Integrative approaches to environmental life cycle assessment of consumer electronics and connected media

by

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Doctor of Philosophy

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Resource Management and Environmental Studies)

The University of British Columbia
(Vancouver)

June 2014

Abstract

The environmental impacts of information and communication technologies and consumer electronics are challenging to evaluate. Organizations and individuals wishing to reduce the impacts attributable to their usage of these products and systems rely on a limited technical knowledge base that struggles to stay current. Using a life cycle assessment approach which expresses environmental impacts quantitatively in terms of greenhouse gas emissions and primary energy demand, this dissertation significantly expands our understanding of the impacts of desktop computers, electronics products in general, and connected media services accessed in the home, in order to support environmentally-conscious decision-making and policy regarding these products and systems.

The first of three studies, a meta-analysis of prior life cycle assessments of desktop PCs, resolves an important ambiguity in this literature and demonstrates that greenhouse gas emissions due to operational energy consumption usually exceed those due to device manufacturing. The second study calculates embodied greenhouse gas emissions of eleven electronics products through a teardown analysis, and finds a linear relationship between mass and embodied emissions, thus demonstrating that lightweight, compact products offer environmental benefits relative to larger products. A comparison to studies of older products also reveals that newer products are more materially efficient, largely due to reduction in integrated circuit content per product. Finally, the third study calculates aggregate US consumer greenhouse gas emissions due to broadcast television, video on demand, online video, other online uses, and offline uses when consumed using televisions, personal computers, tablets, and smartphones, including emissions due to devices in the home, networks, and datacenters. The study concludes that emissions due to video end-uses account for 75% of total consumer ICT emissions. About 71% of consumer ICT emissions arise due to devices in the home, especially TVs and desktop PCs, with the remainder due to networks and datacenters. Mobile platforms using Wi-Fi connections are the least

impactful mode of consuming connected media content.

Collectively, the dissertation argues for a more integrated approach towards impact estimation, in order to surmount issues regarding variation of modeling assumptions across existing studies, longevity of published work, and coverage of emerging products and services.

Preface

The research chapters in this dissertation were written as manuscripts and are each either published in peer-reviewed journals, or intended to be submitted for publication.

Chapter 3 was originally published as "Sources of variation in life cycle assessments of desktop computers", authors Paul Teehan and Milind Kandlikar [1], in the *Journal of Industrial Ecology*, 2012. I conceived of the research, conducted the literature review, performed the analysis, and wrote about 95% of the manuscript. Dr. Kandlikar helped in framing and structuring the manuscript. The copyright to this article is held by the journal publisher, Yale University; republication within this dissertation is permitted under the license terms. The original article has been edited to conform to the dissertation's style regarding table and figure numbering, citations and references, and units. Appendix A contains the supplementary material originally published with the article, edited slightly to conform to dissertation style.

Chapter 4 was originally published as "Comparing embodied greenhouse gas emissions of modern computing and electronics products", authors Paul Teehan and Milind Kandlikar [2], in *Environmental Science & Technology*, 2013. I conceived of the research and designed the study, with some assistance from Drs. Kandlikar, Tony Bi, and Hadi Dowlatabadi, who provided critical feedback in the study's conceptual stages. I conducted 100% of the study, including the teardown analysis, life cycle assessment, and statistical analysis, and wrote about 95% of the manuscript; Dr. Kandlikar provided comments and edits to the manuscript. The statistical analysis was not present in the initial manuscript submission and was suggested by the journal's anonymous reviewers. The copyright to this article is held by the journal publisher, the American Chemical Society (ACS); republication within this dissertation is permitted under the license terms. The original article has been edited to conform to the dissertation's style regarding table and figure numbering, citations and references, and units. The original article's supplementary material is available online under an open access license through the publisher's website[1]. Appendix B contains an edited version of the supplementary material which has been re-organized to improve flow and expanded slightly to improve accessibility for non-specialist readers; extensive laboratory measurements provided in the original supplementary material are not included in Appendix B as they are lengthy and not integral to the communication of the research methods and results.

A preliminary and much smaller version of the study in Chapter 5 was published as "Estimating the changing environmental impacts of ICT-based tasks: a top-down approach", authors Paul Teehan, Milind Kandlikar, and Hadi Dowlatabadi [3], in the conference proceedings of the International Symposium on Sustainable Systems and Technology, 2010, which are not peer-reviewed. The research aims of the preliminary study were initially conceived of by myself and developed through collaborative discussions with Drs. Kandlikar and Dowlatabadi. The present manuscript in Chapter 5 has similar high-level goals to the preliminary study but was re-done from scratch with expanded scope and improved methods and data sources. This manuscript is intended to be submitted for publication in a peer-reviewed journal with authors Paul Teehan, Eric Masanet, and Milind Kandlikar. I designed the methods, compiled the input data, performed 100% of the analysis, and wrote about 95% of the manuscript. Dr. Masanet provided technical feedback on a draft of the study and suggested some improvements to the methods and input data sources. Drs. Masanet and Kandlikar each provided editorial feedback relating to the framing and structure of the manuscript.

[1] http://pubs.acs.org/doi/abs/10.1021/es303012r

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Acknowledgments

This research was primarily supported by the National Sciences and Engineering Research Council of Canada (NSERC), the Pacific Institute for Climate Solutions (PICS), and UBC's Bridge Program. Scientific software used in conducting research in this dissertation was funded by the UBC Sustainability Initiative. The study in Chapter 4 was additionally supported through in-kind donations from Dell Canada and from The Hackery in Vancouver; open access publishing for this study was sponsored by the Center for Climate and Energy Decision-Making at Carnegie Mellon University (NSF SES-0949710).

Sincere thanks to my supervisor, Prof. Milind Kandlikar, for accompanying me on the journey of the last six years with patience and kindness, and to Prof. Hadi Dowlatabadi, for challenging me to better myself. I would like to acknowledge the invaluable technical assistance from Prof. Eric Masanet, my collaborator in the study in Chapter 5, which greatly elevated this work. In addition, I benefited from the expertise of Profs. Kandlikar and Dowlatabadi, as well as Prof. Tony Bi, and my graduate student colleagues at UBC, especially Stefan Storey, Matt Dolf, and Rob Sianchuk. Finally, sincere thanks to the administrative staff at the Institute for Resources, Environment and Sustainability for their continuing hard work and support.

I've been priviledged to share the space at AERL with so many bright, engaged, genuine, and kind personalities, many of whom I am fortunate to count as friends: Stefan Storey, Bertine Stelzer, Cynthia Morinville, Lisa Westerhoff, Tee Lim, Maryam Rezai, Matt Dolf, Joshua Welsh, James Murphy, Elaine Hsiao, Christian Beaudrie, Olivia Freeman, Laura Cornish, Jordan Tam, Gerald Singh, Julia Freeman, Conor Reynolds, Francies Ries, Brian Gouge, Sara Elder, Ed Gregr, Sarah Klain, and all the others. Special thank you to the afternoon writing club, especially Stefan, Matt, and Maryam, for being with me in the final push.

Many thanks to my friends who have been with me during the last six years, festival camp-mates, band-mates, brunch-mates, everyone who was close enough to hug – Eric Jacobsen, Lisa Rockwell, Mike Gevaert, Kristjan Bergey, Kristen Walmsley, Marielle Camozzi, Kerry Freek, Gerrit van Woudenberg, Matt Siegle, Aleeza Gerstein, Kay and Kristin, Xianny Ng, Kerry Nickols, Kurt Vaughan, Claire Ray, James McConaghie, Hande Gungor, Stan Iordanov, Aaron Colin, Steve Luscher, Kate Rossiter, Kyle Sulyma, Bryan Chiu. At this stage, I believe one can count success in life by the frequency and duration of warm, loving hugs. Thanks to my brothers, whom I look forward to seeing more of on the other side, and to my parents, who have done a superb job in deliberately not asking those forbidden questions about progress.

