodied or embedded water. Researchers have imagined a global trade in virtual water where water intensive resources such as agriculture are located strategically where water is plentiful rather than always produced locally to ensure self-sufficiency.

Our discussion of GHG tradeoffs is very much in-line with the notion of virtual water trade, where we propose that electricity intensive goods be manufactured in regions with low GHG-electricity. This is contrary to the notion that we should be only buying our goods and food from local providers to minimize environmental impact and that "food miles" are an appropriate proxy for environmental impacts. Recent research has shown that local is not always better, and "food miles" are not a good proxy for environmental impact [70, 71, 72]. We extend this point here from just food to all manufacturing thus moving towards two points of this dissertation: (1) using one environmental metric as a proxy for another does not work (2) local is not always better.

Chapter 3

Environmental Metrics Design for Decision-Making

Metric development is a critical component in any strategy to enable effective decision-making. It has been stated that GHG emissions measurements and reductions have been chosen as the goal of this dissertation. However, here we develop a methodology to validate that choice for the case studies that will come at the end of this dissertation. It is important to understand how the metric was chosen and how to choose a metric in alternative situations. The reader should understand why GHG emissions were chosen and whether this choice is similarly applicable to their needs.

One of the first definitions to be very clear about is the difference between a "green" and a "sustainability" metric. In simplistic terms "green" metrics are relative to something in the past - showing an incremental improvement today relative to activities in the past. "Sustainability" metrics look to the future, or the environment's ability to provide or absorb the environmental flows from the studied system indefinitely. Green metrics indicate a measured value (e.g., dollars, tons of CO_2, joules of energy) per functional unit of a process, good, or service. Reducing the measured impact is "green" but not necessarily "sustainable". "Green" metrics do not indicate whether the rate of consumption or emissions have achieved a level that can be continued indefinitely. Sustainability metrics indicate the performance of a system or process in maintaining a sustainable level of a specific resource (such as air, or clean water).

"Sustainability" is here understood as the ability of an entity to "sustain" itself into the future without impacting the capacity of other entities in the system to sustain themselves. This definition involves consideration of three main drivers: economics, society, and the environment. The first of these, economics, has traditionally been the focus of the manufacturing research community. Societal concerns have been addressed by researchers as they relate to profit, however, additional social metrics to be considered include poverty, gender equality, nutrition, child mortality, health, education, housing, crime, and employment [73]. Aggregated indices that provide a broad value for "wellbeing" or "environmental sustainability" have also been developed [74]. While these social and aggregate metrics are valuable to make broad decisions, they may not allow for the granular insight and decision-making that is needed within the manufacturing enterprise.

Although sustainability encompasses economics, society, and the environment, here we will specifically discuss metrics related to the environment and environmental sustainability. Environmental metrics are a useful starting point for discussions of sustainability as they often map to societal and economic concerns. Moreover, reducing environmental impacts can reduce costs or increase profit in ways that are unrealized by simple cost analysis. For example, energy cost savings, the reduction of future cleanup or abatement costs, and improved brand image can all come from environmental analysis. Societal concerns, such as health and sanitation, may also be addressed through reduced environmental impacts.

A challenge in selecting metrics for sustainable or green manufacturing is that it is not an inherently intuitive process. Unlike economic or engineering metrics, such as unit cost or part quality, sustainability metrics are not necessarily related to the function of the part being manufactured. Additionally, a complete picture of environmental impact and sustainability requires numerous metrics. However, time and cost considerations limit the number of possible metrics that can be practically considered in a manufacturing analysis. Choosing an appropriate set of metrics is critical as this choice will impact the conclusion of the analysis. For example, Schweimer and Levin [75] conducted an environmental life-cycle assessment of automobile manufacturing and found that 81% of $\mathrm{CO_2}$ emissions occur during the vehicle use phase, 88% of non-methane VOC (volatile organic compound) emissions occur in the fuel production phase, and 83% of dust emissions occur during the vehicle manufacturing phase. If practitioners only measured CO_2 they would be falsely led to assume all other phases are not as impactful; therefore, it is important not to assume any environmental metric is a suitable proxy for another. Selecting appropriate metrics depends upon the utmost clarity on the goal of the environmental assessment and the aspects that are important for a specific industry or world region.

There has also been extensive work in the manufacturing community in characterizing the impacts of specific manufacturing processes and technologies. Dahmus and Gutowski [10, 76] presented a detailed analysis of the environmental impact of machining, taking into account the material removal process as well as the use of cutting fluid and other consumables. Jeswiet and Kara [77] proposed a calculated carbon emission signature for correlating electrical energy use to the GHG emissions of a number of traditional manufacturing processes. Morrow et al. [78] presented a detailed study comparing the environmental impacts of tool and die machining using conventional and laser-based processes. They identified the complex economic and environmental tradeoffs that needed to be made in selecting the most suitable processes for different types of mold designs. Roman and Bras [5] investigated the water and energy consumption of industrial cleaning processes. Jayal et al. [6] investigated the relative health risks associated with mist versus flood cooling. Zhao et al. [9] considered methods to filter and recycle used cutting fluids. Nasr and Thurston [11] have done extensive work characterizing and understanding the remanufacturing of goods. Dornfeld and Wright [79] identified "wedge technologies" to enable the implementation of green manufacturing, where a wedge technology is one that is both scalable and offers a net environmental benefit when implemented.

Furthermore, Gutowski et al. [12] presented a seminal overview of the status of environmentally benign manufacturing technologies in the United States, and compared them to technology in Europe and Japan. The report discussed the competitiveness of US manufacturing practices and identified areas of focus for the US manufacturing industry to improve its environmental impact. Westkamper et al. [62] argued the need for a sustainable manufacturing strategy and discussed several approaches for life-cycle management and its application in sustainable manufacturing. Durham [58] highlighted the need for environmental management of the entire manufacturing cycle, taking into account both global and local effects and the consumption of materials in all parts of the cycle. O'Brien [59] argued that industry had to play a pivotal role in ensuring sustainable development in society and stressed the need for sustainable production systems to this end.

While the environmental studies and metrics used by manufacturing researchers allowed for the identification of hot-spots for reduction, they do not provide the necessary insight for true decision-making. We can look to the world of financial metrics to understand this point. Current environmental metrics are essentially in the phase of "how much does it cost". We need to move forward to "return-on-investment", and "payback time" type metrics for decision-making.

3.1 Metric Selection/Design Methodology

We propose the following 4-part methodology to develop effective environmental metrics [80]. Metrics are identified based on the particular environmental concerns being addressed in the study. Colloquially, we are looking for "the right tool for the job" as it is difficult to conceive an absolute "best" metric. Additionally, this methodology is intended to be flexible and modular over time, which is important given that the effectiveness of the metric is determined only by its usefulness in a specific context. Determination of appropriate metrics is inherently influenced by current "social value, knowledge horizons, and individual perspectives" [81]. Figure 3.1 shows an overview of the metric selection process.

It should be noted that this methodology follows the ISO 14040 standards on life-cycle assessment [17]. The four main steps of life-cycle assessment are goal and scope definition, inventory analysis, impact assessment, and interpretation of results. With this methodology we are essentially performing the first step of ISO 14040 as it is relevant to metric selection. Steps 1 and 2 define the metric's goal, while steps 3 and 4 determine scope.

Step 1: Goal Definition - Determine the goal of the assessment.

This first step requires an understanding of the environmental concerns driving the effort and the needs of stakeholders at multiple levels both internally and externally. Furthermore, if a technology is new, or requires the processing of new materials that are poorly understood, then a comprehensive assessment employing a suite of metrics may be necessary. However, if we are studying specific impacts or the consumption of particular resources, then it is adequate to only highlight these concerns. Care should be taken to not overly simplify the assessment goals; however, with enough information, simplification and scope reduction at this stage can be useful in reducing the time and costs needed for the assessment.

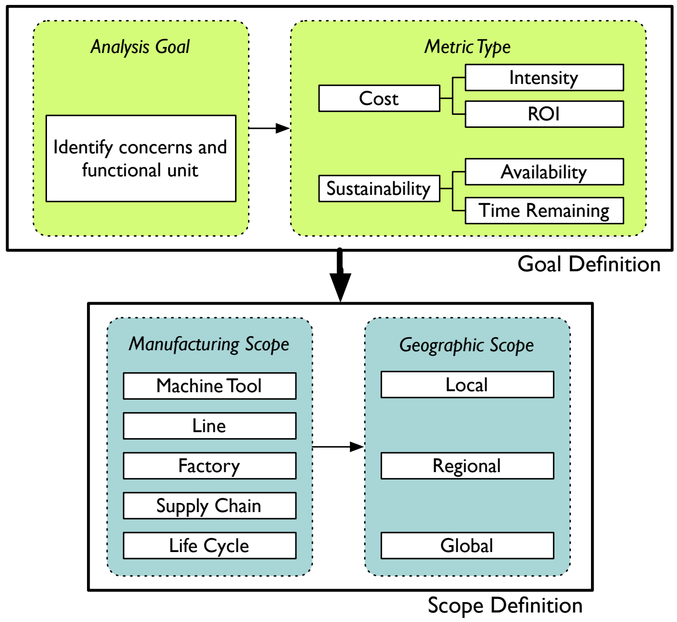

Figure 3.1: Metric design methodology

Step 2: Goal Definition - Choose a metric type.

Generally, metrics for environmental decision-making can be classified as either "green" or "sustainability" indicators. Here, these categories are further broken down into four distinct metric types (summarized in table 3.1).

The first two metric types are analogous to familiar cost metrics. First are the *intensity* metrics, which indicate the cost per functional unit. Second are *return-on-investment* metrics that indicate the savings of a particular investment relative to the input required for the investment.

The third and fourth metric types are based on sustainability concerns relative to resource availability; and are an area requiring further research. Use of resources that are considered "renewable" can be characterized by an *availability factor*, which indicates consumption relative to replenishment rates. The availability is the "amount of resource use" relative to the "total resource availability" in a given time period. This is comparable to machine tool availability metrics used in measuring the efficiency of manufacturing systems.

Furthermore, one way to quickly understand the risk associated with using non-renewable resources is by calculating the *time remaining* of the resource given current consumption patterns and available reserves. While these metrics are useful on a global or local scale, they may be difficult to implement in practice because they require knowledge of other people's use of the resource being considered, not just direct consumption or emissions. Because this value does not enable decision-making at all levels of production, it highlights the need for metrics to understand resource consumption as an important area for future work.

Table 3.1: Overview of metric types. (Impact: monetary or environmental cost; LC: total life-cycle; BAU: business as usual; Investment: replacement for BAU; Use: rate of consumption; Stock: amount available for consumption; SA: sustainable available stock.)

Metric Type	Units	Metric Formulation
Green - Intensity: cost or environmental impact per unit of production	$\frac{Value}{Unit}$	$\frac{Impact_{Investment}}{Functional\ Unit}$
Green - Return on Investment: savings relative to amount emitted/consumed	$\frac{Savings}{Investment}$	$\frac{Impact_{BAU}-LC_{Investment}}{LC_{Investment}}$
Sustainability - Availability Factor: fraction of available resources consumed	$\frac{Used}{Available}$	$\frac{Use_{Investment}}{SA-Use_{GeographicRegion}+Use_{BAU}}$
Sustainability - Time Remaining	$Time$	$\frac{Stock_{GeographicRegion}}{Use_{GeographicRegion}(1-RecyclingRate)}$

Step 3: Manufacturing Scope Definition.

While it is always important in the development of green technologies to consider the life-cycle of the technology – which includes material extraction and conversion, industrial facilities usage, process consumables usage, manufacturing process impacts, supply chain and transportation impacts, product use, and end-of-life – decision-making must often occur on a smaller scope within the larger process. To assist in this effort, we can consider manufacturing across two orthogonal frameworks, spanning spatial and temporal levels of complexity (see Figure 3.2).

Spatially, we can consider manufacturing to span four levels – from the level of the individual devices where unit processes take place through to that of the supply chain. These levels are:

1. Product: At this scale, the product is designed and decisions on materials, modularity, and functionality are made that will influence all remaining decisions throughout the supply chain, manufacturing, and end-of-life.

2. Machine/Device: Defined as an individual device, machine tool, or a logical organization of devices in a facility acting in series or parallel to execute a specific activity, this level includes support equipment such as gage systems, device level oil-circulating systems, etc. Control of lubrication systems and minimum quantity lubrication (MQL) are examples of decisions for sustainable manufacturing at this level. Metrics at this scale reflect the functionality of the machine tool (e.g., emissions per minute or energy

consumption per part). The "ripple" effects of decisions taken at this scale must be considered by analyzing subsequent manufacturing operations (e.g., using MQL could necessitate additional cleaning operations).

3. Facility/Line/Cell: Here the entire factory is incorporated, including support equipment required at the facility level such as power generators, water purifiers, heating and cooling (HVAC) systems, chip conveyers, and tool cribs. For example, the total water and energy consumptions of a semiconductor facility must take into account HVAC and clean-room systems [82].

4. Supply Chain: This level includes the entire manufacturing supply chain, including individual facilities, the infrastructure required to support the facilities, and transportation. At this scale, metrics need to capture the interrelationships between discrete geographical entities in the system and the effect of complex transportation and communication networks [83]. Metrics development for the factory and supply chain scales should also be aware of local, national, and international standards because an economic cost can be associated with these.

5. Life-Cycle Scale: The final level goes beyond the supply chain to include product use and end-of-life decisions. This also includes the supply chains associated with consumables throughout the use-phase, operation and maintenance of the product or service being analyzed, and end-of-life.

Temporally, we can also consider manufacturing to span four levels – from product design through manufacturing and post-processing. These levels are:

1. Product Design: At this stage there is the most opportunity to influence environmental impacts and decisions throughout all future stages. Critical decisions on part precision, materials, and design for assembly/recycling are made, which will influence manufacturing, use, and end-of-life options. Note that there are multiple levels under product design that are being compressed into a single level here for the manufacturing discussion, including functional design, detailed design, and product adjustments

2. Process Design: The product design is fixed; however, here a manufacturing process to suit this design is created. Flexibility to optimize the system is limited to known tools and processes that work with the specified design. Here there is extensive control over the performance of the process in all the criteria as allowed by the product design.

3. Process Adjustments: The basic manufacturing process is fixed but small changes to the process through process parameter selection and optimization is used to control the critical features such as precision, burr formation, and energy or consumable consumption.

4. Post-Processing: Post-process finishing and abatement processes are used in controlling the part-precision and the environmental impact; at this level there is no control over the manufacturing process as it has already been designed.

Figure 3.2 illustrates the interaction between the four temporal and spatial levels. Moving up and to the right in the figure means a loss of decision-making flexibility and impact. For effective decision-making, we need to understand both what quality and quantity of information is available at each level and how decisions will trickle to levels elsewhere in the system. Also, notice that each scale incorporates the effects of lower scales [84]. For example, the supply chain scale includes all the factories throughout the system, plus transportation and logistics. The factory scale includes all of the product lines as well as extraneous factory requirements such as HVAC and overhead. The line scale includes all machines in the line plus transport between machinery. Given the complexity of decision-making across these scales, it is critical to clearly identify at which scale (or scales) the metrics are going to be applied. It may not be possible to select a metric that is relevant or applicable across all the scales; however the farther down and to the left the measure is taken the more strategic the metric will be.

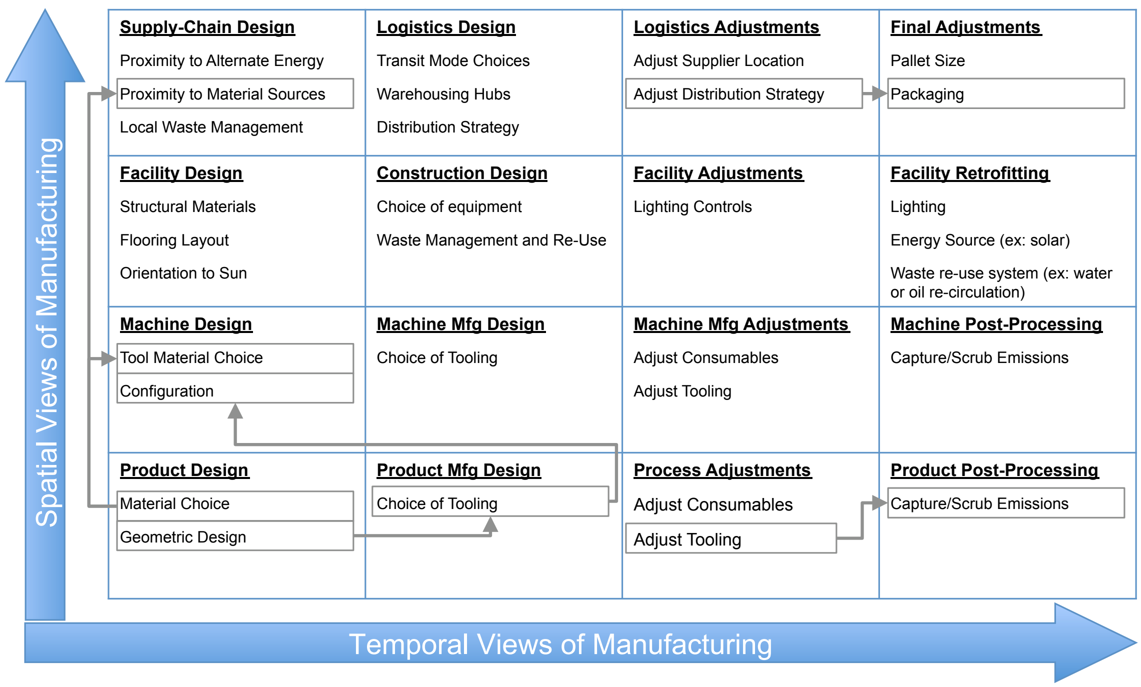

Figure 3.2: An integrated view of manufacturing design levels and the decisions they contain. Arrows represent the flow of information from one decision to another.

Step 4: Geographic Scope of Environmental Concern.

Metric design also requires understanding the geographic range of the environmental concern. Environmental impacts may be highly localized or globalized. For example, GHG emissions can affect global climate change regardless of where they are released. However, if electricity supply is scarce in one location, excessive use of electricity elsewhere is neither harmful nor helpful to the local scarcity. This decision may influence, for example, the normalization factor of the metric selected. For example, factory energy use can be expressed relative to global resource availability or relative to a region's current energy capacity.

Chapter 4

Iterative Financial Hybrid LCA

Chapter 2 provided a review of LCA methodologies and Chapter 3 discussed how to use metrics design and goal formulation to decide what to measure in the LCA. Here we go into the specifics on how to use hybrid LCA to set up the electricity and transportation tradeoffs that will be discussed in Chapter 5. All of this will be brought together in the SolFocus case study in Chapter 6.

4.1 Methodology

The iterative hybrid approach utilized in this dissertation starts with financial data as a way to capture amortized embodied machinery emissions, overhead, scrap, purchased materials, and purchased services. This approach has been discussed by Suh et al. [47], Tukker et al. [85], and Erickson [86]. The iterative hybrid LCA is an effective method to develop a roadmap for additional more detailed LCA work or decision-making. In our case, the iterative hybrid approach is used to establish key areas where regional electricity factors and transportation emissions tradeoffs could lead to GHG reductions.

The financial hybrid approach is extremely effective for both past and future GHG estimates and is ideal for a company that is not yet in production but has already created detailed cost estimates of future products. Where process LCA data is unavailable, these detailed cost estimates are often the only way to ensure all inputs to the product are counted. Additionally, cost data is generally better organized and verified than environmental data in a company.

This is a top-down methodology. It differs fundamentally from traditional bottom-up approaches in that it does not require the practitioner to make an educated guess as to what is or is not important for inclusion in the analysis. This guesswork risks wasted effort on obtaining detailed data for products or processes that turn out to be insignificant or potentially overlooking a product or process that may be more significant. Essentially, the methodology creates a robust framework for the appropriate and efficient use of process-based LCA and supply-chain decision making. Three iterations that could occur with this methodology are illustrated in Figure 4.1, where the final step in this approach is to focus supply chain layout efforts on those specific purchased goods and services that are (a) large contributors to the footprint and (b) have a significant electricity or transportation component to their emissions that may be worthy of further reductions.