In many ways the completion of this program represents the beginning of a new life chapter which promises to be rich, colourful, and alive, in part because of the vision and perspective I've gained over these years. There are three people in particular who were instrumental in helping me achieve this vision, without whom my task would have been immeasurably harder. First, Kevin Tate, my supervisor at Pulse Energy, has been incredibly supportive and flexible throughout the last year, far beyond my expectations; I greatly look forward to the coming years at Pulse. Second, Dr. Douglas Ozier, my counselor, has helped me become the person I've always wanted to be; our work has been transformative and life-changing in ways that are hard to overstate. Finally, Rune McKellar, my fiancée, has shown me that sometimes dreams can come true; that it is okay to believe in love, peace, and truth; and that there can be magic in the world.

For Rune,

who gave me myself.

Chapter 1

Introduction

The research in this dissertation evaluates the environmental impacts related to information and communication technologies and consumer electronics (ICTs), including computers, servers, mobile electronic devices, TVs, and related devices. ICTs impact the environment through many mechanisms, including through operational energy consumption, through material and energy inputs and pollutant outputs in manufacturing and disposal processes, and through changes in human behavior which may affect other industries. This work considers environmental impacts in terms of primary energy consumption and greenhouse gas emissions (GHGs). The high-tech sector is fast-moving, characterized by rapid emergence and uptake of new products and services and corresponding change in the nature of environmental impacts due to ICT.

These impacts have been described through several narratives, which have evolved over time. Growth of e-commerce and the internet in the 1990s was initially cast as a means of achieving "weightless" economic growth [6, 7, 8] leading to a more dematerialized society with reduced resource consumption [9, 10, 11]. A contrary response emerged with studies of the environmental impacts of electronics, notably the pioneering life cycle assessment-based work of Eric Williams [12, 13] and others, investigative reports of social and environmental justice and public health issues surrounding informal e-waste recycling [14, 15, 16], and alarmist forecasts predicting explosive growth in energy consumption due to the internet [17] which were later debunked [18]. Amidst continuing research in each of these strands - see reviews on life cycle assessments [19, 20], impacts due to e-waste [21, 22], and studies of energy consumption of the ICT sector [5, 23, 24] - a more pragmatic re-framing of earlier "weightless" narratives acknowledges the environmental downsides of the ICT industry, estimated to account for about 2 to

3% of global GHG emissions [25] and about 13% of US residential and commercial building energy consumption [26], but argues that the application of ICT could improve efficiency and resource consumption across the economy, targeting the remaining 97% of GHG emissions [27, 28, 29, 30, 31, 32, 33], though these studies are largely conjectural rather than predictive.

Reducing overall impacts, whether considering impacts due to ICTs themselves or due to their application, requires identifying key leverage points at which interventions may be targeted, and supporting the design and implementation of such interventions. There are many dimensions through which impacts due to ICTs may be considered, and thus many different types of interventions which have been historically applied, such as efficiency standards, voluntary labeling schemes, guidance and information programs, restrictions on hazardous substances, and others. The goals of an intervention depend on those of the actor carrying it out; for example, firms may enact interventions in order to reduce their own costs, while governments and non-profit advocacy groups may act to reduce environmental impacts that arise as market externalities and thus will not normally be acted upon through market incentives. Likewise, the mechanism of an intervention depends on the capabilities of the actor; firms and individuals usually act only upon themselves, but government agencies can affect the market directly through regulation, and indirectly through incentives and information programs.

Scientifically rigorous quantifications of impacts play an important role in green decision-making and policy-making, especially for interventions that are designed to reduce impacts that are normally specified quantitatively. For ICT-using firms and individuals, the ability to preferentially support lower-impact products, systems, and behaviors pre-supposes the existence of an operationally useful definition of “lower-impact”. In the case of products, labeling schemes like ENERGY STAR [34] and EPEAT [35] which incorporate fundamental scientific research seek to provide this definition, though they have limitations, such as limited coverage of newer product families. For systems and behaviors that are considerably more complex, guidance is more limited.

The research in this dissertation is designed to support decision-making among ICT-using firms and individuals, both directly through the study of ICT behaviors, and indirectly through contributions to the fundamental scientific literature describing impacts of ICT products. The research findings also suggest priorities for policy approaches to encourage green decision-making relating to ICT. Impacts are defined quantitatively in terms of energy use and GHG emissions using a life cycle assessment (LCA) approach.

1.1 Research approach and goals

Life cycle assessment is an engineering methodology which models products and systems as linear sums of component processes, expressing the impacts of each component in quantitative terms, and aggregating component impacts to determine the overall impact of the product or system. LCA has become a primary methodology for the quantitative determination of environmental impacts due to ICT products and services and has been applied to calculate impacts of products like desktop PCs [13], laptops [36], and monitors [37], and services like reading e-books [38], downloading music [39], and streaming video [40], among others. Chapter 2 introduces LCA and reviews its prior application to ICT producst and services.

LCA studies are, by their nature, highly sensitive to modeling assumptions, such as geographic and temporal scope, method of aggregation, source of industrial process data, and especially the definition of the product or system under study. For this reason, LCAs are most effectively used either as a tool for comparing the impacts of different stages of an industrial process, or for comparing the impacts of alternative means of achieving a function; within the context of a study, modeling assumptions can be held constant allowing for valid comparisons. Comparisons of the results of one LCA study to another are only valid if the studies are carefully adjusted to ensure consistency of modeling assumptions and input data, but carrying out such adjustments is time-consuming and sometimes impossible as the assumptions may be incompletely specified and input data sources proprietary. Nevertheless, it is unrealistic to expect researchers and analysts to start from scratch every time, especially when modeling the impacts of network-driven services which touch many different ICT products and systems including the internet itself; accordingly, the integration of prior results from multiple LCA studies is a standard practice as displayed in several recent studies, e.g. [39, 40, 41, 42, 43, 44, 45]. The knowledge base upon which studies of the impacts of complex ICT systems are built is always imperfect and often out of date, yet a research need to understand these impacts in accurate terms remains. Thus, a fundamental challenge is one of integration, which is hindered by opaqueness in modeling assumptions and source data from existing studies, and by the fast rate of change in the high tech sector that can outpace the academic literature.

ICT is a dynamic, complex field, characterized by rapid emergence and uptake of new products and services which can quickly become embedded throughout societies and economies. Global demand for

ICT products and services is undoubtedly rising, which increases the need to understand the relationship between these products and services and environmental impacts. Fundamental research exploring this relationship is hampered by many challenges, three of which are addressed in this dissertation. First, the interpretation of LCA results is difficult due to the complexity of products being studied and variability in the ways in which they may be used (Chapter 3). Second, ongoing rapid proliferation and obsolescence of devices creates significant knowledge gaps (Chapter 4). Third, the rise of connected "cloud" services greatly increases the complexity of typical ICT end-uses (Chapter 5). Actionable policies targeting green decision-making rely on the precise information which is best obtained through detailed LCA, but responding to the methodological challenges presented by the dynamic ICT sector requires a simultaneous higher-level view, in order to anchor detailed LCA studies within the broader context.