The lowest level of the hybrid analysis is IO and cost inputs where processing data is not available; therefore, data availability determines how many levels there are to the supply chain analysis. This makes this method particularly useful in the development of a new technology where initially many parts are purchased goods but as manufacturing ramps up and parts production moves in-house, additional data specific to processing can be incorporated into the model. Data availability, time constraints, and materiality to the results will effect the levels of supply chain included.

4.2 Data for Electricity and Transportation Tradeoffs

The hybrid approach as described above requires input-output data that can be used for the first iteration of the assessment, followed by adjustments using regional electricity factors and transportation emissions data for supply chain layout design. This section goes into detail on how the IO electricity values are extracted and regionalized, along with a summary of previous work on transportation emissions.

4.2.1 Input-Output Regionalized Electricity

Researchers have looked into ways to develop regionalized input-output databases or modify the US input-output database for other locations. For example, Cicas et al. investigated the use of state-level input-output data along with environmental information to develop US regional input-output tables [87]. Huppes et al. [88] and Tukker et al. [85] utilized CEDA3.0 along with input-output data and environmental data from the European Union (EU) to develop an EU based environmental IO dataset. However, in this dissertation we will simplify the problem by only considering electricity mix tradeoffs and leave research on other regional variations to future work.

Extracting Electricity data from the IO database

To adjust the electricity portion of the IO data from the United States average to another region first requires extracting the electricity portion of the total GHG emissions from the dataset for the industry sector being analyzed. We find there are two different ways to extract the electricity emissions. The traditional equation to get a vector of results broken apart by industry is $Bdiag(Tf_1)$, where $T = (I - A)^{-1}$, where f_1 is a vector that has only one nonzero value. This is currently the method used on Carnegie Mellon's eiolca.net website and is the same method that was presented in section 2.1.1. In this method, each element of the resulting vector is the sum of the direct emissions associated with that industry everywhere the industry has emissions across the supply chain. To make this point clearer, consider a simple example:

Imagine an economy that consists of only two sectors: meat and electricity. B_1 represents the direct GHG emissions per dollar spend on meat. B_2 represents the direct GHG emissions per dollar spend on electricity. A_{ij} is the direct spend on sector i as a result of a dollar spent on sector j. T_{ij} is the total spend in the economy on i as a result of a

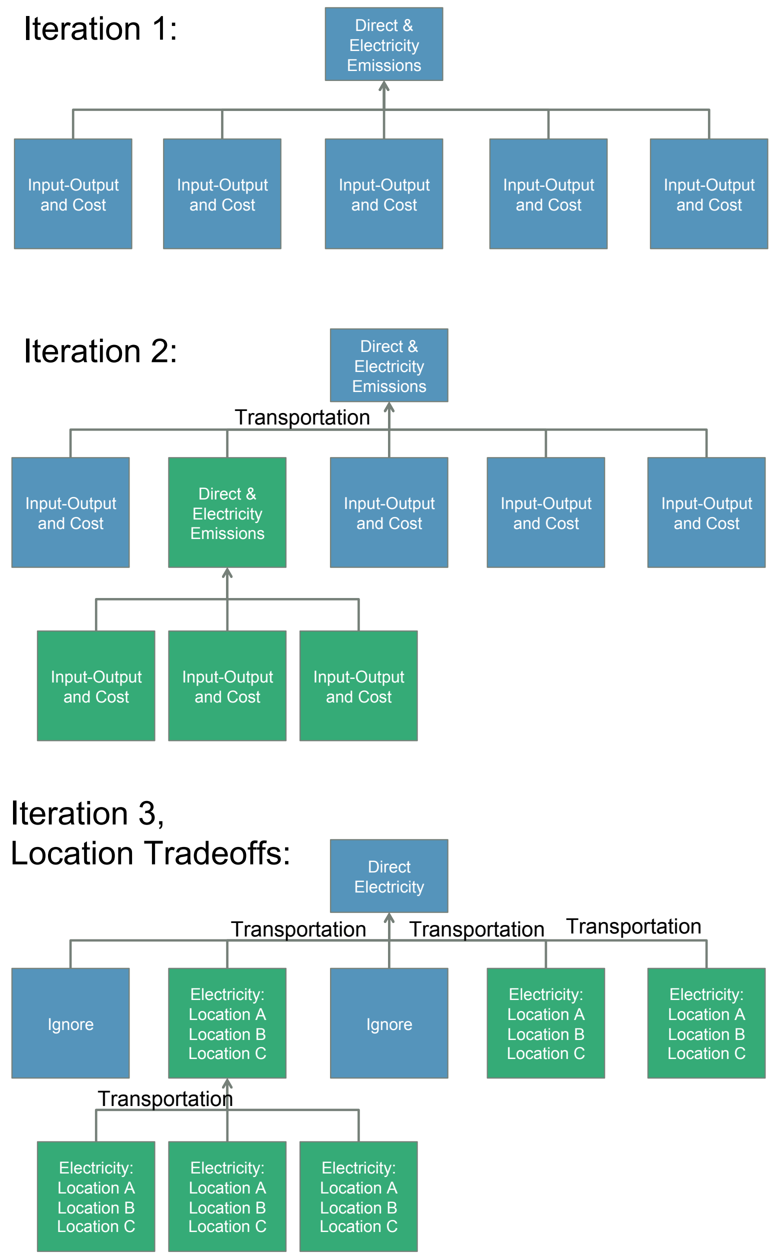

Figure 4.1: Three iterations of the iterative financial hybrid LCA.

dollar spent on sector j. f_1 is our demand vector indicating that we are interested in the emissions associated with spending one-dollar on meat.

In this example we are interested in examining the electricity emissions that occur when we spend one dollar on meat; this results in:

$$T = \begin{pmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{pmatrix} \tag{4.1}$$

$$f_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \tag{4.2}$$

$$B * diag(Tf_1) = \begin{pmatrix} B_1 & B_2 \end{pmatrix} \begin{pmatrix} T_{11} & 0 \\ 0 & T_{21} \end{pmatrix} = \begin{pmatrix} B_1 T_{11} \\ B_2 T_{21} \end{pmatrix} \begin{array}{l} meat \\ electricity \end{array} \tag{4.3}$$

We see in this result that the electricity emissions are simply B_2T_{21}, which is the multiplication of the total spend on electricity anywhere in the supply chain with the direct emissions associated with electricity per dollar. This means that we are capturing all direct emissions associated with electricity everywhere in the supply chain, but we are not capturing emissions from electricity's purchase of meat. All of meats emissions, even those that result from electricity's purchase of meat, are summed in B_1T_{11}. Therefore, summing this vector provides all direct and indirect emissions associated with the dollar spent on meat; however, each individual element of the vector is a rather nonsensical quantity for supply chain analysis.

Instead, imagine that when we look at the second element of this vector to determine "electricity emissions" associated with the purchase of meat, this value should tell us the emissions associated with the meat-producer's purchase of electricity and the supply chain upstream from that purchase. We want the "electricity emissions" value to include the fact that the electricity we are buying includes meat emissions. Figure 4.2 illustrates the difference between the two approaches for electricity in a fictitious furniture supply chain.

Using our simple example of the economy in terms of meat and electricity, we will develop the alternative calculation for electricity, which includes electricity's purchase of meat. To calculate the total supply chain emissions associated with electricity, we want to calculate BTf_{elec} where f_{elec} has only one non-zero value, which represents the spend on electricity as a result of a dollar spent on meat. In mathematical terms, f_{elec} is the spend on electricity from the meat column of A, or $(0\ A_{21})^T$ extracted from equation 4.4.

$$Af_1 = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} A_{11} \\ A_{21} \end{pmatrix} \tag{4.4}$$

Furthermore, we want to know what the spend of A_{21} on electricity will create in total GHG emissions across the supply chain, which is calculated as

$$BTf_{elec} = \begin{pmatrix} B_1 & B_2 \end{pmatrix} \begin{pmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{pmatrix} \begin{pmatrix} 0 \\ A_{21} \end{pmatrix} = \begin{pmatrix} B_1 T_{12} A_{21} + B_2 T_{22} A_{21} \end{pmatrix} \tag{4.5}$$

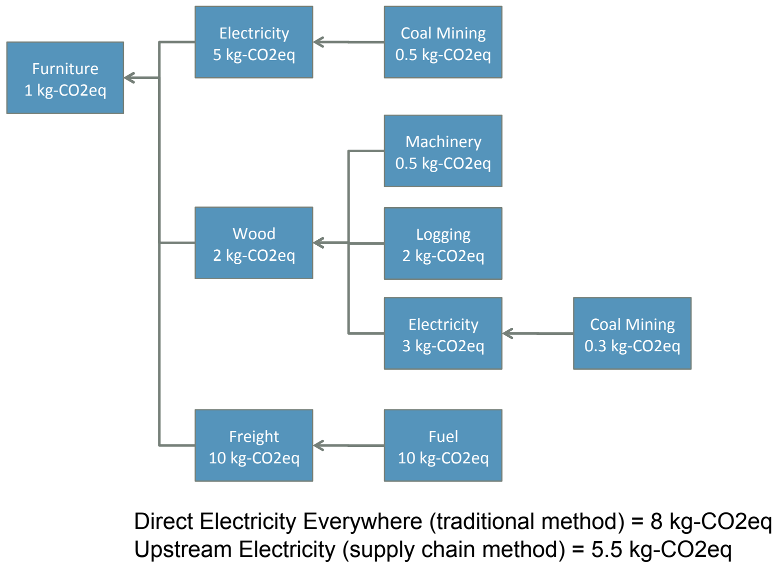

Figure 4.2: Traditional representation of electricity emissions versus supply chain representation

More formally, this method for presenting results can be written as shown in equation 4.6.

$$UpstreamEmissions = BTdiag(Af_1)) \tag{4.6}$$

We can already see this is a very different result than that given in the traditional calculation of GHG emissions for electricity, which resulted in B_2T_{21} emissions from electricity and failed to take into account the emissions associated with the fact that the electricity industry purchases meat. Instead, this new method tells us the emissions from electricity associated with a dollar spent on meat are $B_1T_{12}A_{21} + B_2T_{22}A_{21}$, where the presence of B_1 in the equation represents the meat emissions associated with electricity production.

To summarize, we are interested in knowing the electricity emissions associated with spend on a single sector. The calculation given in equation 4.6 results in a matrix where every row represents the total environmental interventions associated with the first tier spend and all upstream emissions associated with that spend. The formulation that is presented, however, does not include "direct" emissions from the sector that is being analyzed. For example, direct emissions from the meat industry are not represented (except where they occur further upstream as a result of first-tier spending by the meat industry). To rectify this and obtain a comprehensive result, direct emissions from meat, for a dollar spent on meat, can be calculated as Bf_1.

To ensure this result is consistent, we can check that the two methods produce the same final value:

$$BTf = BIf + BTAf$$

$$T = I + TA$$

$$(I - A)^{-1} = I + (I - A)^{-1}A$$

$$I = (I - A) + A$$

$$A = A$$

The difference in the results for electricity emissions for each method is demonstrated in Figure 4.3, which shows the results using both calculations on CEDA3 data for selected manufacturing industries. It becomes clear, then, that the choice of method for quantifying results can have staggeringly different results on determining electricity emissions for a given industry.

Regionalizing electricity emissions

With the understanding that there are essentially two ways to calculate the electricity throughout a supply chain from an IO database, we now need to regionalize these electricity emissions to a local electricity mix.

Electricity emissions can be scaled to a non-U.S. value using data on the local electricity GHG emissions (GHG/kWh). We assume that all other sectors and their interdependencies in the IO-database are constant between locations. Equation 4.7 translates a U.S. based EIOLCA $GHG/\$$ value to a $GHG/\$$ value in Country "A" where GHG_{PG} are the GHG emissions of power generation as given in EIOLCA and $(\frac{GHG}{kWh})_A$ are the GHG emissions per kWh produced in country A.

$$(\frac{GHG}{\$})_A = (\frac{GHG_{total} - GHG_{PG}}{\$})_{US} + (\frac{GHG_{PG}}{\$})_{US}(\frac{(\frac{GHG}{kWh})_A}{(\frac{GHG}{kWh})_{US}}) \tag{4.7}$$

4.2.2 Electricity Emissions Data

In order to utilize the methods discussed in section 4.2.1 to convert electricity data from a U.S. appropriate value to a regional value, reliable data on regional electricity emissions factors is needed. The environmental impact of electricity generation is dependent on electricity distribution efficiencies, energy conversion efficiencies, and the mix of technologies producing electricity. There are multiple data sources and methods to determine regional electricity emissions factors. We will review and compare these datasources here.

Figure 4.4(a) shows the GWP for electricity generation in countries with available data through the EcoInvent database [89]. France has the lowest GHG emissions per kWh because 78% of their electricity generation is nuclear and 12% is from renewables such as wind, solar, and hydro electricity [90]; Germany, on the other hand, derives 27% of its electricity from nuclear and 10% from renewables with the remainder coming from the burning of fossil fuels [91]. The US, on the other hand gets 20% of its electricity from nuclear power and only 9% from renewables, with the remainder from fossil fuels [92].

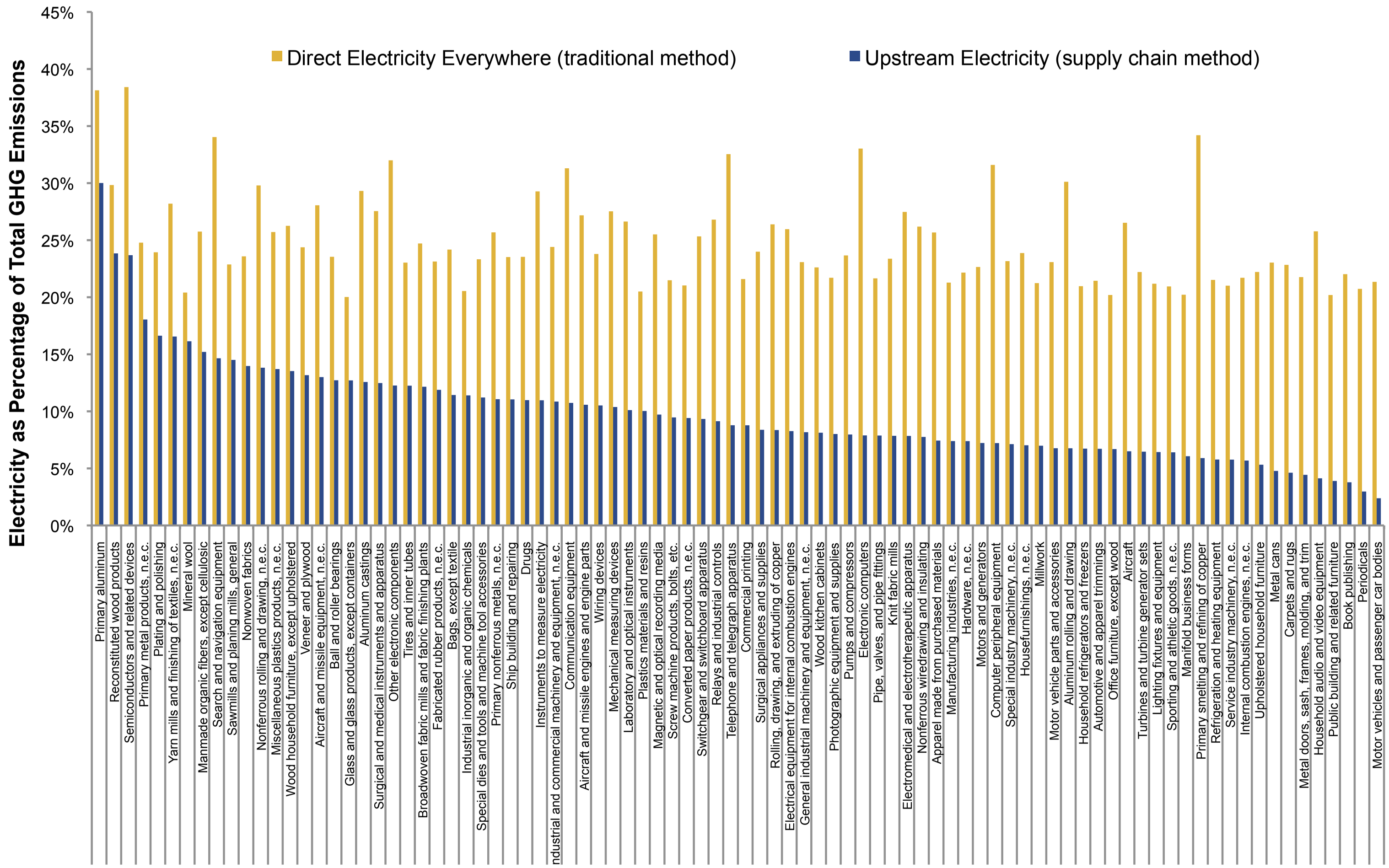

Figure 4.3: Graphical comparison of traditional representation of electricity emissions to supply chain representation

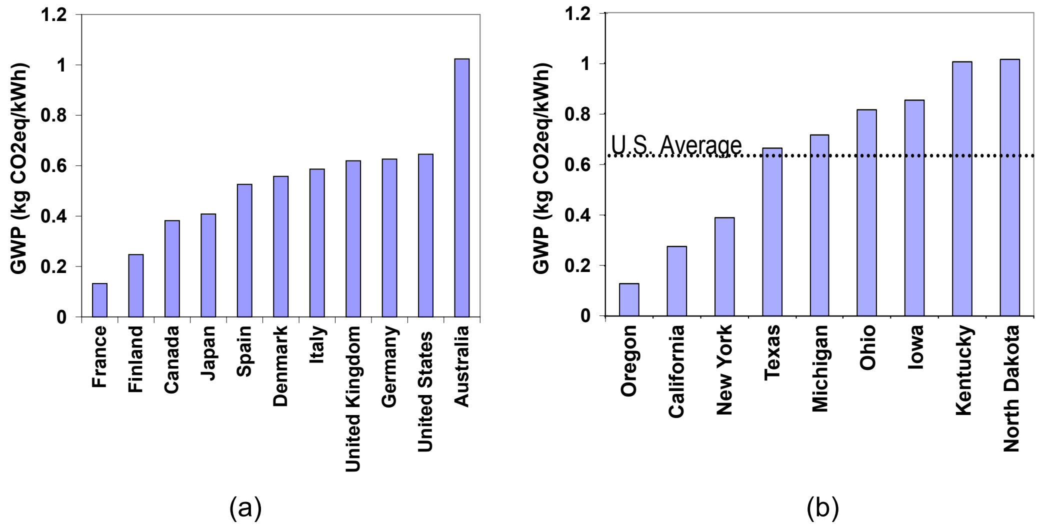

Figure 4.4: Global Warming Potential (a) per kWh of Electricity Consumed [89] (b) of Electricity in U.S. States [93]

Similarly, regional differences within a country can produce variations in the GHG emissions per kWh of electricity demand. This is seen in Figure 4.4(b), for a sample of states within the United States. Again, depending on the energy mix within each state, the emissions vary substantially.

The International Energy Agency also provides data on electricity production, distribution losses, and "own use" of electricity by the producers to run their facilities. The IEA data can be used to calculate estimated GHG/kWh factors for each region. The CO_2 emissions of electricity and heat are provided as a single value by the IEA; however, the electricity and heat production are provided separately. To calculate the GHG/kWh of just electricity, heat production is converted to an equivalent electricity value. It is assumed that fossil fuels are used to first generate heat and then electricity; therefore, because heat does not go through the secondary conversion it has a lower CO_2 per kWh than electricity. It is unknown how much of this comes from cogeneration facilities, which adds further complication, and is ignored here. Aggregation into a single value is done by approximating the heat to electricity conversion efficiency, which is here assumed to be 40% [94]. Equation 2 summarizes the calculation of GHG/kWh, where η is the assumed heat to electricity conversion efficiency.

$$GHG_{ElectricityMix} = \frac{GHG_{Heat,Electricity}}{Electricity + \eta * Heat} \tag{4.8}$$

Table 4.1 shows calculations of GHG/kWh given data from the IEA. Columns A through H are given data points. Column J is a calculation of the GHG emissions for every kWh produced. However, we really want to know the total GHG emissions for every kWh demanded by the end consumer, so losses from production to the consumer must be accounted for. Additionally, the fact that a consumer's demand for electricity causes the

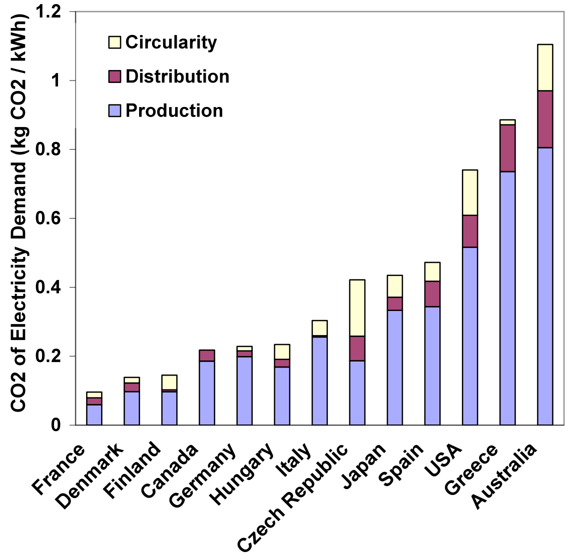

Figure 4.5: CO_2 emissions of electricity generation; supply chain not yet included [95, 96].

power plant to also use electricity (i.e., "own use") must be included. Column N is the total GHG/kWh for every consumer demanded kWh. The CO_2/kWh results based on the IEA data are shown in Figure 4.5.

Finally, the World Resources Institute provides data on country specific electricity GHG factors [97] and the United States Environmental Protection Agency's eGrid factors provide regional electricity factors within the United States [98]. These two datasets are championed by international and U.S. domestic reporting agencies such as the World Resources Institute and EPA climate leaders [99]. The entirety of this data is reproduced in Tables 4.2, 4.3, and 4.4. The eGrid regional codes refer to the regions of the United States as given in Figure 4.7.

It is important to point out that all of these electricity factors are not true life-cycle emissions factors because they only include direct combustion emissions from power plants and therefore ignore upstream, downstream, and non-combustion emissions. For example, France has the lowest CO_2/kWh due to their large percentage of nuclear energy facilities; however, the nuclear energy supply chain may be significant considering the mining and transportation required to supply fuel on a regular basis. The same is true for coal; these emissions calculations do not include the mining, transport, or refinement of coal. Furthermore, emissions from end-of-life are not considered; this may be particularly important for nuclear due to decommissioning and long term fuel storage demands such as cooling, lighting, safety systems, labor, and construction.

Additionally, the WRI and eGrid factors are based on generation by region, not consumption. This means that the total electricity production in the region is divided by total direct emissions from electricity production, which ignores the fact that there is electricity trade between regions, own use of electricity by the producer, and distribution

Table 4.1: calculations of electricity emissions by country based on IEA statistics [95]

A	B	C	D	E	F	G	H	J	K	L	N
Country	Elec. Produced Alone (kToe)	Elec. Produced with Heat (kToe)	Dist. Losses (kToe)	Heat Produced with Elec. (kToe)	Heat Produced Directly (kToe)	Own Use Elec. (kToe)	GHG of Comb. for Electricity (10^6 g-CO_{2eq})	Direct Elec. Emissions (g-CO_{2eq}/kWh)	Own Use Factor	Dist. Factor	Total GHG/kWh (g-CO_{2eq}/kWh)
								$\frac{H*86}{B+C+(E+F)*0.4)}$	$\frac{G}{C+B}+1$	$\frac{D}{C+B}+1$	$J*K*L$
Australia	19400	1179	1257	1179	1465	2232	214	0.85	1.12	1.06	1.00
United States	326942	22761	22805	5638	0	21825	2392	0.57	1.06	1.06	0.65
Germany	45219	7240	2940	13851	14825	5148	366	0.49	1.10	1.06	0.57
Japan	92109	0	4202	0	620	4806	398	0.37	1.05	1.05	0.41
Canada	50732	730	3376	982	0	3872	202	0.33	1.07	1.07	0.38
France	46748	2019	2761	489	146	4905	65	0.11	1.10	1.06	0.13
Poland	191	12928	1234	5236	2883	2469	181	0.95	1.19	1.09	1.24
United Kingdom	31443	2373	2755	0	1354	2460	211	0.53	1.07	1.08	0.61
Spain	20528	3304	2070	0	0	1665	126	0.45	1.07	1.08	0.53
Norway	9454	13	762	91	189	188	13	0.11	1.02	1.08	0.12
Sweden	11931	1113	940	2564	1468	510	12	0.07	1.04	1.07	0.08
Czech Republic	5478	1728	437	2663	0	787	59	0.61	1.11	1.06	0.72
Ireland	2111	57	176	0	0	133	16	0.64	1.06	1.08	0.74
Turkey	12436	524	1999	450	0	615	76	0.5	1.05	1.15	0.60
Italy	18053	7149	1795	4527	0	1914	161	0.51	1.08	1.07	0.59

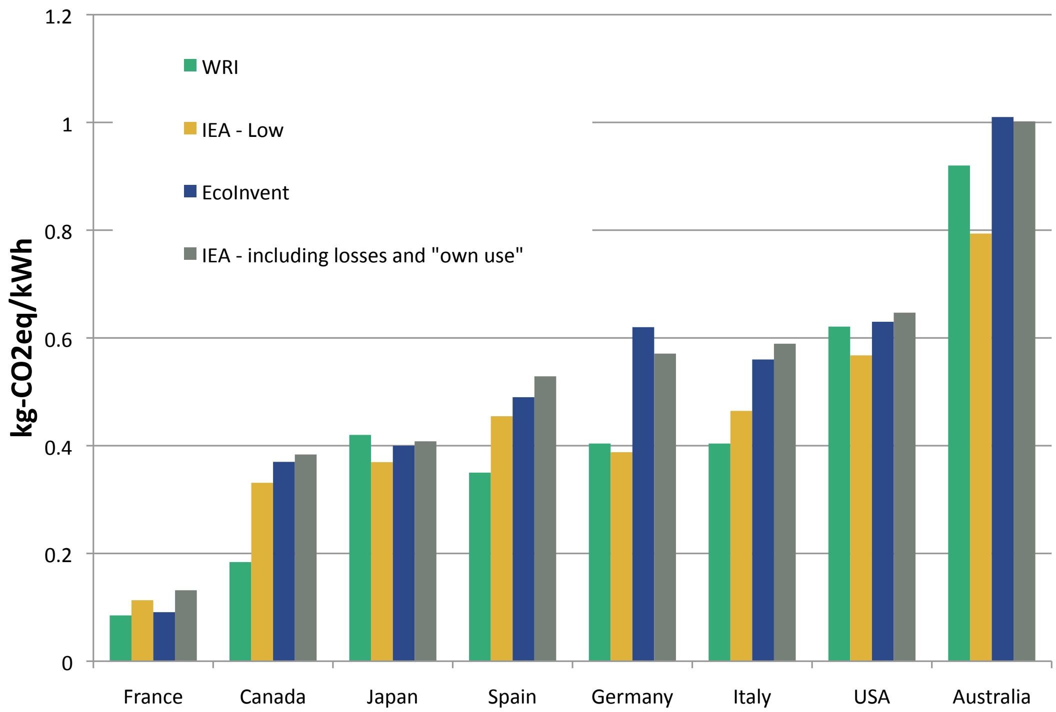

Figure 4.6: GHG emissions of a kWh of electricity - comparison of results.

losses. This also means that adjustments to the mix for the import and export of electricity are not included. Data on total net exports and imports of electricity to each region are known from the IEA, however, it does not say where the electricity goes (when exported) or where it comes from (when imported) so it is not possible for us to create these adjustments. Were that data known, the input-output structure presented in section 2.1.1 could be readily utilized here as well to calculate the comprehensive GHG/kWh for each region. This is one reason eGrid utilizes the regions that are represented in Figure 4.7 to group together states with high levels of inter-state electricity trade. For all of these reasons, when WRI or eGrid factors are used in later chapters, large uncertainty ranges will be introduced to acknowledge that the data is likely under-reporting total emissions.

To summarize this discussion, a comparison of results for select countries is shown in figure 4.7. This data is all for 2005. We expect the "WRI" and "IEA-low" (i.e., unadjusted for distribution losses or own use) to be about the same since they are supposedly based on the same data. We also expect the "EcoInvent" and "IEA including losses and own use" to be about the same because EcoInvent is based on a full LCA of the system. These expectations are roughly reflected in the comparison table but do not hold across all of the data.

We will utilize WRI data for later case studies, despite its many limitations, because it is most readily available for any country and using a single data-source ensures consistency. However, we see from Figure 4.7 that WRI data appears consistently on the low end of the estimates because of the exclusion of own use and distribution losses. Because of the inconsistency of these calculations and the uncertainty introduced by excluding imported and imported electricity variations, we will include significant uncertainty in all future calculations that utilize this data. This will be critical to ensure decision-making occurs on a solid foundation and is not subject to data input error.

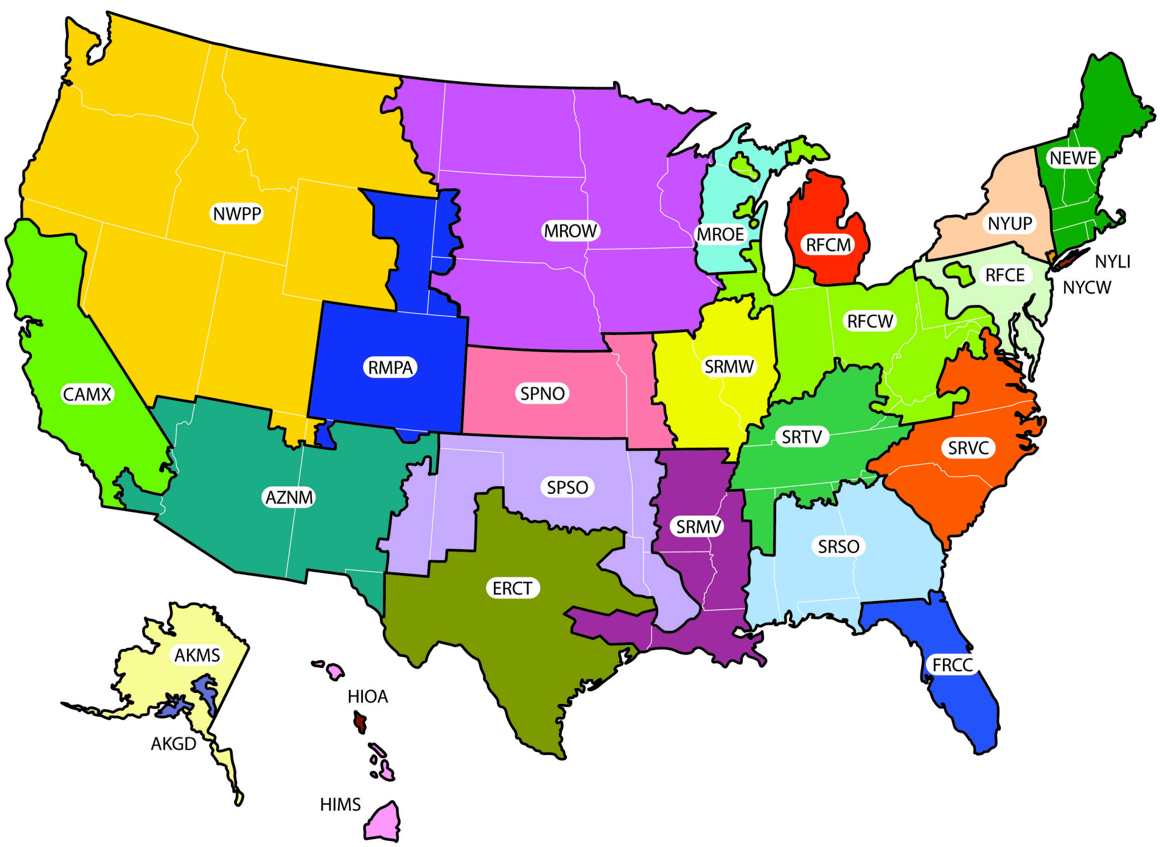

Figure 4.7: Electricity regions of the United States as defined by eGrid. Each color represents a different electricity grid with a different emissions factor. Emissions factors are given in Table 4.4. [98]

Table 4.2: Summary of electricity GHG factors from the WRI - part I [g-CO_{2eq}/kWh]

Albania 34	Algeria 671	Angola 343	Argentina 306	Armenia 138
Australia 873	Austria 225	Azerbaijan 505	Bahrain 890	Bangladesh 557
Belarus 299	Belgium 268	Benin 710	Bolivia 481	Bosnia-Herzegovina 619
Botswana 1848	Brazil 84	Brunei 789	Bulgaria 448	Cambodia 1206
Cameroon 39	Canada 199	Chile 357	China 788	China (& Hong Kong) 788
Chinese Taipei 632	Colombia 163	Costa Rica 27	Cte d'Ivoire 518	Croatia 311
Cuba 987	Cyprus 792	Czech Republic 516	Denmark 284	Dominican Republic 574
Ecuador 369	Egypt 471	El Salvador 263	Eritrea 696	Estonia 665
Ethiopia 7	Finland 194	France 91	Gabon 368	Georgia 89
Germany 349	Ghana 204	Gibraltar 743	Greece 776	Guatemala 384
Haiti 307	Honduras 411	Hong Kong 810	Hungary 339	Iceland 0.6
India 943	Indonesia 771	Iran 534	Iraq 701	Ireland 584
Israel 767	Italy 405	Jamaica 713	Japan 429	Jordan 660
Kazakhstan 1140	Kenya 310	N. Korea 520	S. Korea 418	Kuwait 807
Kyrgyzstan 82	Latvia 162	Lebanon 667	Libya 899	Lithuania 130
Luxembourg 330	Macedonia 645	Malaysia 557	Malta 892	Mexico 515
Moldova 516	Mongolia 533	Morocco 778	Mozambique 1	Myanmar 365
Namibia 26	Nepal 1	Netherlands 387	Netherlands Antilles 718	New Zealand 275

Table 4.3: Summary of electricity GHG factors from the WRI - part II [g-CO_{2eq}/kWh]

Nicaragua 539	Nigeria 403	Norway 6	Oman 855	Pakistan 380
Panama 277	Peru 198	Philippines 495	Poland 659	Portugal 498
Qatar 618	Romania 394	Russia 338	Saudi Arabia 748	Senegal 634
Serbia & Montenegro 748	Singapore 544	Slovak Republic 232	Slovenia 328	South Africa 848
Spain 394	Sri Lanka 398	Sudan 848	Sweden 44	Switzerland 26
Syria 587	Tajikistan 27	Tanzania 607	Thailand 531	Togo 474
Trinidad & Tobago 709	Tunisia 482	Turkey 433	Turkmenistan 795	Ukraine 314
UA Emirates 844	United Kingdom 473	United States Average 573	Uruguay 103	Uzbekistan 443
Venezuela 225	Vietnam 406	Yemen 845	Zambia 6.8	Zimbabwe 572

Table 4.4: Summary of electricity GHG factors from eGrid for regions of the United States [g-CO_{2eq}/kWh]. Regions are defined in Figure 4.4.

US - NEWE 382	US - NYCW 388	US - NYLI 594	US- NYUP 345	US - RFCE 461	US - SRVC 482
US- SRTV US 628	US- SRMV 477	US - SRSO 626	US - FRCC 558	US - RFCM 690	US - RFCW 654
US - MORE 781	US - SRMW 775	US - MROW 762	US - SPNO 829	US - SOSO 740	US - ERCT 597
US - RMPA 856	US - AZNM 527	US - NWPP 387	US - CAMX 369	US - HIMS 612	US - HIOA 726
US - AKMS 202	US - AKGD 528				

4.2.3 Transportation Emissions Data

To evaluate tradeoffs between transportation and electricity we will use the method in the previous sections to estimate electricity emissions for various manufacturing sites, and we will now discuss how to estimate the transportation emissions between sites. This section summarizes transportation emissions data from multiple sources in an effort to ascertain a feasible range of emissions for trucking, air freight, water freight, and train freight transportation that will be used in the case-studies.

Transportation GHG emissions are often given relative to the weight of the goods transported and the distance transported. The GHG emissions of freight transportation can also be normalized by the cargo's volume. There are theoretical problems with both approaches (for example, they assume a vehicle containing no load has no emissions); however, the weight based approach is chosen here. The volume transported may determine how many vehicles are required for transportation, however, weight will directly impact fuel efficiency [100]. Additionally, a weight based approach assumes that packing efficiencies have been optimized so that weight is the driving factor rather than volume. Although the method is imperfect, it provides a reasonable way to estimate emissions when all that is known is weight, mode of transportation, and distance.

Tables 4.6, 4.5, 4.7, and 4.8 summarize a range of emissions factor values from different sources. The variations seen in these values are from the assumptions of the study, regional variability in fuels, and variations in vehicle size and efficiency. To properly utilize the results of these different researchers, it is important to understand their underlying assumptions and analysis boundaries:

- Facanha [100]: Arguably the most comprehensive analysis of freight emissions, Facanha conducted a life-cycle analysis that incorporated emissions associated with infrastructure, vehicle production, vehicle end-of-life, and fuel production and distribution. This goes beyond traditional analyses of freight that only include tailpipe emissions from vehicle operation. For comparison, Tables 4.6, 4.5, 4.7, and 4.8 include Facanha's tailpipe (direct) emissions results as well as total estimates. Facanha demonstrated that tail-pipe emissions contribute approximately 70% to the total emissions for air, truck, and train freight.

- World Resources Institute (WRI) [97] and UK Department for the Environment [101]: The WRI and the UK Department for the Environment utilize United Kingdom statistics on total tailpipe emissions from freight as well as total kg-km traveled by freight carriers to calculate an average kg-CO2eq/kg-km. This value includes return trips but ignores the infrastructure, production, and end-of-life components of the LCA that Facanha incorporated.

- EcoInvent [23]: Ecoinvent data is based on process LCA analyses that are conducted by researchers on the emissions associated with freight transportation in different regions of the world. Each dataset has a specific researcher associated with it and provides information on the boundaries of the analysis. In each of the freight emission cases reported here the emissions are exclusively for tailpipe emissions. It is not clear if return trips are accounted for.

- CE Delft [102]: These emissions estimates are only for water freight and are based on modeled estimates of port activity and fuel use. Again, only "tailpipe" emissions are included. Also, as with air-freight, water emissions depend heavily on the "take-off" and "landing" emissions relative to the total trip distance. This makes the inclusion of uncertainty on later calculations all the more important.

The aforementioned work by Facanha [100] is an excellent example of how to conduct a comprehensive analysis of transportation freight emissions. A similar analysis here is beyond the scope of work; the goal of this section is simply to establish uncertainty bounds on transportation emissions that will be used in later Monte Carlo analyses. Although the results presented by Facanha are the most inclusive of all the calculation methods, they also tend to be at the lower end of the estimation ranges for each transportation type. We could choose to scale-up all "tail-pipe only" emissions by 30% to account for the missing infrastructure, fuel, and other emissions; however, given that these estimates are already high we will leave them in establishing the range of possible emissions factors.

In future work, these results can be taken into account along with the strategic advantages that one transportation mode might offer over another, such as flexibility, timeliness, security, risk, reliability, and service. Air freight is the fastest and most flexible transportation mode; however, it is the least environmentally friendly and the most costly. An optimal choice of transportation has the minimum environmental impact while still meeting needs. These types of tradeoffs must be carefully weighed by planners when considering where to locate facilities and how to transport items between them.

Table 4.5: Water freight emissions (grouped by source)*

Transportation Type	Value [mg-CO_{2eq}/kg-km]	Source
Large container vessel (20,000 tonnes)	13	[101]
Small container vessel (2,500 tonnes)	15	[101]
Transport, transoceanic freight ship	11	[23]
Transport, liquefied natural gas, freight ship	52	[23]
Container	15	[102]
Refrigerated Cargo	77	[102]
RoRo Cargo	59	[102]

*Tankers and barges are not included here.