Given this need, all three studies in this dissertation are integrative in nature. The first study, presented in Chapter 3, is driven by the observation that several prominent LCA studies of desktop PCs have contradictory results regarding the magnitude of GHG emissions attributable to the device, and in particular regarding whether the production or operational phases of the product life cycle are the largest contributor to GHG emissions. Using meta-analysis of existing studies, this study addresses the following research questions:

1. Among existing published LCA studies of desktop PCs, what factors contribute to their disagreement regarding overall impacts and the relative contributing share of product life cycle phases?

2. What can be concluded from existing LCA studies regarding the magnitude of GHG emissions and cumulative energy demand, and the relative contribution of each phase of the product life cycle to these indicators?

The second study, presented in Chapter 4, is motivated by lack of coverage of new products in existing LCA literature, difficulty in making product-by-product comparisons using existing literature due to variations in modeling assumptions across studies, and the challenge of adapting the existing knowledge base to assess new products. Using an LCA approach supported by teardown analysis of 11 products, this study addresses the following research questions regarding embodied GHG emissions of consumer electronics:

1. How do embodied emissions of modern devices compare to equivalent comparable devices from older product generations?

2. How do embodied emissions of small mobile devices (e.g. tablet) and small form-factor devices (e.g. lightweight desktop) compare to those of larger devices (e.g. full-sized desktop)?

3. To what extent may first-order estimates of embodied emissions be generated using limited product information, instead of conducting full LCA studies?

The final study, presented in Chapter 5, is motivated by significant knowledge gaps and methodological challenges relating to the GHG emissions of emerging connected media ICT end-uses which are quickly replacing older modes of ICT usage. Using an integrated model which incorporates secondary data sources from engineering, computer science, and market research domains, the study addresses the following questions:

1. What are the GHG emissions attributable to device, network, and datacenter infrastructure in servicing end-uses consumed on ICT devices, in a US consumer context in 2012 and 2017?

2. How do network and datacenter emissions compare to emissions due to using devices in the home?

3. Which end-uses are the largest contributors to emissions, and how is this likely to change looking forward to 2017?

The studies collectively argue for a reorientation towards higher-level integrated analyses, as opposed to point estimates of individual products or behaviors, in order to sidestep issues of study incompatibility, to allow for better flexibility in adapting to changing market conditions, and to open routes into connecting fundamental LCA results with research questions regarding higher-order environmental impacts of ICT. The significance of each of these studies is summarized in the following section.

1.2 Significance

The research in this dissertation makes several original, significant contributions to knowledge, outlined as follows. First, the meta-analysis of previous LCA studies of desktop PCs presented in Chapter 3 is to date the only published quantitative synthesis of LCA studies of ICT devices. It satisfactorily resolves an ambiguity in the literature which arose due to large differences in modeling assumptions across different studies. Through a thorough review of prior studies of operational energy consumption of desktop PCs, including field measurements, surveys, and data from ENERGY STAR, the study establishes a reasonable range for operational energy consumption of a desktop PC, and identifies unrealistically low assumptions for operational energy among two studies which reported production impacts exceeding operational impacts. The study concludes that energy and emissions due to operation of a desktop PC usually exceed those due to its production. In addition, the study showed that differences in product from factor, e.g. between a large workstation-class desktop and a small integrated desktop, could be a dominant factor influencing the study result.

Second, the study of embodied emissions of consumer electronics in Chapter 4 fills several important research gaps. First, it is the first peer-reviewed study of a tablet, netbook, compact desktop, and thin-client device, and the first study to include a wide cross-device comparison of these devices alongside more highly studied product categories, namely desktop, laptop, and monitor. It demonstrates that smaller form-factor products are less impactful in terms of embodied emissions, and that newer products are more materially efficient than older products due to higher levels of integration, leading to reductions in emissions. Second, it makes an important contribution of primary data: all of the study's laboratory measurements and a complete specification of the model were provided in the published study's supporting information under an Open Access license, making the results fully reproducible and available for adaptation by other researchers. Third, it analyzes product environmental reports published by Apple [46], and finds cross-device trends that are consistent across both the study's results and Apple's reports, which increases confidence in the quality of Apple's reports, despite their lack of peer review or disclosure of modeling assumptions and data sources. Fourth, it proposes a statistical linear model to estimate embodied emissions which suggests a route towards first-order impact estimation that sidesteps time-consuming, expensive LCA.

Finally, the study of connected media in Chapter 5 significantly expands the breadth and depth of our knowledge regarding the impacts of emerging behaviors on emerging platforms. It is the first study to compare the impacts of broadcast TV, video-on-demand, and other online and offline end-uses, and the first to compare impacts of end-uses using TVs against those using PCs, tablets, and smartphones. The derivation of energy and emissions intensity of fixed and mobile networks and datacenters in 2012 and 2017 is by itself a useful contribution to the literature which will improve the ability of other researchers to estimate the impacts of network-enabled end-uses In addition, this study appears to be the first to integrate behavioral data from market research firms alongside energy and emissions data, which was the key factor enabling calculation of total emissions due to each end-use on each platform; the data are presented transparently and completely to facilitate easy adaptation by other researchers.

1.3 Thesis overview

The thesis is structured as follows. Chapter 2 provides background and context for the research. It includes an overview of current trends in the high-tech sector; a review of conceptual frameworks through which environmental impacts have been discussed; a review of energy accounting and LCA, including prior application to the estimation of the impacts of ICT products and services, and knowledge gaps which are addressed in this dissertation; and a discussion of the methodological limitations of LCA, alternative approaches, and constraints on the validity of the findings. Taken together, these topics provide the necessary background for situating the research in both the larger debate on LCA methodology as well as the more specific challenges to environmental impact assessment posed by the rapid transformations in the ICT sector.

Chapter 3 presents a meta-analysis of life cycle assessment studies of desktop PCs. This chapter is an adaptation of a manuscript which was originally published in the *Journal of Industrial Ecology* in 2012 [1], co-authored with Dr. Milind Kandlikar. Supplementary material for this study is in Appendix A.

Chapter 4 presents a study of the embodied GHG emissions of 11 electronics products and derivation of a first-order model for estimation of embodied GHG emissions based on simple product characteristics. This chapter is an adaptation of a manuscript which was originally published in the journal *Environmental Science and Technology* in 2013 [2], co-authored with Dr. Milind Kandlikar. Supplementary material for this study is in Appendix B.

Chapter 5 presents a study of the GHG emissions due to consumer ICT end-uses using televisions, PCs, tablets, and smartphones, considering emissions due to device, network, and datacenter. This chapter is an adaptation of a manuscript, co-authored with Dr. Eric Masanet and Dr. Milind Kandlikar, which is not currently published. Supplementary material for this study is in Appendix C.

Finally, Chapter 6 summarizes the conclusions of each study and situates them within the broader research context, including a discussion of methodological limitations, directions for future work, and opportunities for operational application of the methods and findings put forward in this dissertation.

Chapter 2

Context and background

This chapter begins with an overview of different conceptual frameworks through which the environmental impacts of ICT have been studied. Next, the life cycle assessment methodologies applied in this dissertation are introduced, including methodological fundamentals related to the study of ICT products and services, trends in the ICT sector and associated research challenges, a review of prior work, and an overview of the resarch approach applied in this dissertation. Finally, the methodological limitations of LCA and of the studies on this dissertation are discussed.

2.1 Conceptualizing impacts of ICT

The research in this thesis primarily applies environmental life cycle assessment, a quantitative impact accounting methodology. This section reviews approaches to understanding environmental impacts and ICT, and situates LCA within this context. Two conceptual frameworks are introduced: a three-level taxonomy, and an economic decomposition approach, with focus on the latter as it can be quantitatively linked to the life cycle assessment-based approach used throughout this dissertation.

2.1.1 The three-level taxonomy

A review by Erdmann and Hilty [47] identifies two prominent categories of conceptual framework for considering the large-scale impacts of ICT systems on the environment: economic frameworks that examine ICT as a driver of technological efficiency, economic growth, and structural change; and a three-level taxonomy identifying direct/first-order impacts from the life cycle of ICT hardware; indirect/second-order impacts resulting from the application of ICT on other sectors, e.g. smart grids and smart buildings; and systemic/third-order/feedback impacts, including rebound effects and large-scale societal change, caused by the "emerging effects of ICT in the economic system", e.g. changes in travel patterns due to telecommuting. This taxonomy was first proposed by Berkhout and Hertin in a 2001 study [48] which categorized many of the ways ICT applications could impact the environment. The original characterization from Berkhout and Hertin is excerpted below, though other studies differ somewhat in their classification of different phenomena:

- *First order impacts:* direct environmental effects of the production and use of ICTs (resource use and pollution related to the production of ICT infrastructure and devices, electricity consumption of ICT hardware, electronic waste disposal)
- *Second order impacts:* indirect environmental impacts related to the effect of ICTs on the structure of the economy, production processes, products and distribution systems; the main types of positive environmental effects are dematerialization (getting more output for less resource input), virtualization (the substitution of information goods for tangible goods) and 'demobilization' (the substitution of communication at a distance for travel)
- *Third order impacts:* indirect effects on the environment, mainly through the stimulation of more consumption and higher economic growth by ICTs ('rebound effect'), and through impacts on life styles and value systems.

The three-level taxonomy has been influential, used in large reports by Forum for the Future [49] and the European Commission [50], and recently in what Erdmann and Hilty call the "second wave" of ICT-environment studies [47], a series of reports contrasting the relatively small direct impacts of ICT with potentially large indirect environmental benefits due to the application of ICT [27, 30, 33, 51, 52, 53]. Each of these studies considers a set of applications, calculates environmental benefits possible due to ICT improvements in these applications using LCA or simplified carbon footprinting approaches, and imposes an uptake percentage to predict an overall potential benefit. Each concludes that ICT could deliver reductions in GHG emissions several times larger than the direct emissions of the ICT sector, though none of the studies incorporate behavioral models to predict actual likely outcomes. The Smart2020 report is a representative example [30]; the reported potential savings of 30% in electricity transmission losses due to the introduction of smart grids is not a model output, but rather an assumption.

Erdmann and Hilty present the only quantitative treatment of rebound effects in a model that uses the three-level taxonomy [47]; they used a system dynamics model that attempts to account for feedback between efficiency gains and demand for specific services, finding a mixture of positive and negative consequences for greenhouse gas emissions, and point towards the adoption of economic modeling techniques to account for direct, indirect, and macroeconomic rebound effects. Aside from this study, applications of the three-level taxonomy appear to have been largely conjectural or aspirational. The underlying argument, e.g. that ICT can unlock large savings on the order of 15 to 20% of global GHG emissions by 2020 [30] – is certainly important given the magnitude of the potential savings. However, with the potential efficiency gains spread across multiple domains – power grids, motors, logistics, and building operations, in this case – recommendations for achieving these gains are by necessity high-level. Efficiency gains, the major potential emissions wedge offered by ICT, can be understood through economic frameworks which offer more precise terminology and tools. Behavior change, which underlies the higher-order impacts theorized to be large in many studies that use the three-level taxonomy [54], can be modeled through economic frameworks as well. Accordingly, economic frameworks are discussed below.

2.1.2 Economic frameworks

Changes in environmental impacts may be understood through a resource economics framework, such as was applied in the Digital Europe study of the dematerialization potential of ICT [55], which explored the macroeconomic influence of the ICT sector on the broader economy in Germany from 1991 to 2000. That study's approach, based on a tradition of economic disaggregation approaches from which the IPAT and related equations developed [56], is summarized as follows. Suppose an economy is divided into n sectors each having economic output Y_i, such that the GDP of the economy Y is equal to the sum of each sector's output:

$$Y = \sum_{i=1}^{n} Y_i \tag{2.1}$$

Consider an environmental impact, such as overall GHG emissions, or use of energy, or other resource, which is specified by I, which is likewise attributable to the impacts of the same n sectors:

$$I = \sum_{i=1}^{n} I_i \tag{2.2}$$

The overall impact, I, can be decomposed as follows:

$$I = Y \sum_{i=1}^{n} \frac{Y_i}{Y} \cdot \frac{I_i}{Y_i} \tag{2.3}$$

Here Y is again the overall GDP of the economy; Y_i/Y is the share of economic output attributable to sector i; and I_i/Y_i, the impact per unit of output, is the resource intensity of sector i. We may define technology level, T, to be the inverse of resource intensity, so that an improvement in technology level causes a decline in impact per unit of economic output, and likewise define T_i to be the technology of sector i.

Possible impact trajectories are illustrated in Figure 2.1, which may represent an entire economy, or just an economic sector. At a given level of consumption (equivalently, economic output), Y, the impact is constrained to pass through the diagonal line imposed by the current level of technology, T. Thus, changes in consumption alone, known as the scale effect (either growth or contraction) cause impact to rise or fall along the line specified by T. Changes in technology with consumption held constant will push the impact straight up or down. Most commonly, consumption and technology change simultaneously; growth in consumption accompanied by technology improvements is known as strong de-coupling, if net impact declines, and weak de-coupling, if net impact grows.

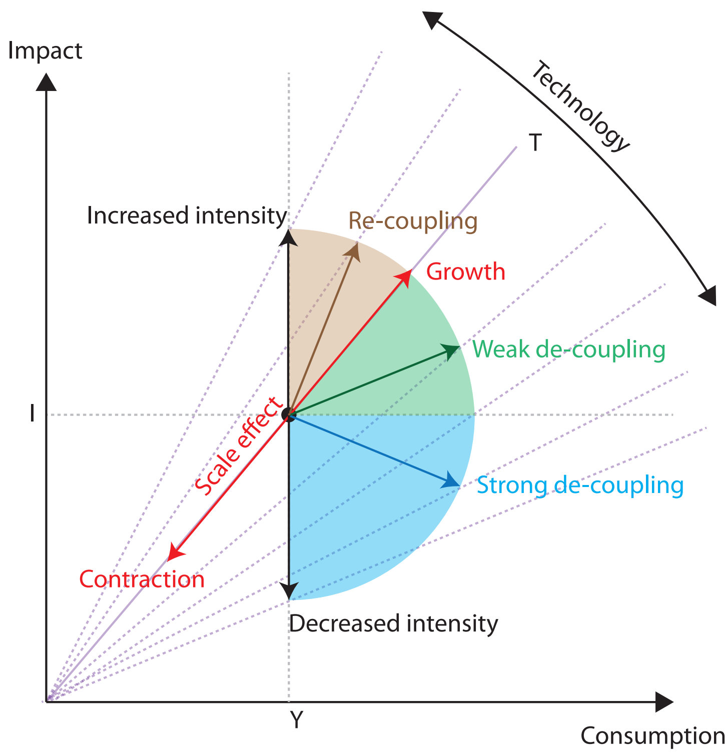


Figure 2.1: Illustration of impact trajectories under consumption Y and technology T.

The Digital Europe study considered two ways in which ICT could impact the environment: through structural change in which the lower-impact ICT sector gains a larger share of the economy, and through induced technological change in other sectors [55]. The latter effect is an equivalent though more precise framing of the "second-order" efficiency gains in the three-level hierarchy discussed above; for example, the 30% decline in grid emissions postulated in the Smart2020 report could be expressed as an improvement in technology in the energy sector which causes the total impact of that sector to decline by 30%. However, a meaningful expression of the impacts of technological change in an economic sector must also characterize the expected change in consumption, whether through rebound effects, or simple economic growth. Such effects can be murky; despite contemporaneous growth in ICT investment and improvements in resource productivity in non-ICT sectors, the Digital Europe study was not able to show a conclusive statistical link between the two [55].