Table 4.6: Air freight emissions (grouped by source)

Transportation Type	Value [mg-CO_{2eq}/kg-km]	Source
Air Transportation (Direct Emissions)	597	[100]
Air Transportation (Total Emissions)	870	[100]
Short haul (<452 km)	1580	[97]
Medium haul (452 to 1600 km)	800	[97]
Long haul (>1600 km)	570	[97]
Long-Haul Flights	610	[101]
Short-Haul Flights	1320	[101]
Domestic Flights	1900	[101]
Transport, aircraft, freight, intercontinental	1068	[23]
Transport, aircraft, freight	1100	[23]
Transport, aircraft, freight, Europe	1669	[23]

Table 4.7: Trucking emissions (grouped by source)

Transportation Type	Value [mg-CO_{2eq}/kg-km]	Source
Road Transportation - Direct	87	[100]
Road Transportation - Total	118	[100]
Road Freight	72	[97]
All articulated - UK average	86	[101]
ALL heavy goods vehicles - UK average	132	[101]
All rigid - UK average	276	[101]
Transport, lorry >16t, fleet average	126	[23]
Transport, lorry 3.5-16t, fleet average	334	[23]

Table 4.8: Train emissions (grouped by source)

Transportation Type	Value [mg-CO_{2eq}/kg-km]	Source
Rail Transportation - Direct	15	[100]
Rail Transportation - Total	17	[100]
Diesel Locomotive	20	[97]
Electric Locomotive	26	[97]
Coal Locomotive	40	[97]
Rail Freight	21	[101]
Transport, freight, rail, Switzerland	15	[23]
Transport, freight, rail	40	[23]
Transport, coal freight, rail, China	44	[23]
Transport, freight, rail, diesel, USA	50	[23]

Chapter 5

Decision-Making: Transportation and Electricity GHG Tradeoffs

Chapter 4 provided a methodology to estimate electricity emissions in a particular location as well as transportation factors to use for estimating emissions from the transfer of goods between locations. Given this foundation, this chapter aims to answer the question, "how do we assess regional tradeoffs between electricity and transportation emissions?"

We develop a methodology to tradeoff electricity and transportation emissions, the two largest contributors to supply chain GHG emissions, which can be done without any further insight into the product or manufacturing design. We do not wish to downplay the importance of design decisions as they are critical to our global environmental goals, but we wish to contribute something new to practitioner's options for GHG reductions, and thus focus on tradeoffs between transportation and electricity. Two key assumptions used to start this analysis are: (1) electricity consumption for the same exact part does not change with location (2) US electricity consumption for part manufacturing is an appropriate estimate for worldwide electricity consumption to make the same part.

5.1 Methodology

The supply chain optimization problem can be formulated in a linear programming framework. With this in place, there are multiple algorithms that can be used to efficiently evaluate the optimal solution, such as the Simplex method [103]. In the case studies given in this dissertation, however, we simply evaluate every possible solution to find the optimal.

The optimization problem can be setup as shown in Figure 5.1, where,

D = Total Demand

C_{jk} = impact in location j per unit of k

T_{ijk} = transportation emissions from location i to j per unit of k

b_{jk} = units of k produced in location j

a_{ijk} = units of k transported from location i to j

i = location

j = location

k = component

$T_{ijk} = w_k d_{ij} t_{ij}$

w_k = weight of k

d_{ij} = distance from location i to j

t_{ij} = transportation emissions per distance per weight from location i to j

* Constraints: Demand, Feasible Locations, Capacity (transit and production)

* Assumptions: Steady state, material availability, linear relationships

* Neglected: lead times, risk, personal connections, flexibility, innovation, non-electricity GHG variability by location (e.g., heating, technology)

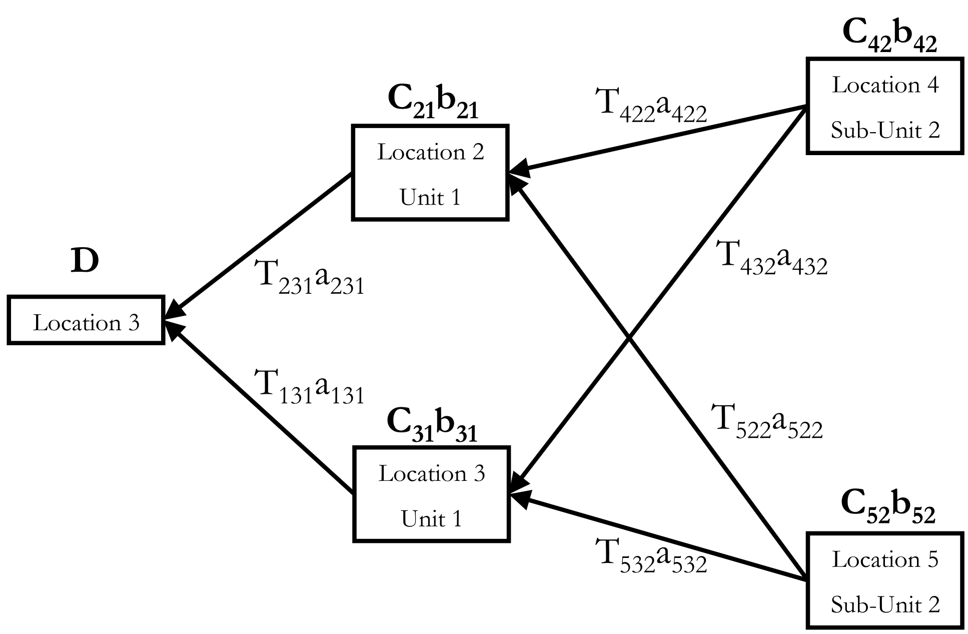

Figure 5.1: Supply chain linear programming setup

The linear programming problem is posed as follows: minimize $\sum T_{ijk}a_{ijk} + C_{jk}b_{jk}$ subject to $\sum a_{ijk} = b_{ik}$ (i.e., all flows out of a facility must equal production in that facility) and $\sum a_{ijk} = b_{ik}$ (i.e., all flows into a facility must equal the production needs of that facility). T and C are given by the transportation and electricity calculations from Chapter 4 along with known transportation distances and product weights.

5.2 Uncertainty

To determine the supply chain configuration that will minimize GHG emissions requires numerous assumptions and incomplete or uncertain data. There are sources of uncertainty introduced at every phase of the analysis: uncertainty in choice of secondary data, uncertainty in the application of this data, uncertainty in measured material, energy, and economic flows, and much more.

Some important causes of uncertainty that must be considered and incorporated for the supply chain GHG optimization based on electricity and transportation tradeoffs are:

- Input output data: Generation of the core input-output data that we modify for these analyses has many areas of uncertainty and error, including error from incomplete or inaccurate data collection from industry, aggregation of multiple products into a single industry category, and the representation of imports as equivalent to goods manufactured in the United States.

- Input-output data use: Applying input-output data to this method introduces additional uncertainty in determining which IO category best matches the item to be analyzed, utilizing data that is from 1998 to represent current activities, the assumption that there is a linear relationship between price and impacts, and the introduction of a price conversion to convert 1998-dollars to 2007-dollars.

- Electricity conversion: As was discussed in section 4.2.2, estimates of electricity emissions factors are error-prone and often underestimated given that regional electricity trade and upstream emissions from fuel supplies are excluded.

- GHG impact characterization: Although the underlying estimates of quantities of various GHG gases are uncertain in the input-output data, there is also uncertainty in the IPCC emissions factors that are used to characterize those gases into $CO2_{eq}$ emissions, and there is uncertainty in our decision to use a 100-year time horizon.

- Regional data conversion: We are utilizing United States specific IO data and only adjusting the electricity mix to account for other regions of the world. There is uncertainty in this assumption given that many other factors may also affect emission variability by region, including the technology being used for manufacture, local regulations on emissions abatement (such as catalytic converters on vehicles), and climactic influences on heating, cooling, and air conditioning.

- Transportation emissions: There is large uncertainty in the transportation emissions factors utilized in this dissertation, as was discussed in section 4.2.3. There is uncertainty in truck size, engine efficiency, road conditions, fuel type, packing efficiency, and the boundaries of the analyses that provide estimates of GHG emissions for different modes of transportation.

- Model uncertainty: The supply chain model we are using introduces uncertainty in its underlying assumptions. These assumptions include material availability, linear relationships between demand and production, and negligible non-electricity GHG variability by location (e.g., heating and technology differences at different plants that make electricity use or energy use non-uniform between locations).

- Human decisions: The life of a product, how it is manufactured, methods of shipping, types of fuel, and end-of-life are all subject to human decision. Additionally, LCA practitioner decisions on allocation methods and boundaries effect the accuracy of a result without real knowledge of variability.

As a practitioner there are two approaches that can be taken to address known uncertainty: undergo further research to reduce uncertainty, or incorporate uncertainty into the analysis through statistical techniques [104]. We utilize the second approach here and address aspects of this uncertainty through the use of Monte Carlo Analysis. Specifically, uncertainty ranges are introduced to every variable that is used to calculate a result for the Automotive and Concentrator Solar PV case studies. In some cases the uncertainty is determined from bounds that we established from previous researchers, such as the range of transportation and electricity emissions factors. In other cases, the uncertainty range is an educated guess in an attempt to account for unknown uncertainty in the specified value. The chosen ranges for each variable will be introduced at the time of their use for the case study.

Monte Carlo methods refer to a class of problem solving algorithms used when the inputs to a particular problem are uncertain. The Monte Carlo simulation method utilizes values that are defined statistically across a range, which can be any continuous distribution (uniform, triangular, gaussian, etc). A sample value is taken from each input range, run through a set of algorithms (such as the supply chain optimization), and the deterministic result is calculated. This sampling is repeated until a range of results is observable. A key element of this approach is that the sampling is determined by the continuous distribution of each value, where the probability density of each variable defines how likely the sample value is to come from a specific point within the variable's range. In this way, statistical variance in input values translates to a statistical range on the final value.

In the Automobile Manufacturing and Concentrator Solar PV case studies we will specify the range of values to be used for each input variable. In both case studies uniform distributions are assumed across the given range. This is a defensive position given that we have no knowledge whether the end-points of the distribution are any more or less likely than the center points; therefore, the uniform distribution represents the average of all possible distributions. And, although it may be just as reasonable to assume a gaussian distribution, the uniform distribution assumes a higher uncertainty; we prefer to over-estimate rather than under-estimate uncertainty when presenting results.

Unfortunately, there are also certain types of data are difficult to capture through uncertainty distributions. This is true for human decisions such as allocation methods and model uncertainties. We attempt to account for un-quantified uncertainty by putting distributions on all variables being used in the analysis, but acknowledge it is imperfect.

5.3 Example: Automotive Manufacturing

To demonstrate the use of the hybrid methodology and datasets discussed in chapter 4, and the supply chain tradeoffs discussed here, we will create a semi-fictitious simplistic example of automobile manufacturing. This will make clear both the strength of this approach, and detail the methodology.

5.3.1 Automotive Problem Setup

Consider the manufacture of an automobile. In the CEDA tables, we can lookup "motor vehicles and passenger car bodies" manufacturing and equation 4.6 can be used to construct a crude average supply chain map for an automobile. This is shown in Figure 5.2. We see in CEDA that stamping is a large contributor to the GHG footprint of automobile manufacturing, therefore this example will explore some potential vehicle assembly and automotive stamping locations to observe variability in GHG emissions between different supply chain configurations.

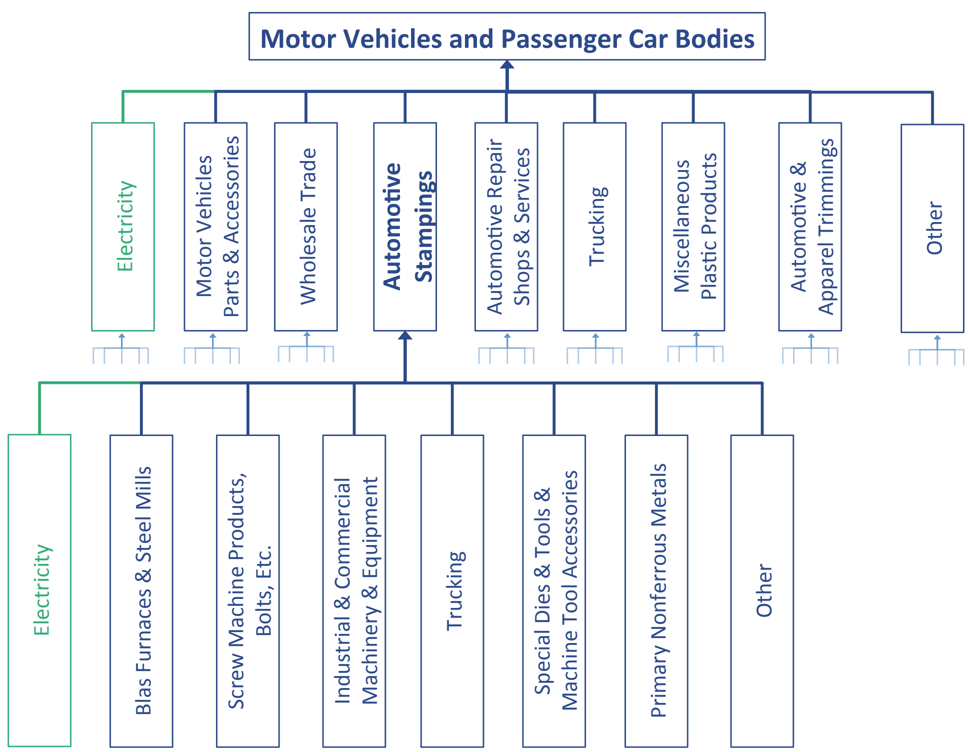

Figure 5.2: Automotive supply chain based on CEDA 3.0

We will utilize the following simplifying assumptions:

1. The automobile assembly and the automotive stampings can occur in Shanghai, China; Detroit, United States; Nagoya, Japan; and Stuttgart, Germany (Figure 5.3).

2. The vehicle can be manufactured and sold in Japan, China, the United States, or Germany.

3. There is no variation in the required material, energy, or service inputs by location for a given part.

4. Necessary transportation infrastructure exists in each location.

5. Regional electricity emissions are as given by the World Resources [WRI]:
   China = 788 kg-CO_2/kWh
   Detroit, United States = 690 kg-CO_2/kWh
   Japan = 429 kg-CO_2/kWh
   Germany = 349 kg-CO_2/kWh
   United States Average = 573 kg-CO_2/kWh

6. The vehicle wholesale cost is $10,000.

7. The stamped body cost is $700 (based on CEDA economic IO tables and vehicle cost of $10,000).

8. The vehicle weight is 1500 kg [105].

9. The stamped body weight is 1000 kg (70% of vehicle weight) [106].

10. The shipping ports are Shanghai, China; New York, New York; Nagoya, Japan; and Hamburg, Germany.

11. The distances from manufacturing sites to ports are:
    Japan = 0 km
    China = 0 km
    United States = 1000 km
    Germany = 700 km

12. The port to port distances [107] are:
    Japan to/from China = 1700 km
    Japan to/from US = 20,000 km
    Japan to/from Germany = 21,000 km
    China to/from US = 21,000 km
    China to/from Germany = 20,000 km
    US to Germany = 7,000 km

13. The GHG emissions factors for transportation are:
    Land (truck) = 0.000122 kg/kg-km
    Sea = 0.000015 kg/kg-km

14. The manufacturing electricity emissions factors scaled from from CEDA 3.0 average to regional values are:
    Assembly in Japan, China, US, Germany = 0.173, 0.318, 0.279, 0.141 kg-CO_{2eq}/$
    Stamping in Japan, China, US, Germany = 0.237, 0.436, 0.382, 0.193 kg-CO_{2eq}/$

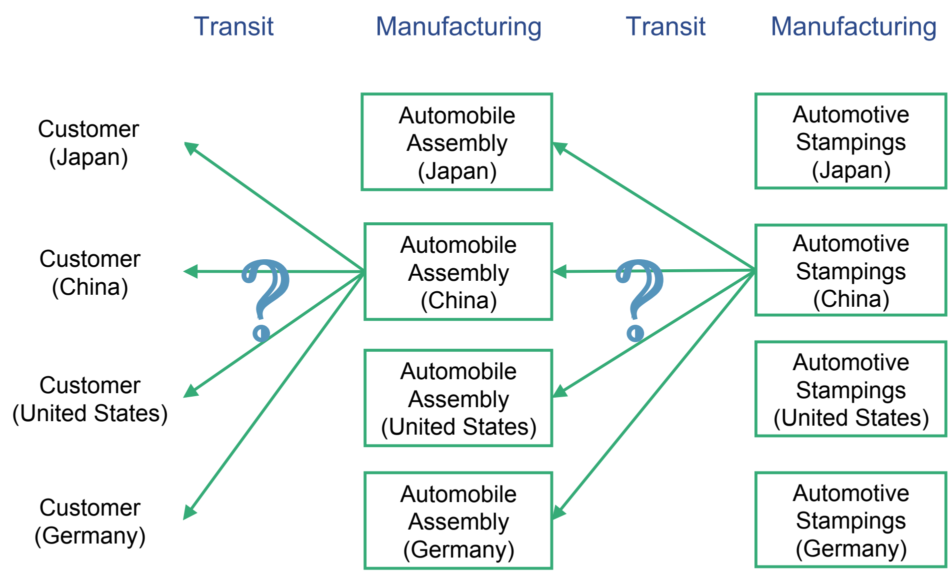

Figure 5.3: Options for arrangement of supply chain

Table 5.1: Optimal solution for each customer location

	Germany	Japan	United States	China
Elec and Transit GHG [tons-CO_{2eq}]	1400	1730	1860	1900
assembly	Germany	Japan	Germany	Japan
stamping	Germany	Japan	Germany	Japan

5.3.2 Automotive Results

Results are shown in Tables 5.1 and 5.2. The optimal supply chain configuration for a German or Japanese customer is local; whereas the optimal supply chain for a US or Chinese customer is foreign. For any customer, the total emissions from electricity and transportation more than double when going from the optimal solution to the worst possible solution.

For the US customer, the worst to best possible supply chain results in a net savings of 2.8 tons-CO_{2eq} per vehicle. The average to best possible supply chain is a savings of 1.5 tons-CO_{2eq} per vehicle. This savings is equivalent to roughly 30-60 tree seedlings grown for 10 years [108].

5.3.3 Automotive Uncertainty and Sensitivity

As was discussed in section 5.2, there is uncertainty in all of the input variables to the automotive problem that were listed in section 5.3 in addition to model uncertainty; therefore it is important to understand how robust a particular optimal supply chain is to this variability. We will go about this analysis in two ways (1) uncertainty: Monte Carlo

Table 5.2: Least optimal solution for each customer location

	Germany	Japan	United States	China
Elec and Transit GHG [tons-CO_{2eq}]	4050	3770	4160	3920
assembly	China	US	China	US
stamping	US	China	US	China

assuming a continuous and uniform distribution for each input variable to observe variability in the discrete solutions (2) sensitivity: increase and decrease the value of each variable by 1% until the discrete supply chain solution flips from one optimal solution to another.

Automotive Monte Carlo Analysis

We utilize the Monte Carlo Method (section 5.2) to assess how uncertainty in the input variables effects the results of our analysis. This method will demonstrate the overall robustness of the solution given uncertainty in each input parameter. As a simple example of the Monte Carlo method applied to this case study, we assume that all the variables are uncertain to plus or minus 40%. For the SolFocus analysis of chapter 6 we will be more rigorous in assigning uncertainties to each variable based on known distributions where possible. The simulation was run 10,000 times and results are shown in Table 5.3.

From these results a couple interesting points emerge. First of all, even at plus or minus 40% uncertainty there are three optimal solutions or less for each customer location. Given that this example has 64 possible supply chains, narrowing the solution to one of three alternatives is powerful for a decision maker. Used in conjunction with additional decision variables (cost, lead time, part quality) a decision maker is well informed to choose a supplier.

A second interesting observation is that depending on customer location, the result is more or less robust to uncertainty. For example, a customer in Germany can feel fairly confident that their optimal Assembly and Stamping sites are in Germany. However, a customer in China or Japan cannot be so certain. Essentially, this can be explained by thinking of all possible solutions as existing in a step function – where each step represents a particular supply chain solution. The robustness of the result depends on the width of any given step, and how close a solution is the step edge. The "closeness" to the step edge is evaluated in sensitivity analysis.

A final observation from these results is that the optimal location for the assembly is always the same as the optimal for the stamping location. This is because the optimal for the assembly has already minimized the electricity transportation tradeoffs and is located at a low electricity emissions site; therefore this is also a good site for the stamping to occur. We will see more difficult tradeoffs in the solar case study where all parts are not manufactured in all locations.