Macroeconomic impacts of ICT have been studied using economic frameworks similar to the one shown above, especially in the context of productivity [57, 58, 59], changes in economy-wide energy intensity due to ICT [60, 61], and the concept of the information society [62, 63, 64], but are beyond the scope of the research in this dissertation. Likewise, large non-linear changes to society (some of the "third-order effects" in the three-level hierarchy) are not easily captured with simple linear models and are similarly out of scope. However, economic decomposition provide a useful framework for of categorizing and comparing impacts of ICT products and services in aggregate, which can be illustrated through the history of study of the effects of ICT on travel.

The potential for telecommunications to reduce the need for travel has been studied since at least the early 1980s, and arguably even since the invention of the telegraph [65]. Salomon reviewed the topic in 1986 [66], and identified a complex relationship including stimulative effects of telecommunications on travel which counteract substitution effects. Telecommuting and teleconferencing have clear environmental advantages over physical travel when compared on a functional unit basis, i.e. working from home does in most cases offer energy and GHG emissions advantages over commuting to an office [67, 68], and the replacement of a physical trip with videoconferencing does result in substantial emissions savings [44]. However, empirical analysis by Mokhtarian showed that despite increased availability of ICT services, most indicators of travel demand continue to climb [69]; furthermore, there is compelling evidence of a complementary or even stimulative relationship between ICT and travel [70, 71]; use of ICT may indeed diminish the need for some trips, but simultaneously generates desire for other trips.

Consider Equation 2.3, but simplified to consider only the impact of a specific sector, I_i:

$$I_i = Y_i \cdot \frac{I_i}{Y_i} \tag{2.4}$$

This formulation, though very simple, isolates the critical distinction between efficiency or technological improvements, which affect $\frac{I_i}{Y_i}$, and overall consumption, which affects Y_i. A more pragmatic version of this equation can be applied to specific services, such passenger travel, measured in vehicle-kilometers (vkm). In that case, considering impact in terms of GHG emissions:

$$I_{\text{travel}}[\text{kg}\,\text{CO}_2\text{e}] = Y_{\text{travel}}[\text{vkm}] \cdot \frac{I_{\text{travel}}}{Y_{\text{travel}}} \left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{vkm}}\right] \tag{2.5}$$

The impact due to all travel is equal to the total amount of travel consumed, Y_{travel}, measured in vkm, multiplied by the average fleet GHG intensity, $I_{\text{travel}}/Y_{\text{travel}}$, measured in $\text{kg}\,\text{CO}_2\text{e}/\text{vkm}$. The latter, being expressed in terms of emissions per functional unit, can be determined using an LCA approach, and would be influenced through technological efficiency gains, such as the introduction of lower-emissions vehicles. The former is driven entirely by human behavior and must be studied empirically, perhaps through the use of equilibrium economic models, surveys, or field measurements. In the case of the influence of ICT on travel, while telecommuting was shown to be a more efficient activity, such that a unit decline in travel accompanied by a unit increase in telecommuting would lead to a net reduction in emissions, growth in total travel demand caused a continuing rise in overall emissions.

Some studies consider the impact of a product or service per functional unit, usually performed using life cycle assessment, while others estimate the level of consumption of a product or service, derived empirically or through models of human behavior. Studies of overall impact must combine the two. For example, when considering the impacts due a product such as a desktop computer, the overall impact is the product of the installed base of the product, IB, and the unit impact per product:

$$I_{\text{devices}}[\text{kg}\,\text{CO}_2\text{e}] = IB[\text{devices}] \cdot \frac{I_{\text{devices}}[\text{kg}\,\text{CO}_2\text{e}]}{IB[\text{devices}]} \tag{2.6}$$

$$= IB[\text{devices}] \cdot I_{\text{device}} \left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{device}}\right] \tag{2.7}$$

A new quantity, I_{device}, is defined to be the unit impact per device which can be determined using LCA, but the installed base IB is an empirical quantity which may be estimated using sales data and other empirical sources.

Likewise, when considering the impacts of network-enabled ICT services that involve communication, the network portion of the impact may be modeled as follows, where data traffic associated with communication is measured in gigabytes (GB):

$$I_{\text{communication}}[\text{kg}\,\text{CO}_2\text{e}] = \text{Traffic}[\text{GB}] \cdot \frac{I_{\text{communication}}[\text{kg}\,\text{CO}_2\text{e}]}{\text{Traffic}[\text{GB}]} \tag{2.8}$$

$$= \text{Traffic}[\text{GB}] \cdot GI \left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{GB}}\right] \tag{2.9}$$

Again a new quantity is defined, GI, to represent the GHG intensity of communication, which can be multiplied by the total amount of traffic to obtain an estimate of total impact. The energy intensity of the internet, in $\text{kg}\,\text{CO}_2\text{e}/\text{GB}$ or related units, is a widely used statistic (see review in [72]) and a central feature of the study in Chapter 5 of this dissertation.

Life cycle assessment is a methodology for estimating impacts per functional unit of products or systems (e.g. I_{device} or GI above). The following sections introduce LCA and its application to the study of ICT products and services.

2.2 LCA and ICT products

This section introduces the energy accounting and life cycle assessment methodologies used in this dissertation to quantify impacts of ICT products, discusses recent trends in the ICT sector and their research implications, and motivates the research in Chs. 3 and 4 of this dissertation. ICT services are discussed in Section 2.3.

2.2.1 Methodological approaches

The unit impact quantity, derived in Equation 2.7, represents the total impact of a device over its life cycle. This can be conceptualized by considering a set of life cycle phases, P, which may be broadly defined as 'production', 'operation', and 'disposal'. The production phase may itself include several sub-phases, such as raw materials extraction, parts manufacture, final assembly, and transportation to consumer. The impact of the device is the sum of the impacts due to each life cycle phase:

$$I_{\text{device}} = I_{\text{device,production}} + I_{\text{device,operation}} + I_{\text{device,disposal}} \tag{2.10}$$

The basic premise of LCA is that impacts of a system can be determined by specifying that system in terms of physical flows and applying characterization factors which linearly map those flows to impacts, and while there are some issues with this premise which are discussed in Section 2.4, LCA is a widely used and accepted method for quantifying impacts in many research domains. Consider the impact of a device, D, which can be described as a number of flows of substances f, such as steel, electricity, semiconductor chips, etc., where each flow has quantity Q_f. In LCA, the impact of the device I_D is determined as follows:

$$I_D[\text{impact units}] = \sum_{f \in D} Q_f[\text{flow units}] \cdot \text{CF}_f \left[\frac{\text{impact units}}{\text{flow units}}\right] \tag{2.11}$$

The collection of flow units $\sum_{f \in D} Q_f$ is called the *life cycle inventory* (LCI) of D. The characterization factors are collectively defined through one of many possible *life cycle impact assessment* (LCIA) schemes, which include IPCC [73], TRACI [74], Impact 2002+ [75] and Impact World+ [76], EDIP [77], and others; these schemes each allow for calculation of impacts in a number of dimensions with different impact units, including global warming potential (in $\text{kg}\,\text{CO}_2\text{e}$), ozone depletion potential (in $\text{kg}\,\text{CFC}-11\text{e}$), eutrophication potential (in $\text{kg}\,\text{NO}_\text{x}\text{e}$), and many others. LCA modeling is hierarchical; complex non-physical flows, such as energy (in kWh) or travel (in vkm), may be defined in terms of fundamental physical flows. Matrix formulations are required to determine the impacts of complex systems and especially to account for circular flows; details are available in textbooks [78].

The conventional form of LCA discussed above is known as ‘process-sum’ or simply ‘process’ LCA [79], which is a bottom-up method, so called because the total estimate of impact is obtained by summing the impacts of components. Bottom-up methods offer high degrees of precision, but are vulnerable to truncation errors due to components excluded from the modeling boundary, which are potentially substantial [80, 81]. Section 2.4 discusses this issue and alternative approaches. Impact quantification in practice uses scientific software and databases to define characterization factors, and to specify models which describe finished materials and components (e.g. steel, electricity, etc.) in terms of more fundamental industrial processes and physical flows to environment. Ongoing fundamental research in the LCA field aims to improve characterization factors, industrial models, and environmental damage models. The research challenges in determining the impacts of a product using LCA lie in accurately describing the components of the product, and in obtaining and applying appropriate industrial models which model those components in terms of physical flows. Operational energy consumption is discussed below to illustrate the mechanics of an LCA calculation.

Operational impacts of electronics are determined by the amount of energy they consume, along with the characteristics of the energy source, typically a power grid. Applying the framework above, operational impacts are assessed by defining a quantity Q of electricity and multiplying by a characterization factor. For energy-using devices, the quantity of electricity consumed in one year under average conditions is often called the unit energy consumption (UEC), measured in kWh/yr [4, 5, 82]. The characterization factor which converts an electricity flow to an impact quantity is known as the grid emissions factor, EF. Operational impacts are thus expressed as follows:

$$I_{\text{device,operation}} \left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right] = \text{UEC}\left[\frac{\text{kWh}_{\text{USA}}}{\text{yr}}\right] \cdot \text{EF}\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{kWh}_{\text{USA}}}\right] \tag{2.12}$$

Here the model requires an additional assumption: the location of the power grid from which the energy was drawn, e.g. USA in the equation above. Grid emissions factors are a specific example of a characterization factor, which converts a physical flow, in this case one kWh of electricity generated in USA, with an impact, in this case global warming potential, measured in kg CO_2e, obtained through the use of empirically-driven models that describe the current physical energy infrastructure in the USA.

Unit energy consumption, a required input for calculating operational impacts in a life cycle assessment of an energy-using product, is of key importance and is thus discussed in detail below.

Device unit energy consumption

The unit energy consumption is a major determinant of device overall impact, and is thus an important component of a device LCA study, but it may also be studied on its own for studies which consider energy use only. In its most basic formulation, the energy consumed by an energy-using device over a period of time, defined by times t_1 and t_2, is equal the integral of the instantaneous power consumed by the device over that interval:

$$E = \int_{t_i}^{t_2} P(t)\, dt \tag{2.13}$$

Power, $P(t)$, may fluctuate over time. However, if the average power draw over a period of time is known, then energy may be obtained by multiplying average power draw by a time amount. In this case, energy per year can be obtained by multiplying average power draw over the year by the number of hours in a year:

$$\text{UEC}\left[\frac{\text{kWh}}{\text{yr}}\right] = P_{avg}\,[\text{kW}] \cdot 8766 \left[\frac{\text{h}}{\text{yr}}\right] \tag{2.14}$$

In most cases, device average power over a year will not be known. However, researchers have recognized that while device power draw will fluctuate over time, most devices have steady operating power draws in one of several *power modes*, such as 'active', when the device is being actively used at its highest level of functionality; 'idle', when the device is on but not being actively used; 'sleep', when the device is on but in a low-power sleep mode; and 'off', when the device is switched off, but still plugged in (again, for examples see [4, 5, 82]). Total energy consumption is then obtained through a sum of the energy consumed in each power mode:

$$\text{UEC}\left[\frac{\text{kWh}}{\text{yr}}\right] = \sum_{i \in \text{PM}} E_i = \sum_{i \in \text{PM}} P_i\,[\text{kW}] \cdot t_i \left[\frac{\text{h}}{\text{yr}}\right] \tag{2.15}$$

Here P_i represents the average power draw while in power mode $i \in$ PM, where PM represents the set of power modes; power draws can be obtained through laboratory measurement of equipment under simulated operational conditions using power meters, and are sometimes reported by product manufacturers. The time spent per year in each power mode is t_i; this is a strictly empirical quantity which depends on human behavior, and on device power management features; for example, many devices will automatically enter a sleep mode after being left idle, but this may depend on whether power management features are enabled. Time spent can be estimated via consumer surveys or field measurements.

Koomey applied a similar approach to his calculations of energy due to servers in data centers, but since servers are usually on all the time, each server's energy was calculated using an average power estimate as in Equation 2.14 [23, 83]. In addition, the study of data centers in particular often requires estimates of the often significant overhead energy consumed due to cooling, power distribution, and other non-computational energy use. A common formulation is as follows:

$$
\begin{aligned}
E_{\text{total}} &= E_{\text{active}} + E_{\text{overhead}} && (2.16)\\
&= (E_{\text{active}} + E_{\text{overhead}}) \cdot \frac{E_{\text{active}}}{E_{\text{active}}} && (2.17)\\
&= \left(\frac{E_{\text{active}} + E_{\text{overhead}}}{E_{\text{active}}}\right) \cdot E_{\text{active}} && (2.18)\\
&= \text{PUE} \cdot E_{\text{active}} && (2.19)
\end{aligned}
$$

Here E_{active} represents energy consumed due to operation of service, storage, networking equipment, and other devices used in the processing of information; E_{overhead} is all other operational energy consumed in the data center; and PUE, the power usage effectiveness, is the ratio of total energy to active energy. PUE has emerged as a rule of thumb for assessing the efficiency of data centers, where PUE of 1.0 is the theoretical no-overhead minimum; it can also be used to facilitate first-order estimates where only active energy is known. Koomey applied a US and global PUE of 2.0 in his 2007 study [83]; for 2010, he estimated US average PUE to have declined to between 1.92 and 1.83 [23], based on third-party surveys of US data centers. Highly efficient enterprise or cloud-scale data centers can have PUEs well below the average; Google reports an average PUE of 1.12 over 2013 for their datacenters, having declined from 1.2 in 2009 [84]; Facebook reports PUEs of 1.09 over the last year for each of its Oregon and North Carolina data centers [85].

In summary, the quantification of impacts of ICT products relies on several pieces: first, an inventory describing the material and energy inputs which arise in various phases of the product life cycle; second, a database or dataset of industrial models which allows for expression of the material and energy inputs in terms of fundamental physical flows to environment; and third, a life cycle impact assessment scheme which converts these flows to a relevant impact category through a set of characterization factors. In practice, the latter two steps may be satisfied using scientific databases such as ecoinvent or GaBi along with LCA software which implements characterization schemes, though there is an ongoing need to improve industrial models of ICT production and disposal processes. If these are available, then the major research challenge is in obtaining an accurate model of the product's components and inputs, as well as the behavioral characteristics of the product's users which influence energy consumption. Due to rapid change in the ICT sector, such models and data sources may rapidly fall out of date, as new products are introduced and new behaviors emerge. The following section briefly discusses some drivers of change in the ICT sector and their research implications.