Table 5.3: Monte carlo results for uniform +/-40%

	1st Optimal	2nd Optimal	3rd Optimal	4th Optimal
Japan Customer				
Likelihood	67%	30%	2%	
Assembly	Japan	Germany	China	
Stamping	Japan	Germany	Japan	
China Customer				
Likelihood	63%	33%	3%	
Assembly	Japan	Germany	China	
Stamping	Japan	Germany	Japan	
US Customer				
Likelihood	76%	18%	5%	1%
Assembly	Germany	Japan	US	US
Stamping	Germany	Japan	US	Germany
Germany Customer				
Likelihood	95%	5%		
Assembly	Germany	Japan		
Stamping	Germany	Japan		

Automotive Sensitivity Analysis

The Monte Carlo method demonstrated the robustness of the solution to uncertainty in the input variables; however, it did not specify which variables should be the focus of further refinement or analysis. Therefore, we will utilize one-at-a-time sensitivity analysis to ascertain how sensitive the final solution is to change in each variable. This is necessary to provide guidance on where additional research and refinement on inputs is needed for robust decision-making.

The sensitivity analysis here is not simply interested in a percent change in the final GHG value for the supply chain relative to a change in an input variable. Instead, we are really interested in knowing what amount of variability in each input value results in a discrete change from one optimal supply chain to another.

To assess this discretized sensitivity, we investigate each variable in turn, and increase or decrease the variable by 1% at a time until the solution flips from the original optimal solution to another optimal solution. The percentage change in that variable that is necessary to cause the solution change is then recorded. These results for a customer in China and the US are shown in Tables 5.4 and 5.5.

As was discussed in the last section on uncertainty, sensitivity is dependent on the point of the optimal in the solution space – as is demonstrated by the differing sensitivity of the model for a customer in China and the US.

Table 5.4: One at a time sensitivity analysis for a customer in China. Values represent the percentage change that induced a new optimal supply chain. Where the percentage change was negative or exceeded +500% the result is not given.

Variable	OAT sensitivity
land distance Japan	–
land distance China	–
land distance US	–
land distance Germany	–
water distance Japan to Japan	–
water distance Japan to China	–
water distance Japan to the US	–
water distance Japan to Germany	–
water distance China to Japan	–
water distance China to China	–
water distance China to US	–
water distance China to Germany	–
water distance US to Japan	–
water distance US to China	–
water distance US to US	–
water distance US to Germany	–
water distance Germany to Japan	–
water distance Germany to China	-70%
water distance Germany to US	–
water distance Germany to Germany	–
GHG emissions of trucking	–
GHG emissions of ocean freight	-70%
assembled weight	–
stamping weight	-60%
electricity emissions - Japan	+30%
electricity emissions - China	-50%
electricity emissions - Detroit, US	-70%
electricity emissions - Germany	-40%
electricity emissions - US Average	-60%
IO electricity factor assembly	-90% and +150%
IO electricity factor stamping	–
cost of the assembled vehicle	+160%
cost of the stamping	–

Table 5.5: One at a time sensitivity analysis for a customer in the United States. Values represent the percentage change that induced a new optimal supply chain. Where the percentage change was negative or exceeded +500% the result is not given.

Variable	OAT Sensitivity
land distance Japan	–
land distance China	–
land distance US	–
land distance Germany	–
water distance Japan and Japan	–
water distance Japan and China	–
water distance Japan and the US	-90%
water distance Japan and Germany	–
water distance China and Japan	–
water distance China and China	–
water distance China and US	–
water distance China and Germany	–
water distance US and Japan	–
water distance US and China	–
water distance US and US	–
water distance US and Germany	–
water distance Germany and Japan	–
water distance Germany and China	–
water distance Germany and US	+300%
water distance Germany and Germany	–
GHG emissions of trucking	+300%
GHG emissions of ocean freight	+300%
assembled weight	–
stamping weight	+150%
electricity emissions - Japan	-40%
electricity emissions - China	-70%
electricity emissions - Detroit, US	-30%
electricity emissions - Germany	+50%
electricity emissions - US Average	+150%
IO electricity factor assembly	-50%
IO electricity factor stamping	–
cost of the assembled vehicle	-60%
cost of the stamping	–

Chapter 6

Case Study: SolFocus Concentrating Photovoltaics (CPV)

SolFocus Inc. is a startup company developing the utility scale concentrator photovoltaic systems shown in Figure 6.1 [109]. The SolFocus panels are a great case study for the methods presented in this dissertation because SolFocus has developed sophisticated cost models of their products, production is dependent on a global supply chain, and energy metrics currently used to evaluate solar technologies are insufficient for decision making. Here, we consider the second generation of SolFocus CPV systems that was being manufactured and developed in the Summer of 2008.

The research focus for solar energy has thus far been on specific technological improvements in manufacturing, materials selection, and design; however, manufacturing decisions that are not specifically related to the technology also have the opportunity to reduce GHG emissions. We explore this possibility here through the 3 step approach of appropriate metrics, comprehensive LCA, and regionalized supply chain decision-making.

6.1 Metrics Development for Solar

There are many potentially competing environmental indicators that could be used to assess the environmental impact of a solar system, including eutrophication, toxic releases, acidification, and particulate emissions. All of these are important, however, we should consider the goal of renewable energy development when choosing an appropriate metric. Renewable energy systems are being developed to satisfy three main goals: (1) provide reasonably priced energy (2) mitigate climate change (3) provide energy independence. We focus on the second of these goals here through the development of a GHG return on investment metric.

The GHG return-on-investment metric (GROI) addresses the drawbacks of decision-making solely using Energy Return-On-Investment (EROI) and GHG/kWh for new energy technologies. Specifically, EROI does not address climate change concerns, the primary goal

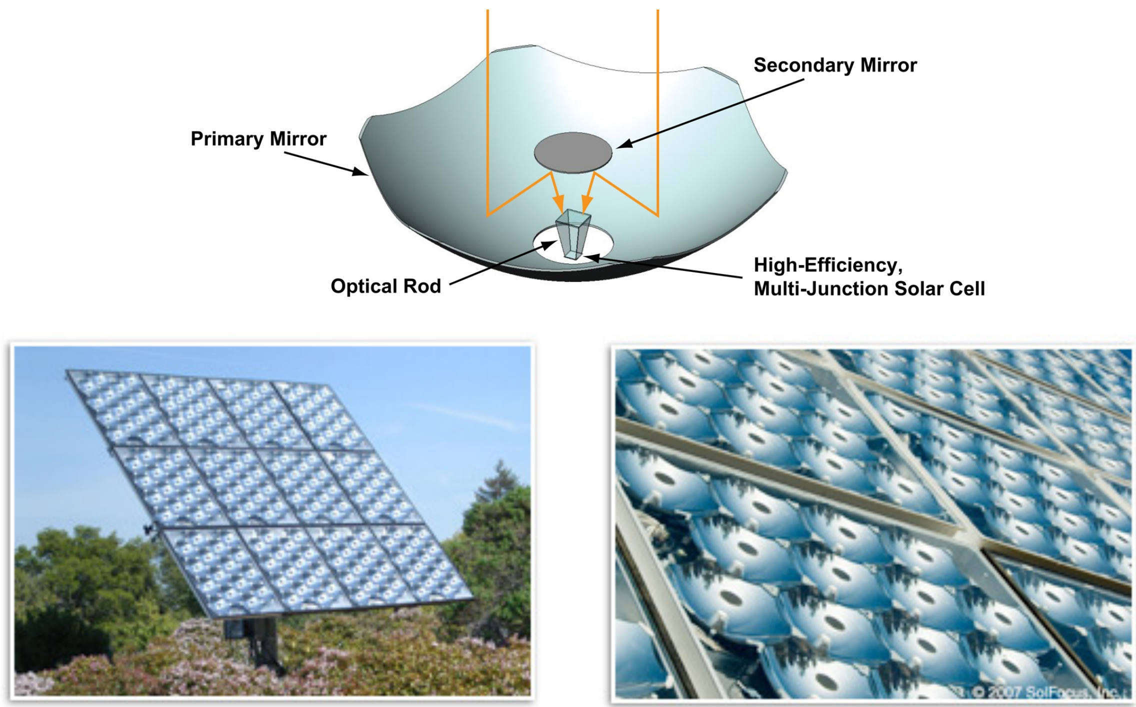

Figure 6.1: Imagery of the SolFocus panels being studied [109]

of alternative energy; and GHG/kWh only accounts for insolation differences of alternative installation sites. GROI accounts for the types of energy used during the technologies' life-cycle, the electricity delivered net of distribution losses, and the type of energy being offset at the point of use.

We will first review energy metrics because of their prominence in the field and then develop the GROI metric for solar.

6.1.1 Energy Metrics

The most common metric used by solar researchers today is the Energy Payback Time (EPT). EPT is described as the number of years a technology must output electricity to "payback" the energy required for its manufacture.

Researchers have incorrectly referred to the EPT as simply a measure of technological efficiency. This simplistic statement is incorrect because a conversion factor is required in the EPT formula that translates produced electricity back to primary energy using the local electricity mix efficiency (C_{elec}). Therefore, EPT is actually an indicator of the number of years a technology must offset the use of primary energy from another electricity source, to offset the total energy required over its lifetime (E_{LCA}) (equation 6.1). The electricity output by the system is here called $Elec_{useful}$ because it accounts for useful electricity leaving the system; electricity consumption by peripherals, wiring losses, and conversion efficiency from DC to AC should already be accounted for.

The drawback of EPT is that it does not acknowledge differences in technology lifetime. For example, two technologies with an EPT of 5 years are not equivalent if one lasts 10 years and the other lasts 20 years. Therefore, researchers have suggested the Energy Return-On-Investment (EROI) metric (this has also been called the Energy Return Factor), which is calculated as the technology lifetime (standard assumption is 20 to 30 years) divided by the EPT [110] [111]. EROI indicates how many MJ of primary energy are saved from consumption for every MJ of primary energy consumed.

$$EPT[years] = \frac{E_{LCA}}{C_E * Elec_{AnnualUseful}} = \frac{E_{LCA} * \eta_{elec}}{Elec_{AnnualUseful}} \tag{6.1}$$

Furthermore, the formulation of EROI as it has been given by previous researchers is not in-line with ROI metrics as they are used in economic theory. The metric should represent net energy savings versus input energy rather than the gross energy produced by the system versus the input energy. Therefore, the equation should be as shown in equation 6.2. In this revised formation, a positive EROI is good and a negative EROI is bad.

$$EROI[\frac{E_{savings}}{E_{consumed}}] = \frac{C_E * Elec_{AnnualUseful} * Lifetime - E_{LCA}}{C_E * Elec_{AnnualUseful*Lifetime}} \tag{6.2}$$

This formulation of EROI is now consistent with that discussed in the metrics chapter of this dissertation and elsewhere in economics.

6.1.2 Greenhouse Gas Emission Metrics

Researchers have been focused on optimizing EPT and GHG/kWh; however, if the goal is to slow GHG emissions by using alternative energy technologies, these are not the best metrics. In the global game of reducing GHG emissions it may not be necessary to ensure that less energy goes into the technology than comes out of it. What is more important is the type of energy going in - or the quantity of GHG emissions produced to make the technology. For example, if it takes 30% more energy to manufacture a solar energy technology than is output by the technology over its lifetime, then the EPT or EROI metrics would indicate there is a problem. But, if the manufacturing electricity is one-tenth the GHG per kWh of the electricity being replaced by the solar technology then we have reduced overall GHG emissions. In this feasible scenario energy metrics lead to a false conclusion.

Therefore, as was discussed in the chapter on metrics, because the goal is GHG reductions, researchers should be measuring and optimizing around GHG emissions. The GHG emissions metric used by previous researchers is GHG/kWh, which is calculated as the LCA determined GHG emissions to manufacture the device divided by the total kWh output by the system over its lifetime (dependent on solar radiation at installation site). The drawback of this metric is that it does not account for installation differences.

GHG payback time (GPBT) and return-on-investment (GROI) are proposed here for assessing energy technology supply chains and installations. Following the example set by EPT and EROI, which incorporate the conversion efficiency of electricity at the location site, GROI (equation 6.4) and GPBT (equation 6.5) are proposed to indicate which technology and supply chain scenario will enable the fastest route to climate change mitigation. Similar to EROI, GROI indicates the GHG emissions prevented for every unit of GHG emitted. Notice that here we use the modified formulation of EROI as the guide for GROI, where a positive GROI is good and a negative GROI bad.

GHG_{LCA} are the emissions of the technology determined through LCA. GHG_{Offset} are the emissions prevented by installing new electricity capacity, whether it is the marginal emissions from a power plant, or the life-cycle emissions of an alternative installation. GHG_{Offset} accounts for installation location differences such as circularity, the electricity supply chain, distribution losses, consumer needs, and regional electricity capacity. The nuances of GHG_{Offset} will be discussed in the next section.

$$GPBT[years] = \frac{GHG_{LCA}}{C_{GHG} * Elec_{AnnualUseful}} \tag{6.3}$$

$$GROI[\frac{GHG_{saved}}{GHG_{emitted}}] = \frac{GHG_{Offset} - GHG_{LCA}}{GHG_{LCA}} \tag{6.4}$$

$$GHG_{Offset} = Lifetime * C_{GHG} * Elec_{AnnualUseful} \tag{6.5}$$

The complicated nature of determining the offset emissions of a new technology is an important feature of this metric. It allows for dynamic location based decision-making by inherently acknowledging that a choice to install a technology is a choice to not install or utilize an alternate technology. GROI encourages the quickest pathway to a reduction of GHG emissions globally, by rewarding the replacement of high GHG/kWh technologies. Furthermore, the GROI metric can be used by policy makers to establish incentives and is applicable to decision-making beyond energy technology.

Offset GHG Emissions

One of the most interesting pieces of the GROI metric is the consideration of the quantity of GHG emissions that are being offset by the installation or use of solar technology. Determining GHG_{Offset} requires an understanding of the consumer, the current electricity supply, and alternative new installations. There is a difference between a technology installed directly at the point of use and one installed to the grid; solar technology installed at the point of use offsets both the production and distribution losses, while a grid-tied option only offsets production. [1] Additionally, there is a difference between providing electricity to new customers, who would require additional capacity in the grid regardless of technology, and providing electricity to customers in a system with available capacity and who already have full access to the current electricity grid.

Each potential offset scenario will involve offsetting a subset of the following:

1. Electricity Production: The direct GHG emissions associated with the production of electricity. This depends on the specific electricity mix of a location.

2. Distribution Losses: Losses of electricity from production to consumption. This depends on the distribution efficiency and distances.

[1] In some cases solar is placed along a power-line to reduce distribution losses and improve power stability. In these cases the solar is offsetting production and some portion of the distribution losses [112].

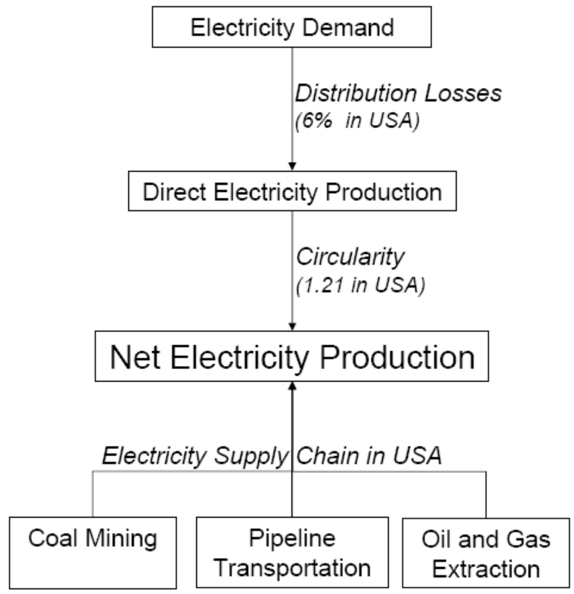

Figure 6.2: Contributors to the net GHG/kWh of electricity example based on USA. Distribution losses from the IEA [95], circularity and supply chain data from CMU [52].

3. Circularity: An economic concept based on the amount of additional electricity consumed internally by the electricity sector when a kWh of electricity is produced. For example, production of a kWh of electricity requires additional electricity for lighting, pumping, and powering peripherals at the power plant.

4. Production Supply Chain: The GHG emissions associated with the mining, materials, transportation, and all other goods and services consumed directly or indirectly by the electricity industry to produce a kWh.

5. Technology Life-Cycle: The GHG emissions of materials extraction, transportation, manufacturing, installation, maintenance, and end-of-life for the entire power plant. The technology life-cycle includes and goes beyond the GHG of electricity production, the supply chain, circularity, and distribution; and is only offset in a situation where a new energy technology is being installed in place of the complete installation of a different technology.

The relationship between production, distribution, circularity, and the supply chain is illustrated in Figure 6.2 with the US as an example. Every kWh of electricity demanded in the US requires the gross production of 1.29 kWh, when losses and circularity are accounted for [95, 96]. Additionally, there are CO_2 emissions associated with the supply chain necessary to support each kWh produced by the electricity industry. The three largest contributors to GHG/kWh of the USA electricity supply chain are coal mining, pipeline transportation, and oil and gas extraction activities [52].

To clarify the possible offset scenarios, consider three questions: (1) is the potential

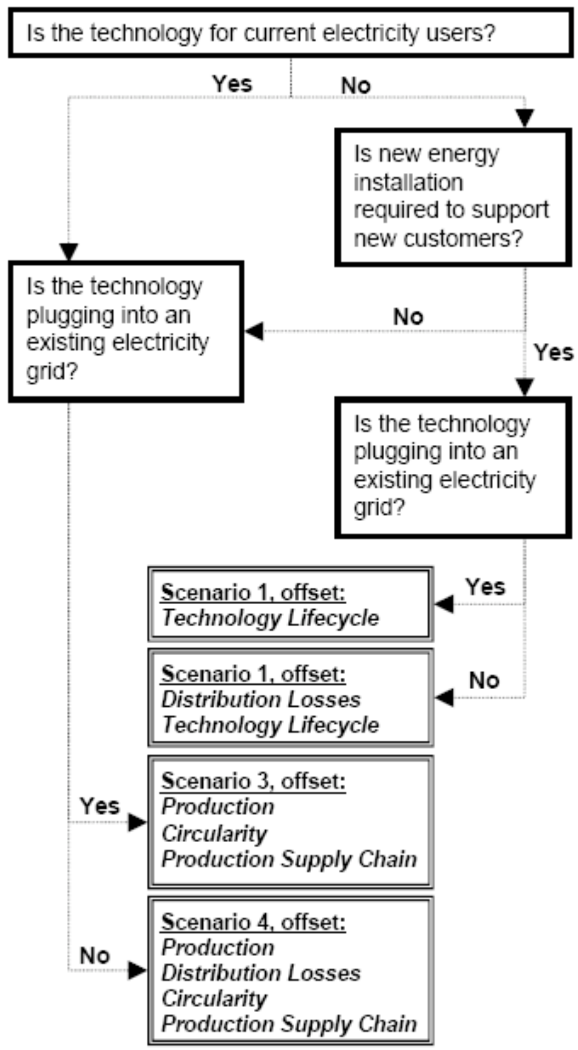

Figure 6.3: Decision tree for determining the appropriate offset scenario for GROI.

customer currently using electricity (2) will the new technology supply electricity to an established grid or directly to the customer (3) is new capacity required to satisfy the demands of the customer? These questions and the potential outcomes are outlined in Figure 6.3. The result is 4 possible scenarios:

1. The installation of a new technology to the grid electricity mix. This new technology will satisfy new electricity demand that could not be satisfied by the current grid capacity. In this case new capacity must be installed in any case ; therefore the new energy technology is preventing the entire life-cycle GHG emissions of an alternate technology installation.

2. The installation of a new technology at the point of use. This installation is for a customer who previously did not consume electricity and who would require additional capacity from the grid if not for this direct point of use installation. As in scenario 1, this customer offsets the entire life-cycle. In addition, the distribution losses from electricity distribution are offset.

3. The installation of a new grid-tied technology for a customer who does not require additional capacity installed to meet demand, but who requests lower carbon intensive energy. Unlike Scenario 1, the life-cycle impacts are not offset. Only the marginal emissions of production, circularity, and the supply chain are offset.

4. The installation of a new technology at the point-of-use for a customer who does not require additional capacity installed to meet demand and will receive electricity directly. This offset scenario is similar to scenario 3, except distribution losses are also offset.