2.2.2 Industry profile: On Moore's Law and energy

ICT is a dynamic, fast-moving field, characterized by short product lifespans and frequent emergence of new products. Regular technological improvements in semiconductor fabrication processes are the major driver of change in the electronics sector. This process is known as 'scaling', as each improvement enables a higher area density of transistors on silicon die, thus allowing circuit geometries to be scaled downward in size. The quantity of transistors per unit area has increased exponentially, doubling approximately every two years, following an empirical trend known as Moore's Law, originally formulated in 1965 [86]. The transistor is a fundamental building block of both computation and memory, so a chip with more transistors has more computational functionality. Scaling has reduced the cost per computational instruction by a factor of 100 per decade for the last forty years [87], meaning that modern electronics are significantly less expensive and significantly more powerful than older counterparts. According to an industry report, biennial semiconductor fabrication process upgrades will continue through at least 2028 [88].

When transistors are fabricated at smaller sizes, their operational power consumption declines in proportion to their area (to first order), according to Dennard's scaling law which describes the physics of scaling MOSFET transistors [89]. Thus, while transistor density and computational power per device have grown exponentially over time due to scaling, electrical power density has remained roughly constant, implying that computational power per unit of operational energy has also grown exponentially. Koomey explored this trend empirically, and showed that the number of computations per operational kWh in computers has been doubling about every 1.6 years since the dawn of the computing era in the 1940s [90].

Semiconductor scaling has enabled an unrelenting march of improvements in consumer and business electronics products which offer greatly enhanced functionality relative to previous generations, roughly following the 2-year cycle of semiconductor fabrication process improvements. Electronics producers offer products in various form factors to target different use cases, exploiting a tradeoff between higher-performance and higher-energy-consuming components typically used in desktop PCs, and lower-performance but lower-energy-consuming components typically used in mobile electronics. The smartphone emerged as as a computing platform in the mid-2000s; its processor was sufficiently powerful to allow the device to offer levels of performance sufficient to support web and media applications that were formerly the exclusive domain of PCs. The tablet has emerged as another computing and media platform bridging laptops and smartphones in the product-space; soon after the "phablet" emerged in the space between smartphones and tablets, as did hybrid devices which have characteristics of both tablets and laptops. Additionally, within a product category such as laptop or desktop, one can find a range of devices which may have significantly different sizes, costs, performance, and energy characteristics [5]. This proliferation of devices creates challenges for researchers, as the existing energy and LCA literature has limited coverage of newer electronics products.

2.2.3 Knowledge gaps and research approach

Reviews of prior applications of LCA to ICT devices were conducted in 2011 [19] and more comprehensively in 2014 [91]; the literature reviewed in the latter includes coverage of PCs, monitors, phones, servers and datacenters, semiconductors, network devices, and TVs. Studies of ICT services and end-uses, which were also included in the 2014 review, are discussed in Section 2.3.

LCA studies may vary on several dimensions, as cataloged in [91]: which type of LCA methodology to use; how to define the scope and boundary of the devices or systems under study; how to model the contents of the device or system, whether through primary disassembly, proprietary manufacturing data, or other data sources; what data source to use to model upstream processes of manufactured components and inputs, such as an LCA database like ecoinvent or GaBi, or proprietary industrial data sources; what impacts to calculate and what set of impact characterization factors to use; and naturally what high-level goals underpin the study. This multi-dimensional research space has many frontiers. The exploration of hybrid LCA methods to calculate device impacts while correcting for truncation error are an important methodological advance, having been developed by Eric Williams and others through case studies of a desktop PC [13] and laptop PC [92]; see discussion in Section 2.4.2. Industrial data describing electronic component manufacturing processes underpins all LCA studies and is in need of continual refreshment. Better models of recycling and disposal processes are needed, especially informal recycling activities which are not currently modeled in any LCA frameworks. In addition, empirical data relating to device use and lifespan, e.g. through surveys and field measurement campaigns, is needed to accurately model device operational impacts.

The research in this dissertation addresses the challenge of interpreting this literature in an operational context. Due in part to these multiple dimensions of variation, different LCA studies of similar products may produce significantly different results [93], producing challenges for ICT-using organizations and individuals who rely on such studies to support decision-making. In the case of desktop PCs, which are the most-studied device [91], numerical results of existing LCA studies estimating greenhouse gas emissions and primary energy consumption vary by more than an order of magnitude, and some studies show dominant impacts from the operational phase while others show dominant impacts from the production phase. Chapter 3 conducts a meta-analysis of 13 such studies to examine sources of variation, identify the source of the disagreement regarding the relative impacts of the production and operational phases, and produce reasonable bounds on the greenhouse gas emissions and primary energy demand of a typical desktop PC used under average operating conditions. Due in part to the challenge in identifying modeling assumptions and input data sources, this study remains the only published quantitative synthesis of LCA studies of ICT devices.

The study in Chapter 4 of this dissertation addresses the additional problems caused by device proliferation. Despite the number of LCA studies – about 60 reviewed in [91] – it is unfortunately difficult to draw general conclusions regarding the impacts of ICT devices from this literature, precisely because there are so many dimensions of variation. During the design phase of the ICT systems for the Centre for Interactive Research on Sustainability (CIRS) building at UBC in 2010, stakeholders inquired about the relative impacts of available products in order to help guide decisions towards lower-impact options. Product coverage in the literature was an immediate concern; some of the products under consideration, such as tablet PCs, lightweight desktops, and thin client devices, had not yet been the subject of an LCA study. Comparison was another; understanding the impacts of provisioning laptops instead of desktops (for example) requires a scientifically valid comparison of the two with consistent data sources and modeling assumptions. At the time, only the ecoinvent V2 database, which includes fully transparent studies of a desktop PC, laptop PC, LCD monitor, keyboard, mouse, and network device [94, 95], provided a consistent modeling framework allowing for comparisons of one device against another; this was adapted for a screening study of the CIRS ICT systems [96] which motivated the study in Chapter 4. This work includes estimates of the embodied GHG emissions and primary energy of 11 ICT devices with device data from primary teardowns and component data and modeling assumptions from ecoinvent. The framework allows for comparisons of the studied devices against one another and also against the older-generation ICT devices modeled in ecoinvent. In addition, Apple's product carbon footprints are compared against the study's results.

Research into impacts of ICT products lays the foundation upon which we may assess the broader impacts of ICT usage in society. In many cases, it is desirable to focus the analysis not on products, but on the functions for which the products are used, which implies a different and possibly significantly larger modeling scope and a different set of methodological challenges, discussed in the next section.

2.3 LCA and ICT services

Services and end-uses may also be assessed using a life cycle assessment approach. An end-use is defined to be a specific behavior for which ICT devices are used, such as reading the news or watching video, while an ICT service is defined to be a collection of software and infrastructure which users can access, such as Netflix. In other words, a service can be a means through which an end-use is performed. Some end-uses like using productivity software on a computer are relatively simple to model, as they involve only a portion of the operational impacts of the computer, but many end-uses involve the transfer of data over communication networks, and thus require some means of assessing the impacts of those networks and allocating an appropriate share. Such models invariably have larger scopes than the product LCAs discussed in the previous section, because they must at minimum account for the impacts of the devices through which the services are consumed, as well as all of the infrastructure systems that support the services. Methodological approaches to assessing the impacts of ICT services are discussed below, followed by an overview of domain-specific trends and research challenges, and a discussion of prior work and the research approach taken in Ch. 5.

2.3.1 Methodological approaches

Impact of a service can be modeled as follows:

$$I_{\text{service}}[\text{impact units}] = \sum_{i \in \text{devices,systems}} I_{i,\text{service}} \tag{2.20}$$

Each device and system which is involved in the delivery of the service must be included in the model. In each case, an impact of the device or system which is attributable to the service, $I_{i,\text{service}}$, is defined.