An important difference between the first two and last two scenarios is whether the new energy technology is offsetting marginal or life-cycle GHG emissions. However, the distinction may not always be obvious. For example, a utility company may desire to install a new technology that will supply electricity to both current and new customers. How does the utility calculate GROI in this situation? One solution might be to use a weighted average of the offset scenarios based on the number of customers in each category.

In scenarios 1 and 2 presented above, there is an inherent choice being made between alternate electricity installations. In this case, the entire life-cycle of a new energy installation is compared with the installation of an alternate one. GHG_{Offset} is then the life-cycle GHG/kWh emissions of the alternate technology. Previous researchers have analyzed the life-cycle GHG/kWh of energy [113, 114], with their results summarized in Figure 6.4. This data does not account for distribution losses for a particular location, which will be discussed in the next section. Note that this data is presented as CO_2 rather than net GHG emissions due to data availability; however, it provides a reasonable comparison between technologies. Nuclear (Europe) and nuclear (USA) are different because of the electricity mix used for the materials in the plant's construction.

Offset scenarios 3 and 4 assume electricity exists and is available, but its use is being replaced by a new energy installation. In this case, the installation of the old electricity has already occurred, and only marginal GHG/kWh emissions are prevented by the new

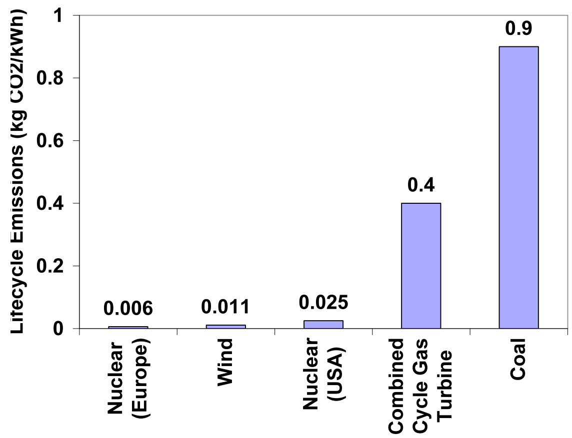

Figure 6.4: Life-cycle CO_2 emissions for energy technologies [113, 114]

installation. For these scenarios, information on the regional electricity mix in GHG/kWh is needed. Details on determining the GHG emissions for different regions of the world can be found in section 4.2.2.

It should be understood that using an aggregated country level analysis for GHG_{Offset} in GROI, overlooks the differences between offsetting base versus peak load electricity. For example, solar energy in the USA likely offsets peak demand, which may be provided by natural gas; whereas wind energy offsets base demand in the evening, which is primarily coal based in the USA. Additionally, the analysis assumes an average mix that is homogenous across a region.

6.2 LCA development for Solar

6.2.1 Previous Work

The development of solar energy technology has become an important part of global efforts to mitigate climate change [115] by replacing traditional fossil fuel based energy sources. To ensure these new technologies are environmentally beneficial, researchers have been interested in measuring their environmental performance. An ongoing series of assessments comparing the environmental impact of alternative energy technologies have been published by Professor Fthenkis of Columbia University and Professor Alsema of Ultrecht University in the Netherlands. These collaborative reports cover a comprehensive spread of technology including fossil fuels, nuclear, biomass, wind, multicrystalline silicon, and CdTe thin film. Fthenakis and Alsema use company data on materials requirements along with databases relevant to the United States and the European Union to obtain their results. In 2006, Fthenakis and Alsema conducted an energy and GHG based review of fossil fuels, various silicon technologies, and CdTe technology [114]. Alsema, additionally, reviewed the GHG emissions and energy demands of fossil fuels, nuclear, biomass, wind, multicrystalline silicon, and CdTe technologies [113]. Most recently, Fthenakis et al. conducted an updated review of Silicon and CdTe photovoltaic technology investigating the life-cycle energy use, GHG emissions, SO2 emissions, NOx emissions, and heavy metal emissions as compared with fossil fuels, nuclear, and hydro electricity generation [116]. Peharz and Dimroth investigated the energy payback time of the FLATCON fresnel concentrator solar technology in 2005 [117], one of only a few analyses of concentrator technology. Their conclusions are summarized in Table 6.1.

Table 6.1: Review of energy technology LCA results.

Technology	EPT (years)	GHG Intensity (g-CO_{2eq}/kWh)	Reference
Si	2.2-2.7	30-55	[114] [116]
CdTe	1.1	21-25	[114] [116]
Concentrator PV	0.7-1.3	-	[117]
Solar Thermal	2.2-3.9	34.7-37.6	[118] [119]
Wind	0.27-0.7	8.8-18.5	[120] [121]
Coal	-	900	[113]
CC Gas Turbine	-	400	[113]
Nuclear	-	20-40	[113]

The LCA methods used by previous researchers compare technology differences rather than installation and supply chain differences using constant assumptions about solar resources and electricity mix while omitting transportation emissions. However, using LCA tools and databases that are only accurate for a single region of the world (Europe or the United States) is a serious weakness in these studies efforts to quantify the true impact of solar technologies. Given that components actually come from multiple regions of the world, their results do not reflect the actual impact of the manufactured technology or provide the type of insight suggested by this research into supply chain re-organization.

In summary, there are three important drawbacks to previous LCA studies of solar energy technologies:

1. It is inherently assumed that the electricity mix is constant for what is actually a varied mix of electricity types across the supply chain.

2. Transportation is generally not included or is only included in the final leg of the supply chain from assembly to installation.[2]

3. The metrics used by previous researchers do not acknowledge differences in installation site based on what is offset by the new technology. For example, a technology installed to replace coal-fired power is preferable to one installed to replace hydro power, in terms of GHG emissions.

[2]Note that assessments using economic input-output databases (for example [119]) automatically include transportation in the way the LCA database is created, however, they assume only regional distances are crossed.

6.2.2 Financial Hybrid LCA of Concentrator Solar Photovoltaics

To conduct a comprehensive analysis of SolFocus concentrator PV systems that incorporates electricity mix variation and transportation emissions, a financial hybrid LCA is developed by linking together SolFocus' detailed product cost estimates [122] with input-output data and more detailed manufacturing measured or modeled data estimates where available.

The SolFocus system is designed to concentrate sunlight 500 times onto a costly triple-junction PV solar cell. As shown in Figure 6.1 this concentration happens by reflecting light off two mirrors that send the sunlight into a glass prism and finally onto a triple junction solar cell. The SolFocus system is comprised of the following major components:

- Concrete and rebar: foundation to support the steel pole and the panel.
- Steel pole: pole to hold the panel off the ground so it can move throughout the day to track the sun.
- Tracker: motors and computer controller to ensure the panel tracks the sun throughout the day (the concentrating system only accepts light that is perpendicular to the panel's surface).
- Aluminum backpan: five sides of the rectangular enclosure for the system of mirrors and the PV cells.
- Glass window: sixth side of the enclosure, which sits on the front of the backpan to allow light through to the mirrors.
- Primary and Secondary mirrors: mirrors to concentrate light onto the receiver.
- Receiver: the glass prism, PV cell, and aluminum heat sink assembly.
- Balance of systems (BOS): the wiring, inverters, and transformers necessary to connect the panels, convert the electricity produced by the system into a usable form, and transmit it to the grid.

This hybrid LCA ties together with a sophisticated "Levelized Cost of Energy" estimation tool at SolFocus [122]. The LCOE cost model provides the perfect platform and framework to tie with the financial hybrid LCA. Just as the GROI metric goes beyond a simple GHG/kWh metric to understand installation variables, the LCOE metric is a step beyond the traditional dollars-per-watt metric that is generally used for solar energy. Dollars-per-watt is the cost of materials in the solar panel divided by the peak wattage of the system. Peak wattage does not indicate actual performance at a specific installation and material costs do not reflect the total cost to produce a solar system; therefore, SolFocus wanted to have real estimates on the cost of each kWh of electricity produced by their system at each potential installation site. To this end, SolFocus developed a sophisticated cost model that takes into account the full costs of their system (including overhead, packaging, transportation) along with regional solar insolation variables to estimate electricity output. The LCOE financial estimates are more sophisticated than a simple bill of materials and capture overhead, machinery depreciation, transportation, and packaging. LCOE also takes into account the financial structure for a solar project including debt, equity, insurance and other forms of guarantee. Note, however, that SolFocus has yet to evaluate end-of-life considerations (such as take-back, remanufacturing, and recycling) or the need for electricity storage or a back-up generator with the installed system. Both aspects are important areas for future work; but are not included here.

To calculate the results of the financial hybrid LCA for SolFocus, both 1997 IO data from Carnegie Mellon University [52] and 1998 IO data from Professor Sangwon Suh at University of Minnesota [54] are used. The application of the hybrid methodology to SolFocus systems, given available data, results in the supply chain tree shown in Figure 6.5. Note in particular that transportation is not yet included for every component.

A summary of data received from SolFocus is provided in Table 6.2. All data used for this analysis either comes from an IO database (CEDA or CMU), the SolFocus LCOE tool, or SolFocus manufacturing estimates of resource use. Finally, while IO data is the primary source of manufacturing GHG data for this analysis, IO data is not necessarily appropriate for emerging processes and new materials; therefore, for this analysis, the photovoltaic cell environmental impact is approximated from work by Peharz and Dimroth [117]. The IO values used for this analysis are summarized in Table 6.3. Shown in Figure 6.6 are the inputs, database, and metric outputs of this analysis.

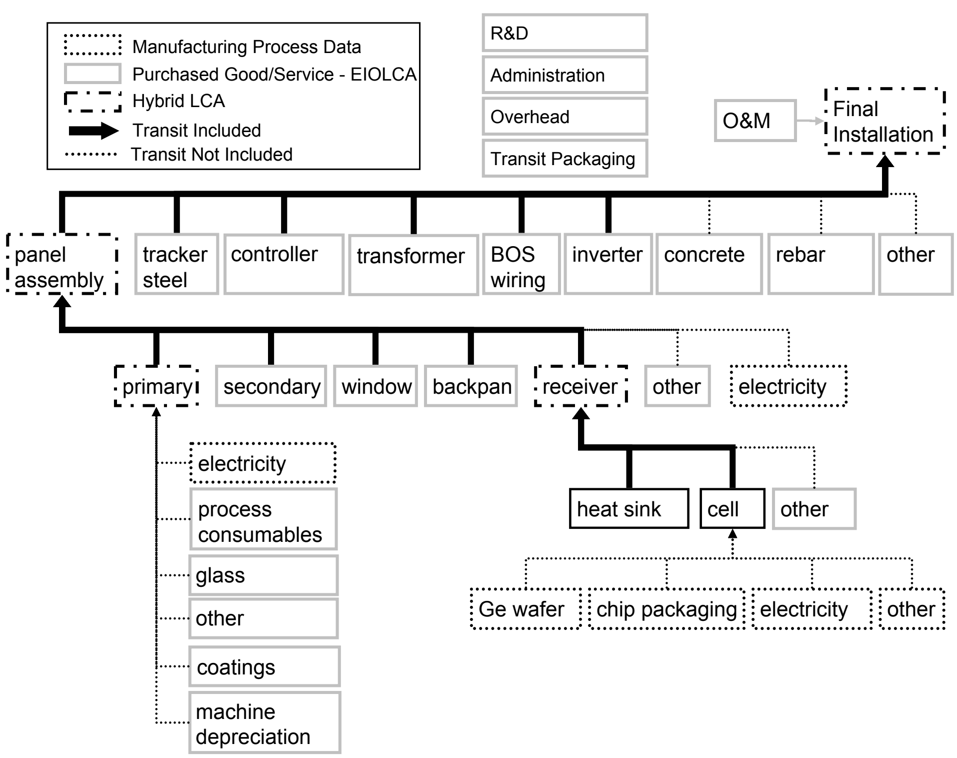

Figure 6.5: SolFocus supply chain determined by available data.

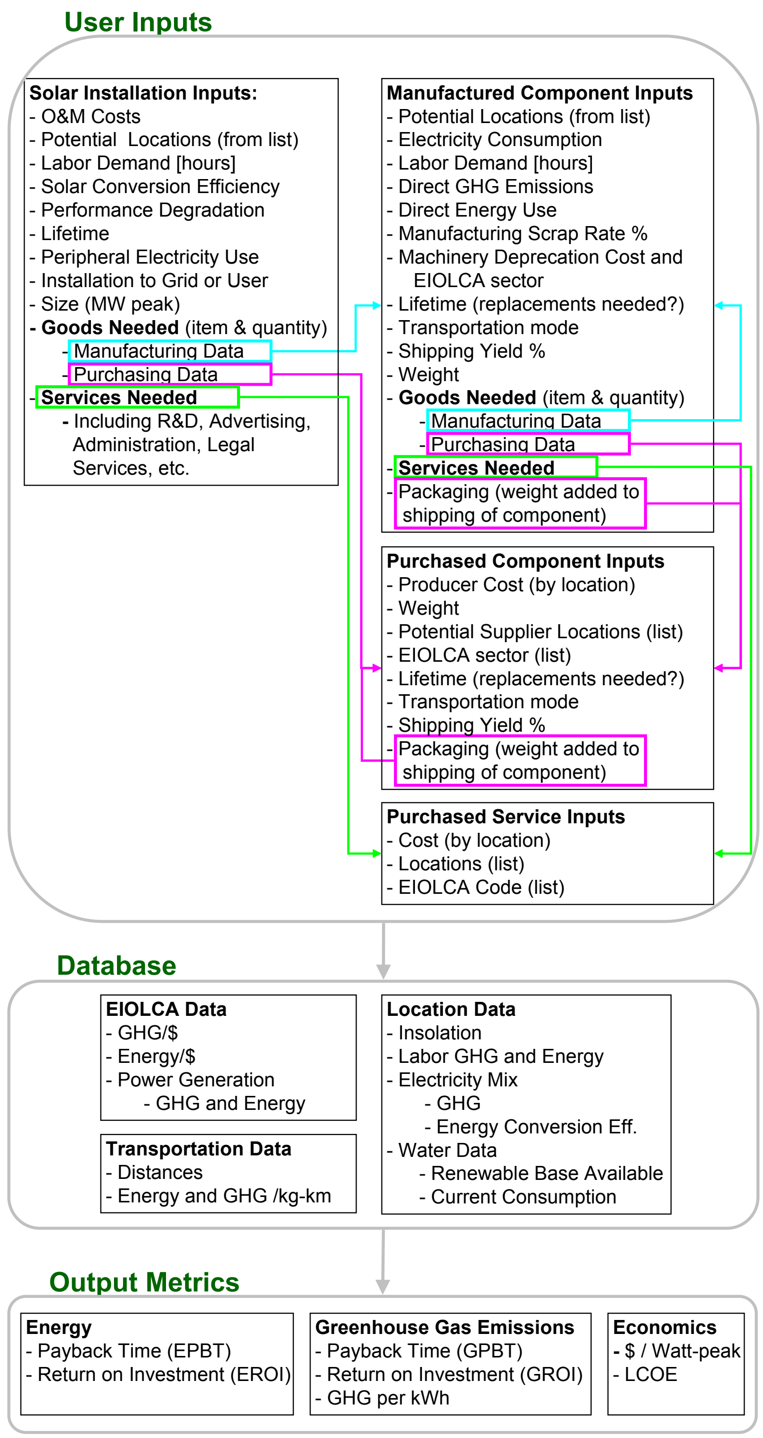

Figure 6.6: Data structure for the financial hybrid LCA

Table 6.2: Summary of SolFocus data

	LCOE Data	Manufacturing Data
	Annual Electricity Generated	
Installation	Foundation Cost	
Installation	Rebar Cost	
BOS	Total Wiring Costs*	
BOS	Inverter Cost	
BOS	Number of Inverters	
BOS	Transformer Cost	
BOS	Number of Transformers	
Tracker	Tracker Weight	
Tracker	Tracker Steel Cost	
Tracker	Number of Trackers	
Tracker	Tracker Controller Cost	
Tracker	Tracker Motor and Gears Cost	
Tracker	Tracker Paint Cost	
Panel	Number of Panels	Window support cost
Panel	Panel Cost	VHP Tape cost
Panel	Panel Weight	Glass alignment pin cost
Panel		Silicone cost
Panel		Gasket cost
Panel		Nut costs
Panel		Screw costs
Panel		Electrical connection cost
Panel		Label cost
Panel		Nylon cable tie cost
Panel		Spacer seal cost
Panel		Gasket cost
Panel		Wiring cost
Panel		Protective cover cost
Panel		Electricity panel cost
Receiver	Number of Receivers	Heatspreader cost
Receiver		optical power module cost
Receiver		Diode cost
Receiver		Solder cost
Receiver		Substrate cost
Receiver		Adhesive cost
Receiver		Rod holder cost
Receiver		Encapsulant cost
Receiver		Wiring costs
Receiver		Dielectric costs
Receiver		Screw costs

Continued on Next Page...

Table 6.2 – Continued

	LCOE Data	**Manufacturing Data**
Receiver		Silicone costs
Receiver		Prism costs
Window	Glass Cost	
Primary Mirror		Glass Cost
Primary Mirror		Coating Materials Cost
Primary Mirror		Consumables Cost
Primary Mirror		Machinery Depreciation
Primary Mirror		Electricity Consumption
Photovoltaic Cell		Cost and Size
Overhead	Admin. & management costs	

*this is just the cost of the actual wire. In the LCOE model, trenching costs focused on the cost of labor, but future work on vehicle emissions and machinery for the trenching to lay the wires is needed.

Table 6.3: CEDA vs. CMU IO Data [kg-CO_{2eq}/\$]. The data has been separated into all except electricity, and the electricity portion.

	CEDA 1998	CEDA Elec	CMU 1998	CMU Elec
Aluminum Extruded Products	1.3	0.6	2.1	0.6
Fabricated Structure Metal	1.2	0.2	0.8	0.2
Glass Products	1.3	0.3	0.9	0.3
Ready mix concrete	2	0.3	2	0.3
Plastics material and resin	1.5	0.3	1.7	0.3
Motor and Generators	0.8	0.2	0.6	0.2
Wiring Devices	0.7	0.2	0.6	0.2
Misc. Electrical Equipment	0.4	0.2	0.6	0.2
Turned screws, nuts, bolts	0.9	0.2	0.6	0.2
Electronic components	0.5	0.2	0.5	0.2
Plastic pipe, fittings, profiles	1.0	0.3	1.1	0.3
Wood container and pallets	1.3	0.3	0.7	0.2
Adhesive manufacturing	1.7	0.3	1.1	0.2
Semiconductors	0.4	0.2	0.4	0.1
Rolled steel shapes	2.4	0.4	1.4	0.5
Paint and coatings	0.9	0.2	1.2	0.2
Sheet metal	1.1	0.2	0.8	0.2
Administrative Services	0.2	0.07	0.09	0.05

6.3 Analysis Using Carnegie Mellon IO Database and CEDA IO Database

We present results for a system installed in Phoenix, Arizona with 1800 inverters, 50 transformers, 1800 trackers, and 54000 panels. This installation scenario is not real; however, installation in Phoenix Arizona is a common point of comparison for solar systems and this scenario is the one used by SolFocus to establish cost baselines and draw comparisons with competitors. According to the LCOE model, the system will generate roughly 28,000,000 kWh of electricity annually.

Table 6.4 and Figure 6.7 shows the results of the GHG LCA for an installation in Phoenix, Arizona (Direct Normal Insolation of 6.9 kWh/m^2/day). The installation is utility scale and assumed to replace rather than supplement the local electricity mix. Electricity values shown in these results are all based on the average United States electricity mix - these will be regionalized in the optimization section. This assessment finds that the SolFocus panels have GHG emissions of 49 GHG/kWh (CMU) or 64 GHG/kWh (CEDA), and the GPBT is 3 years.

Although Table 6.4 assumes all electricity consumed is the average US electricity mix, transportation around the world is included as "All Transportation" in the table. The following transportation is explicitly added to the LCA: (1) Panel transport from India to Arizona (2) Tracker and controller transport from Spain to Arizona (3) BOS Transformer transport from Wisconsin to Arizona (4) BOS Inverter transport from Tennessee to Arizona (5) Tracker Steel transport from China to Arizona (6) Primary Mirror, Secondary Mirror, Receiver, Window, Backpan, and Heatsink transport from China to India (6) PV Cell transport from Southern California to China. Trucking distances are obtained from Google Maps [123] and sea travel distances are obtained from online port to port statistics [107]. Transportation emissions factors are assumed to be 154 mg-CO2eq/kg-km by truck and 35 mg-CO2eq/kg-km by sea.

Figure 6.8 shows the GHG breakdown based on CEDA data where total electricity has been stripped from each component and put into its own portion of the pie chart. Figure 6.9 shows this same information based on CMU data. Separating electricity in the results is unusual, however, it is important here to show that the total electricity and transportation emissions sum to 35-40% of total emissions and there is therefore a large opportunity for GHG reductions through supply chain re-design.

Table 6.4: Results of SolFocus GHG LCA - assuming all US Electricity - in kg-CO_{2eq}. The data has been separated into all except electricity, and the electricity portion.

	CEDA [kg-CO_{2eq}]	CEDA Elec [kg-CO_{2eq}]	CMU [kg-CO_{2eq}]	CMU Elec [kg-CO_{2eq}]
Concrete Foundation	192,000	26,000	165,000	28,000
Foundation Rebar	150,000	24,000	60,000	30,000
BOS Wiring	416,000	128,000	255000	125,000
Inverters	3,000,000	1,410,000	1,830,000	1,036,000
Transformers	105,000	49,000	63,000	36,000
Tracker Steel Support	6,637,000	829,000	3,400,000	789,000
Tracker Controllers	1,888,000	875,000	1,137,000	643,000
Tracker Motors & Gears	3,114,000	904,000	1,642,000	747,000
Tracker Painting	1,173,000	256,000	1,230,000	287,000
Panel Assembly	1,989,000	1,652,000	1,140,000	1,647,000
Backpan	4,662,000	1,992,000	4,887,000	2,198,000
Receiver Assembly	5,987,000	1,693,000	3,587,000	1,688,000
Glass Window	299,000	67,000	132,000	67,000
Secondary Mirror	3,144,000	708,000	1,390,000	708,000
Primary Mirror	1,600,000	453,000	1,190,000	508,000
Overhead	9,500	3,600	4,300	2,400
	Not from CEDA or CMU but included for completeness:			
All Transportation	9,396,000			
PV Cell	6,226,000			

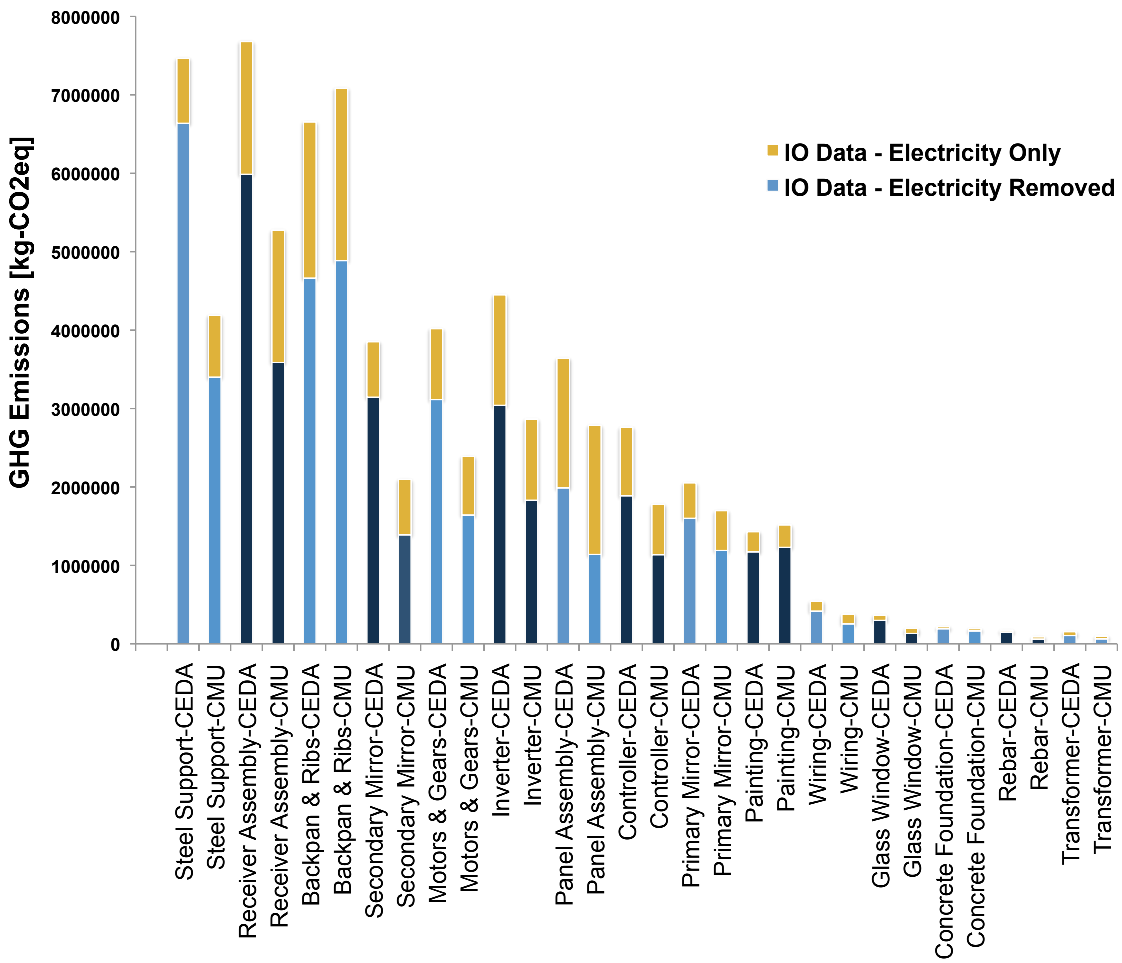

Figure 6.7: CEDA versus CMU comparison of results for SolFocus

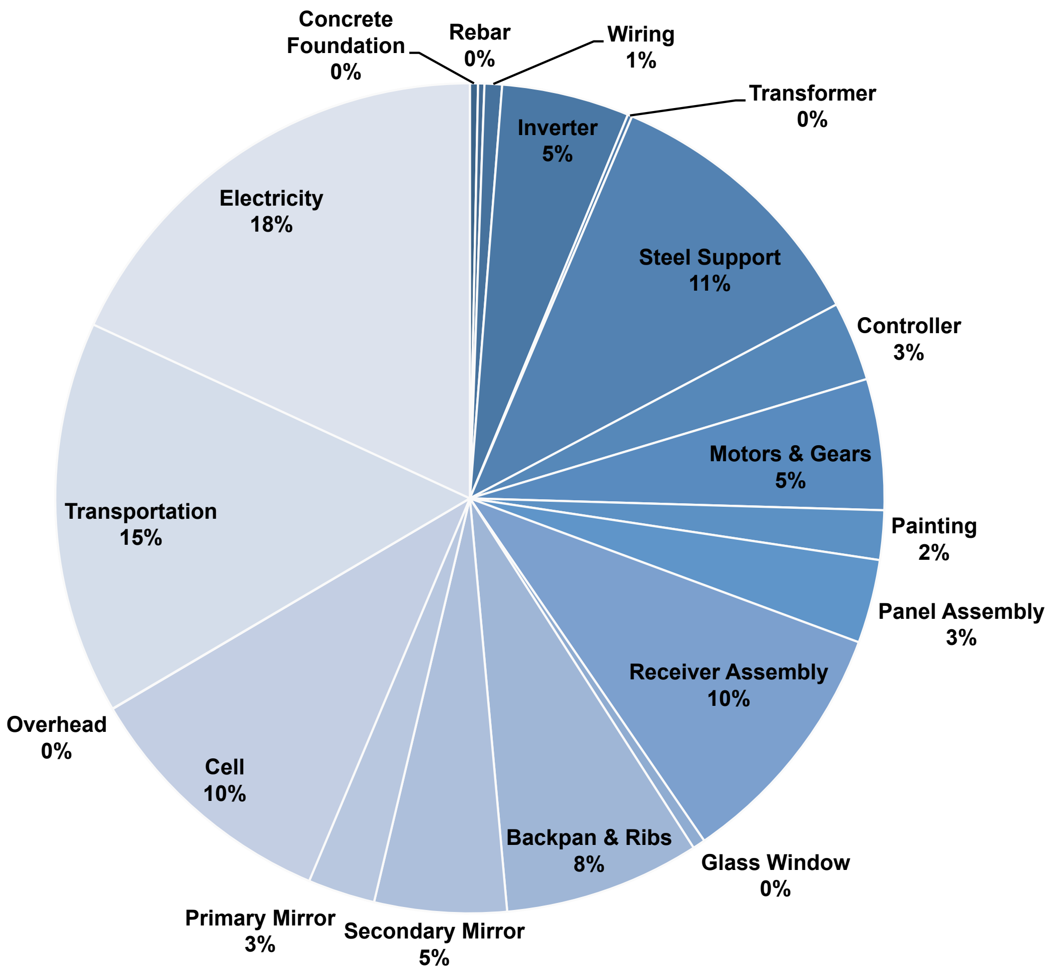

Figure 6.8: SolFocus GHG breakdown using CEDA data with electricity shown separately

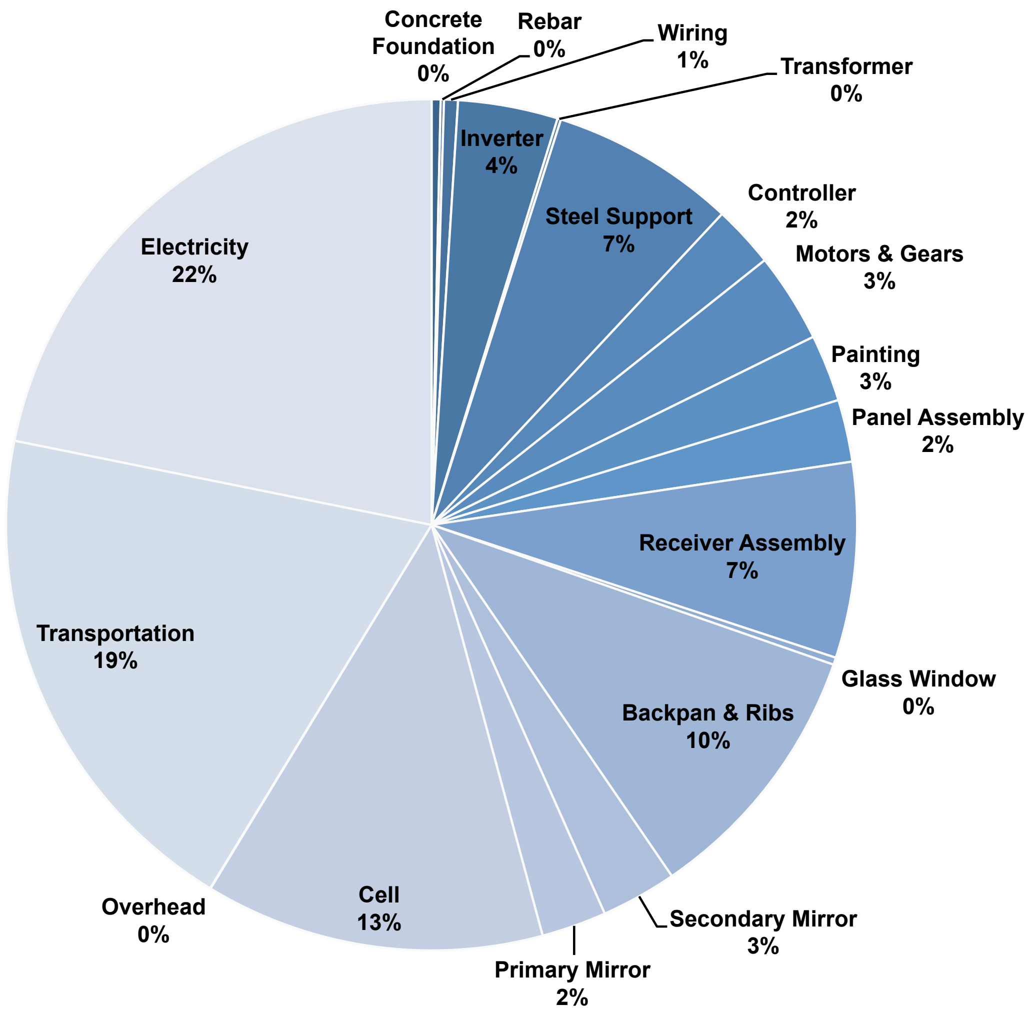

Figure 6.9: SolFocus GHG breakdown using CMU data with electricity shown separately

6.4 SolFocus Supply Chain Optimization

There are two ways to optimize the SolFocus supply chain: (1) minimize the electricity and transportation emissions for a fixed installation site (2) maximize the overall GROI given multiple possible installation sites. We will explore both options here. For the optimization, uncertainty, and sensitivity analyses we will utilize only the CEDA3 results (not the CMU based results shown in Figure 6.9).

In this optimization, five potential installation sites are investigated for SolFocus: Mountain View, California; Puertollano, Spain; Phoenix, Arizona; Crete, Greece; Sydney, Australia; and Shanghai, China. Assuming that the SolFocus panels will be grid-tied utility scale installations, the marginal offset electricity emissions from the WRI are utilized for GROI calculations (Table 4.2).

Additionally, through conversations with engineers at SolFocus a few feasible supply chain alternatives have been developed, which are illustrated in Figure 6.10. By choosing between alternatives, a supply chain that will minimize GHG emissions can be obtained.

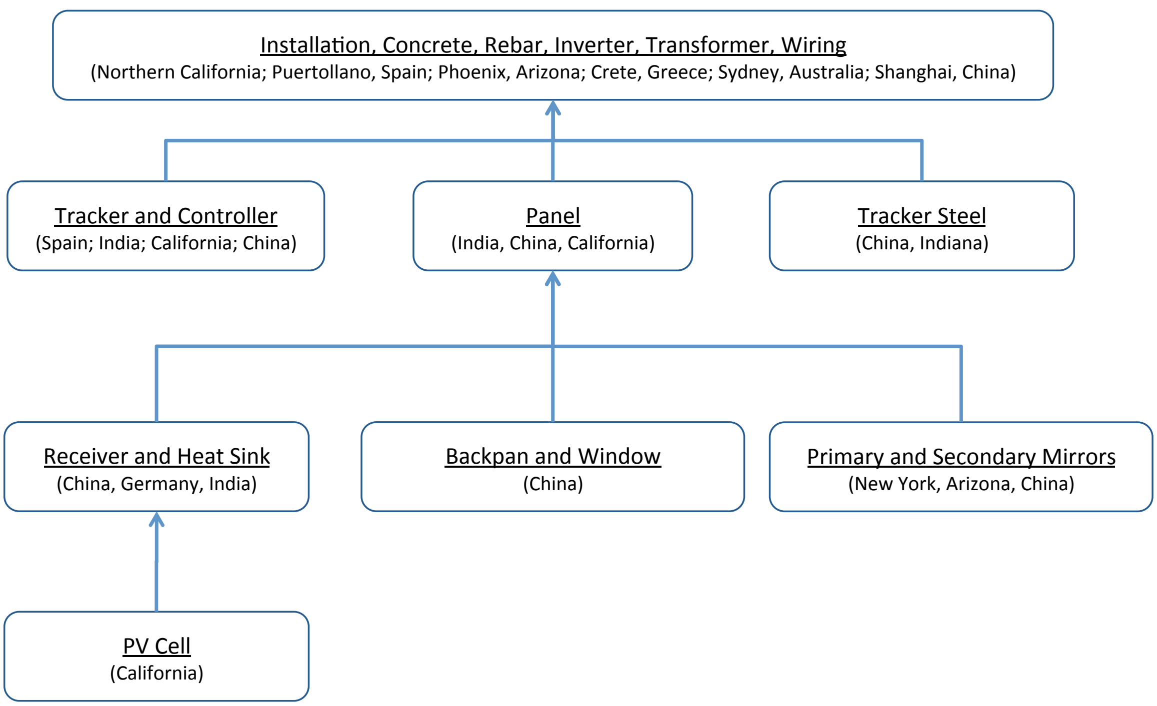

Figure 6.10: Supply chain alternatives for SolFocus

Results are shown in Tables 6.5 and 6.6 for the current and optimal supply chain in each installation location. Assuming a fixed installation point, electricity and transportation emissions are reduced in each case by approximately 25%. This illustrates that the supply chain optimization was effective. Furthermore, although the total emissions in each location do not vary by much, it is clear that an installation in Sydney has twice the opportunity of all other installations to mitigate climate change because of its high GROI. If SolFocus was not using GROI to make decisions, but instead focused on GHG/kWh or total GHG emissions, they would not see this opportunity to both market their product to the Australian market and policy makers and to have an even greater impact on global GHG emissions.

GHG intensity is directly influenced by the DNI in each installation location; however, GROI shows such a powerful variability by location because it is influenced proportionally by both DNI and the offset GHG/kWh in each location. While DNI shows little variability by location (6, 7, 5, 6, 7 kWh/m^2/day in Puertollano, Phoenix, Sydney, Mountain View, and Crete respectively) the offset GHG/kWh shows a significant variation (0.4, 0.5, 0.9, 0.4, 0.8 kg-CO_{2eq}/kWh for Puertollano, Phoenix, Sydney, Mountain View, and Crete respectively). Therefore, even though Sydney has the lowest DNI and would produce less electricity per year than another installation, the opportunity for GHG reductions is great enough to make it the optimal installation site for GHG-reductions.

Table 6.5: Current supply chain for each installation location

	Puertollano	Phoenix	Sydney	N. Cali.	Crete
Elec and Transit GHG [tons-CO_{2eq}]	15,000	16,000	16,000	15,000	16,000
Total GHG [tons-CO_{2eq}]	55,000	56,000	56,000	55,000	56,000
GHG Intensity [g-CO_{2eq}/kWh]	56	66	48	53	65
GROI [kg-CO_{2eq}/kg-CO_{2eq}]	7	8	18	7	12
tracker steel	Shanghai	Shanghai	Shanghai	Shanghai	Shanghai
panel assembly	India	India	India	India	India
controller and motors	Spain	Spain	Spain	Spain	Spain
mirrors	Arizona	Arizona	Arizona	Arizona	Arizona
receiver assembly	N. Cali.	N. Cali.	N. Cali.	N. Cali.	N. Cali.

Table 6.6: Optimal solution for each installation location

	Puertollano	Phoenix	Sydney	N. Cali.	Crete
Elec and Transit GHG [tons-CO_{2eq}]	12,000	12,000	13,000	11,000	13,000
Total GHG [tons-CO_{2eq}]	52,000	52,000	53,000	51,000	53,000
GHG Intensity [g-CO_{2eq}/kWh]	55	59	44	46	60
GROI [kg-CO_{2eq}/kg-CO_{2eq}]	7	9	20	8	13
tracker steel	Indiana	Shanghai	Shanghai	Shanghai	Indiana
panel assembly	N. Cali.	N. Cali.	N. Cali.	N. Cali.	N. Cali.
controller and motors	N. Cali.	N. Cali.	N. Cali.	N. Cali.	N. Cali.
mirrors	New York	New York	New York	New York	New York
receiver assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart

6.5 SolFocus Supply Chain Uncertainty and Sensitivity

As was discussed in section 5.2, the Monte Carlo method is utilized here to estimate the effect of variable uncertainty on the optimal supply chain for SolFocus. We assume the following uniform variable distributions:

- All two-hundred transportation distances by land and sea vary uniformly by plus or minus 10%.
- All electricity IO factors from CEDA vary uniformly by plus or minus 20%. Although there is little variability seen between CEDA and CMU electricity factors (Table 6.3) this variation is meant to capture unknown differences in regional electricity demand to produce the same part.
- All electricity emissions factors (GHG/kWh) vary uniformly by -10% to +20%. This variability is based on Figure 4.7, which demonstrates the WRI factors chosen for this model tend to be low estimates.
- Trucking emissions vary uniformly by -90% to +120% to accommodate the possibility of rail and account for the full range of emissions factors given in tables 4.7 and 4.8.
- Sea emissions vary uniformly by -70% to +120% as seen in Table 4.5.
- The weight of each item is fixed.

We see in Table 6.7 that roughly 4 solutions emerge for each installation location. Although it sounds like a lot of options, this is a great result given that there were over 1,000 possible supply chains. We argue that it is a strength of this approach that multiple alternatives have emerged that are essentially equally beneficial, giving the decision maker the ability to make a decision on more than just carbon.

For some items in the supply chain, location of the installation influences their manufacturing location; and for some items, regardless of installation location, the optimal locations are the same. To gain more insight into this difference, we will consider each component in turn:

- Steel: For installation in Puertollano, Crete, and Phoenix, steel from Indiana is shown to be the best solution. For installation in Sydney and N. California, steel from Shanghai is shown to be the optimal. This result is based solely on transportation emissions because electricity emissions in Shanghai and Indiana are equivalent. Therefore, travel by land from Indiana to Mountain View has greater GHG emissions than travel by sea from Shanghai to San Francisco and then truck to Mountain View. Similarly, travel by land from Indiana to the sea and then by sea is worse than travel by sea from Shanghai to Sydney.
- Panel Assembly: In almost every case, panel assembly is optimal in Northern California. The alternative locations were either India or China. In this case, electricity mix is the major driver, rather than transportation, because the electricity mix emissions in Mountain View are a third of those in India or China. Additionally, the Panel

is forced in this scenario to receive its backpan and window from China, making the location on the west coast advantageous to reduce the transportation emissions from these heavy items. The exception to this is installation in Sydney where the shorter transportation distance from Shanghai overrules the reduced emissions in N. California.

- Controller and Motors: There is a preference in all the solutions for getting these items from N. California, however, Spain emerges as a strong alternative location. The other possible locations were India and China. It is clear, then, that electricity emissions are driving the solution because the Spain and N.California electricity mixes emissions are half of the emissions for India or China.
- Mirrors: The mirrors are a component of the panel assembly, which is optimally occurring in N. California. The optimal mirror manufacturing sites are New York and Phoenix, where the sub-optimal alternative is to manufacture in China. Again, electricity emissions are driving location more than transportation here, particularly since the mirrors are lightweight.
- Receiver Assembly: The optimal solution for receiver assembly is always in Stuttgart. This is completely driven by electricity variability because the other two locations were China and India whose electricity emissions are 3 times greater than Germany. But because the cell is lightweight its transportation emissions by sea to Hamburg and then by land to Stuttgart are negligible relative to the electricity emissions savings from manufacturing the receiver in Germany.

Sensitivity results are shown in Tables 6.8 and 6.9. There were 228 variables tested in the sensitivity analysis, however, only variables that induced a solution change within +500% to -100% are shown in the table. We will examine each variable where uncertainty is shown to be important by the sensitivity analysis:

- Trucking emissions factor: Trucking is shown to be sensitive at -30% and +40%. We know from Table 4.7 on transportation emissions that trucking emissions are not particularly well known and can be anywhere from 15-334 mg-CO_{2eq}/kg-km, or -90% to +120%, indicating that transportation variability is a major driver for the multiple solutions seen in the Monte Carlo analysis.
- Sea emissions factor: Sea freight emissions are shown to be sensitive to at least -60% and +50%. We used a value of 35 mg/kg-km and from Table 4.5 we know sea emissions can vary from 11 to 77 mg/kg-km; or -70% to +120%, indicating that transportation variability is a major driver for the multiple solutions seen in the Monte Carlo analysis.
- Steel weight: A reduction in steel weight of 60% for a Phoenix install or 80% for a Sydney install changes the driver of the analysis from transportation to electricity. This example shows the scope for product re-design to influence the optimal choice of supply chain.

- Panel IO electricity factor: Reducing the panel IO electricity factor by 60-90% flips the result for Puertollano, Phoenix, Sydney, and Crete. This is because the driving factor for manufacturing the panel was electricity mix for these install locations; however, if the electricity is brought low enough, then transportation becomes the driving factor. Note that the IO sensitivity reflects both the sensitivity of the CEDA IO factor for electricity and the producer price index scaling that adjusted the price from 1998 to 2007. Changes in either of these can bring about the solution change.

- Mirrors IO electricity factor: At a -40% change in the IO electricity factor for the mirrors, the solution flips for all installation locations. This change represents the flip from an optimal in NY to an optimal in Phoenix where suddenly the ability to travel the shorter distance from Phoenix to N. California outweighs the reduced electricity emissions in NY. Note that the IO sensitivity reflects both the sensitivity of the CEDA IO factor for electricity and the producer price index scaling that adjusted the price from 1998 to 2007. Changes in either of these can bring about the solution change.

- All electricity factors: The solutions are shown to be sensitive at a variation in the electricity GHG emissions of greater than +/- 20%. This leads to two insights (1) manufacturers that want to remain the optimal solution can choose to opt out of a regional electricity grid and utilize low-carbon renewable energies such as wind, solar, or hydro (2) further research is needed on regional electricity grid emissions. We assumed the electricity grid mix emissions given by the WRI [97], and we showed in section 4.2.2 that these values tend to be on the lower end of estimates made by researchers in this field and that there is wide variability in the GHG/kWh estimates depending on the source. Note that there is high sensitivity for every electricity mix except India and Germany. India is not as sensitive because it had the highest estimated emissions and therefore requires larger percentage reductions before a change occurs in the optimal supply chain. Germany is not as sensitive because it had the lowest estimated emissions and therefore requires a larger percentage increase before a change occurs.

The overall conclusions from this are that either electricity emissions or transportation emissions may be the factor driving manufacturing location depending on what manufacturing sites are proposed (i.e., how different is the electricity mix in the feasible manufacturing locations), the variability in the distance between feasible sites, the quantity of electricity used to make the component, and the weight of the component.

Table 6.7: Monte carlo results for 10,000 iterations

	1st Optimal	2nd Optimal	3rd Optimal	4th Optimal	5th Optimal
Puertollano Installation					
Likelihood	36%	30%	16%	14%	2%
Tracker Steel	Indiana	Indiana	Indiana	Indiana	Indiana
Panel Assembly	N. Cali.	N. Cali.	N. Cali.	N. Cali.	Shanghai
Controller & Motors	N. Cali.	N. Cali.	Spain	Spain	N. Cali.
Mirrors	Phoenix	New York	Phoenix	New York	New York
Receiver Assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart
Phoenix Installation					
Likelihood	30%	27%	12%	12%	8%
Tracker Steel	Indiana	Indiana	Indiana	Indiana	Shanghai
Panel Assembly	N. Cali.	N. Cali.	N. Cali.	N. Cali.	N. Cali.
Controller & Motors	N. Cali.	N. Cali.	Spain	Spain	N. Cali
Mirrors	Phoenix	New York	Phoenix	New York	Phoenix
Receiver Assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart
Sydney Installation					
Likelihood	29%	23%	17%	15%	7%
Tracker Steel	Shanghai	Shanghai	Shanghai	Shanghai	Shanghai
Panel Assembly	Shanghai	N. Cali.	N. Cali.	Shanghai	N. Cali.
Controller & Motors	N. Cali.	N. Cali.	N. Cali.	Spain	Spain
Mirrors	New York	Phoenix	New York	New York	Phoenix
Receiver Assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart
N. California Installation					
Likelihood	37%	31%	14%	12%	2%
Tracker Steel	Shanghai	Shanghai	Shanghai	Shanghai	Indiana
Panel Assembly	N. Cali.	N. Cali.	N. Cali.	N. Cali.	N. Cali.
Controller & Motors	N. Cali.	N. Cali.	Spain	Spain	N. Cali.
Mirrors	Phoenix	New York	Phoenix	New York	New York
Receiver Assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart
Crete Installation					
Likelihood	22%	21%	17%	13%	8%
Tracker Steel	Indiana	Indiana	Indiana	Indiana	Indiana
Panel Assembly	N. Cali.	Shanghai	N. Cali.	Shanghai	N. Cali.
Controller & Motors	N. Cali.	N. Cali.	N. Cali.	Spain	Spain
Mirrors	Phoenix	New York	New York	New York	Phoenix
Receiver Assembly	Stuttgart	Stuttgart	Stuttgart	Stuttgart	Stuttgart

Table 6.8: One at a time sensitivity analysis for a customer in each location - part I. Values represent the percentage change that induced a new optimal supply chain. Where the percentage change was negative or exceeded +500% the result is not given. Where a variable was shown to have no sensitivity for any installation case it is not included.

Variable	Puerto-llano	Phoenix	Sydney	Mountain View	Crete
land dist. Mountain View to Phoenix	–	+300%	–	–	–
land dist. Indiana to Puertollano	+90%	–	–	–	–
land dist. Indiana to Phoenix	–	-30%	–	–	–
land dist. NY to Crete	–	–	–	–	+40%
land dist. NY to Mountain View	+40%	+40%	+40%	+40%	+40%
sea dist. Shanghai to Malaga	+40%	–	–	–	–
sea dist. Shanghai to Sydney	–	–	+140%	–	–
sea dist. Shanghai to San Francisco	+240%	+280%	+180%	+170%	+190%
sea dist. Shanghai to Heraklion	–	–	–	–	-30%
sea dist. San Francisco to Malaga	+280%	–	–	–	–
sea dist. Shanghai to San Francisco	–	–	+150%	–	–
sea dist. Mountain View to Heraklion	–	–	–	+120%	–
sea dist. NY to Malaga	+240%	–	–	–	–
sea dist. NY to Australia	–	–	-80%	–	–
sea dist. NY to Heraklion	–	–	–	+40%	–

Table 6.9: One at a time sensitivity analysis for a customer in each location - part II. Values represent the percentage change that induced a new optimal supply chain. Where the percentage change was negative or exceeded +500% the result is not given. Where a variable was shown to have no sensitivity for any installation case it is not included.

Variable	Puerto-llano	Phoenix	Sydney	Mountain View	Crete
trucking emissions factor	+50%	-30% & +50%	+50%	-60% & +50%	+40%
sea emissions factor	-90%	+50%	+210%	+170%	-60% & +220%
panel weight	–	–	+470%	–	+320%
mirror weight	+50%	+50%	+50%	+50%	+50%
steel weight	–	-60%	-80%	–	+100%
backpan weight	+230%	+270%	+170%	+310%	+180%
panel IO elec factor	-80%	-90%	-60%	–	-60%
steel IO elec factor	–	+90%	+240%	+310%	-60%
mirrors IO elec factor	-40%	-40%	-40%	-40%	-40%
elec factor - Spain	-20%	-20%	-20%	-20%	–
elec factor - Phoenix	-20%	–	-20%	-20%	–
elec factor - China	-40%	-50% & +30%	-40% & +50%	-50% & +60%	-20%
elec factor - Mountain View	+20%	+20%	+20%	+20%	+20%
elec factor - Indiana	+50%	-30%	-60%	-70%	+20%
elec factor - NY	+20%	+20%	+20%	+20%	+20%
elec factor - India	-60%	-80%	-60%	-80%	-50%
elec factor - Germany	+140%	+140%	+140%	+140%	+140%

Chapter 7

Conclusions

Through the introduction of environmental return-on-investment metrics and regionalized greenhouse gas tradeoffs, this dissertation introduces a method to reduce global greenhouse gas emissions without the need for new product design. We have demonstrated that because transport and electricity can represent 30-40% of life-cycle GHG emissions, and vary widely by region, tradeoffs between regions provide a significant opportunity for GHG reductions. Furthermore, the use of a GHG return-on-investment metric takes advantage of electricity variability in both production and installation of new technologies (e.g., install solar panels, new high-efficiency machinery, or low energy buildings in high GHG electricity regions). This opens the door for global policy and decision-making about where it is optimal to install new technologies and where it is optimal to manufacture goods.

To enable the efficient implementation of green manufacturing, this dissertation proposes the following three-pronged approach to management and reduction of GHG emissions in manufacturing:

1. Metrics design for environmental decision-making: A 4 step methodology is proposed for decision-making metric design: goal definition (what is being measured), analysis scope definition (what geographic region is being included), environmental scope definition (what is the scope of the environmental concern), choice of metric type (green or sustainability).

2. Iterative financial hybrid LCA: An iterative financial hybrid LCA approach utilizing modified IO-LCA and process data is recommend. This method can be used by someone with a range of available data from a simple bill of materials to detailed manufacturing data.

3. Optimization to take advantage of regional tradeoffs: Regional electricity factors are used with IO electricity data to visualize supply chain electricity and transportation GHG emissions tradeoffs and reduce GHG emissions through supplier location choices.

The primary new contributions from this research are:

1. A method for global GHG reductions, separate from product re-design, through optimization of supply chain layout based on transportation and electricity GHG emissions tradeoffs.

2. Development of effective and targeted return-on-investment environmental metrics to guide decisions that promote the fastest route to reduce environmental impacts in manufacturing.

3. Validation of the feasibility of using top-down iterative financial hybrid LCA to ensure a comprehensive LCA and to guide regional input-output electricity estimates and tradeoffs in key areas.

4. Demonstration and development of the greenhouse gas ROI metric, iterative hybrid LCA methodology, and supply chain layout decision-making for concentrator solar PV.

7.1 Lessons Learned and Important Take-aways

Using the three-pronged approach in the automotive and solar energy case studies, multiple interesting observations emerge:

- While decision-making on product design relative to function, materials selection, and end-of-life are critical to a "sustainable" future, decisions based on electricity mix and transportation tradeoffs within the supply chain present significant opportunities for reductions in ways that require no re-design of the product.

- Supply chain decision-making has been focused on end-of-life, minimizing transportation distances, and regional conditions related to risk and fate of environmental emissions. But simply re-locating suppliers to optimize tradeoffs between electricity mix emissions and transportation emissions can reduce global GHG emissions. The solar energy case study showed reductions of over 25% in the transportation and electricity emissions through a re-organized supply chain. The automotive case study showed reductions of over 50% to the transportation and electricity emissions through a re-organized supply chain. Offering alternative locations for the manufacturing of each component could allow for even greater reductions.

- It is important to be clear about the difference between a "sustainability" metric and a "green" metric, where the former indicates use relative to a renewing resource and the latter indicates consumption. The GROI metric presented for solar energy is an excellent example of a "green" metric in that it promotes global reductions of GHG emissions but does not indicate when emissions have reached a sustainable level.

- Use of proxy environmental metrics for other metrics could lead to missed decision opportunities. For example, the use of exclusively energy-based metrics for solar energy limited researcher's ability to understand regional GHG tradeoffs between electricity grids when using and offsetting electricity.

- The GHG return-on-investment (GROI) metric is introduced in this dissertation to reward the replacement of high GHG/kWh technologies. GROI is most favourable when a technology is produced using low GHG/kWh electricity and installed to offset high GHG/kWh electricity. GROI is also effective for making any decision that will have an influence on GHG emissions (such as the purchase of a new machine tool or a new regulation on fuel economy).

- The Automobile Case study demonstrated:

  1. Transportation and Electricity emissions could be reduced by 50% through intelligent decisions on supplier location.
  2. Local manufacturing is not always optimal. For customers in locations with high GHG electricity (e.g., Detroit, U.S.), purchasing their automobile from overseas, despite the transportation, has lower emissions than local manufacturing.

- The SolFocus Case study demonstrated:

  1. Despite large uncertainty in the transportation emissions, a small number of optimal solutions emerged providing a platform to further narrow down the final decision based on additional criteria such as cost and quality of product.
  2. Either electricity emissions or transportation emissions may be the factor driving the location of manufacturing depending on what manufacturing sites are proposed (i.e., how different is the electricity mix in the feasible manufacturing locations), the variability in the distance between feasible sites, the weight of the component, and the quantity of electricity required for manufcaturing. Furthermore, a similarity in the magnitude of these tradeoffs leads to an optimal result that is relatively unstable to uncertainty.
  3. Current metrics used for decision-making on solar energy technology are EROI and GHG/kWh which both lack important components of a characteristic metric. EROI fails to address one of the main motivations of alternative energy technologies: mitigating climate change. For example, EROI does not distinguish between a component manufactured using solar energy or one manufactured using fossil fuel energy. Furthermore, GHG/kWh does not distinguish between replacement of a coal-fired power plant or a hydro-power facility.
  4. The GHG return-on-investment metric accounts for the types of energy used during the technologies' lifetime, the efficiency of energy distribution, and the energy being offset at the point of use. It was demonstrated that installation in Australia had double the GROI of all other chosen installation sites because of the opportunity for offsetting Australia's coal-fired electricity.

- A set of guidelines to ensure a successful supply chain analysis are:

  1. Potential supplier and manufacturing locations must be known along with the resource (materials, water, energy) availability and infrastructure at each potential location.
  2. The resource requirements of each manufacturing stage must be quantified (modeled) for comparison.
  3. Important tradeoffs between transportation cost, lead-time flexibility, and environmental impact must be understood by the supply chain designer.

7.2 Future Work

This research sets the stage for regionalized environmental tradeoff analysis based on variations in the impact of using resources in different regions. In this dissertation we focused on the variations in emissions from electricity usage and transportation based on location. Future work could include variations in the use of other resources by region (such as water) as well as differences in the impacts of emissions by region (such as particulate emissions) and continue to build a harmonized global set of regionalized tradeoffs for environmental supply chain analysis. Furthermore, this work can be developed into a "Supply Chain Optimization and Planning for the Environment" (SCOPE) tool that would enable users to manage and optimize their supply chains based on environmental and economic constraints [49].

In addition to new tool development, there are significant opportunities for building on the research of previous researchers and this dissertation, including:

- Metrics Research
  - How to promote wider utilization of environmental ROI metrics: These metrics can be applied to benchmark products and systems for use in investment decisions or in government incentives to promote environmental impact reductions.
  - Methods for environmental design budgets: Metrics design is the precursor to defining "environmental design budgets" for engineered products and systems. These enforce a fixed maximum of environmental impacts a specific product or system can have to drive the design and performance of the product or system under consideration. Engineers and designers can then define environmental thresholds for sub-systems and components.
- Supply Chain Research
  - Methods for end-of-life supply chain optimization: The opportunity for regionalized tradeoffs is applicable to end-of-life supply chains as well.
  - Methods for operational supply chain optimization: There are operational factors in supply chain design that could be added to the analysis, including production sizes, transfer times, changeover times, inventory levels, warehousing, and scheduling.
  - Development of inter-regional electricity factors: To increase accuracy, regional electricity emissions factors need to account for traded electricity between regions. The model structure used for input-output analysis could be used for this analysis.
  - How to incorporate economic concerns into environmental optimization: As costs are the driving factor for most business decisions, an integrated cost model should be included in future analyses. Two possible ways to do this include: (1) use a multi-objective method where a weighted objective function is utilized to make decisions (2) assign a cost to environmental impacts and optimize the system based only on cost.

  - Development of methods to regionalize environmental input-output data: Integration with regional environmental IO tables and further analysis of regional variability is needed to capture technological, economic, and climactic differences other than transportation and energy mix.
  - Development of new methods to calculate and utilize Transportation GHG factors: Transportation emissions factors are currently provided in terms of distance, distance and weight, or distance and volume. Transportation values should also be reported as a base (empty vehicle emissions per km) plus a marginal factor (emissions per kg-km) for more accurate decision-making.
  - How to apply supply chain optimization at the government level: This entire discussion on the importance of including supply-chain analysis for comprehensive LCA also applies to country or regional analyses. A country that considers itself only responsible for emissions within its borders ignores the actual impact of consumers within that region on global emissions [124] and ignores the opportunity for global reductions.

- Energy LCA
  - How to incorporate energy storage into Solar LCA: Most large-scale renewable energies rely on the grid to provide power when they are non-operational (i.e., for solar at night). However, the growth of renewables will make the inclusion of energy storage into LCA increasingly important for a comprehensive analysis and could inform innovations in energy mix design for the optimal combination of solar, wind, other renewables or electricity technologies, and energy storage by region.
  - How to incorporate virtual water research into solar decision-making: Solar energy consumes little water during the use phase but a lot in the manufacturing phase. It is logical, then, to organize the solar supply chain so manufacturing occurs in regions with plentiful water supply and installation occurs in parched regions to offset the use of high water-demanding thermal technologies. Incentives, metrics, and policy to encourage this behavior could be crucial to water savings.

In conclusion, we have demonstrated the potential for reductions through return-on-investment metrics and regional GHG tradeoffs. This work sets the stage for the creation of a multi-objective environmental regionalized model. The strength of this approach is its ability to operate almost independently from new product design and re-design, therefore offering an additional opportunity towards meeting global sustainability needs. We envision this approach used in conjunction with other efforts of industrial ecology, new materials and products, increased efficiencies, and reduced demand, to improve our ability to reduce environmental impacts and move toward a sustainable future.

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