Suppose the impacts of the device or system may be allocated linearly according to some functional flow with quantity Q, which could be time spent, or data traffic generated, or a similar metric. Then impact of the service can be expressed as follows:

$$I_{\text{service}}[\text{impact units}] = \sum_{i \in \text{devices,systems}} I_i[\text{impact units}] \cdot \frac{Q_{i,\text{service}}[\text{flow units } i]}{Q_{i,\text{total}}[\text{flow units } i]} \tag{2.21}$$

For each device and system i within the study boundary, the overall impact I_i is required, as well as the total quantity of functional flow $Q_{i,\text{total}}$, and the quantity of functional flow attributable to the service $Q_{i,\text{service}}$. The fraction $Q_{i,\text{service}}/Q_{i,\text{total}}$ is a ratio beween zero and one which expresses the portion of the device or system attributable to the service. Alternatively, the equation may be re-stated as follows:

$$I_{\text{service}}[\text{impact units}] = \sum_{i \in \text{devices,systems}} \frac{I_i}{Q_{i,\text{total}}} \left[\frac{\text{impact}}{\text{flow units } i}\right] \cdot Q_{i,\text{service}}[\text{flow units } i] \tag{2.22}$$

The data requirements are unchanged, but it is sometimes more convenient to calculate an impact intensity per functional flow for the device or system, $I_i/Q_{i,\text{total}}$, and then multiply this intensity by the amount of functional flow attributable to the service, $Q_{i,\text{service}}$. This formulation is equivalent to the example in Equation 2.8, which expressed impacts in terms of GHG emissions, functional flow in terms of GB of data transfer, and defined GI, the GHG intensity, to be equivalent to total GHG emissions divided by total data transfer.

In some cases, it is useful to differentiate between the impacts of one usage of the service, and the aggregate impacts of many uses of the service. In order to facilitate this comparison, assume that I_{service} represents the total aggregate impact from all uses of the service, and likewise $Q_{i,\text{total}}$ is the aggregate functional flow on device or system i due to all uses of the service. The service may be defined in terms of a functional unit, such as an hour of video, or one web page, and so on. Let the total consumption of the service be Y_{service}, measured in service functional units. In that case, the overall impact due to the service can be expressed as follows:

$$I_{\text{service}}[\text{impact units}] = Y_{\text{service}}[\text{service units}] \cdot \frac{I_{\text{service}}}{Y_{\text{service}}} \left[\frac{\text{impact}}{\text{service unit}}\right] \tag{2.23}$$

In other words, a new quantity I/Y is the impact per functional unit, where the aggregate impact I is the product of Y and I/Y. Impact per functional unit may be restated as follows:

$$\frac{I_{\text{service}}}{Y_{\text{service}}}\left[\frac{\text{impact}}{\text{service unit}}\right]=\sum_{i\in\text{devices,systems}}\frac{I_i}{Q_{i,\text{total}}}\left[\frac{\text{impact}}{\text{flow units } i}\right]\cdot\frac{Q_{i,\text{service}}}{Y_{\text{service}}}\left[\frac{\text{flow units } i}{\text{service unit}}\right] \tag{2.24}$$

This formulation makes a distinction between the functional unit of the service being considered, and the functional unit of any devices and systems that the service requires. Consider, as an example, a network service that accesses the internet. Where system i is the internet, suppose internet impacts may be allocated according to functional flow of data, so that Q_i is measured in GB. The impact intensity of the internet, $I_i/Q_{i,\text{total}}$, may be known from third-party studies. Suppose the network service is consumed by the hour, so that Y measures the number of hours. Then, $Q_{i,\text{service}}/Y_{\text{service}}$ is a ratio that maps the functional unit of the service to the functional unit of the internet and in this case is measured in GB/hr. $I_{\text{service}}/Y_{\text{service}}$ measures the impact of the service per hour; and I_{service} is the aggregate impact of all hours of the service consumed.

This framing is simple but highlights an important distinction between the impact per functional unit, I/Y, and overall impact, I. When comparing the impacts of two different services, it is possible for one service to be both more efficient (i.e. I/Y is lower) and also more impactful in aggregate (i.e. I is larger), if the differences in consumption Y are sufficient to overwhelm efficiency gains. An example of this is the rebound effect, well-known in the study of energy efficiency, in which the lower cost of a service allow people to consume it more.

Assessments of specific ICT services tend to be integrated models, incorporating prior estimates of impacts for devices, networks, and datacenters. The field is characterized by the usage of energy intensity of data transfer as a means of allocating impacts due to networks, including the Internet; this approach was first applied by Koomey in 2004 [97]; see a 2014 review by Coroama and Hilty for more detail [72]. The determination of allocation shares for devices and systems that a service uses is a primary research challenge in the assessment of impacts of ICT services, exacerbated by the speed at which new ICT services arise and ICT-users' behavior changes. The following section discusses current trends related to ICT end-uses and associated research challenges.

2.3.2 Industry profile: connected media and the cloud

Three key trends are significantly changing consumer media consumption habits. First, TV sets are becoming connected to internet services, either through game consoles or connected set-top-boxes, or through integrated functionality within products known as connected TVs or smart TVs [98]. The portion of global TVs connected to the internet was estimated to be 12% in 2013, forecast to grow to 27% in 2018 [99]. The internet link allows for streaming of video content over the internet, either through video-on-demand services which are typically run by telecommunication network operators such as cable TV subscription providers, or through internet streaming services like Netflix or YouTube. High uptake of these services along with high bandwidth of video relative to other forms of internet traffic generates disruptive effects on internet traffic patterns, and will certainly drive future infrastructure development, especially in provisioning high-speed internet access to the home [100]. Laptop and desktop PCs are also major platforms for the consumption of streaming video via internet.

Second, tablets and smartphones are both gaining prominence as media platforms as well [98, 101]. These devices rely on either Wi-Fi or mobile (cellular) network connections. Explosive growth in data traffic due to these devices on both Wi-Fi and mobile networks is forecast in coming years, driven by demand for high-bandwidth internet services, but also enabled by infrastructural upgrades, such as the introduction of 4G or LTE mobile networks which support much higher data rates than previous 3G mobile networks [102, 103, 104, 105].

Third, the emergence of scalable internet platforms such as Amazon Web Services (AWS) along with high penetration of broadband connectivity via fixed and mobile links has enabled a proliferation of internet services known as "cloud" services [106]. The National Institutes of Standards and Technology defines cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [107]. The definition therefore includes any from of software, platform, or infrastructure which is hosted and operated on a scalable remote compute grid rather than on dedicated servers and/or client computers, and encompasses a broad range of modern ICT services including social networking (Facebook, Twitter), managed file storage (Dropbox), streaming video (Netflix, Hulu, Youtube), streaming audio (Pandora, Spotify, Grooveshark), productivity software (Google Documents, Microsoft Office 365), and a wide range of commercial software applications. Cisco estimates that by 2017, nearly two-thirds of all global data center workloads will be processed in the cloud, and global cloud IP traffic will account for more than two-thirds of total data center traffic [108].

These combined trends lead to several major developments in the short term:

1. Proliferation of connected media devices that access cloud services, including smart glasses and smart watches, along with increased adoption of tablets, smartphones, and similar devices [109, 110, 111, 112].

2. Technological convergence in the digital media space, especially with respect to television broadcast systems which will increasingly merge with internet content delivery systems [100, 113].

3. Increased uptake of cloud services that may be accessed from multiple different devices, in which processing and storage infrastructure exists via remote providers [114, 115].

These trends create a research need for forward-looking studies that can capture the complexity of modern services, which are hosted in flexible compute grids and accessible from multiple devices.

2.3.3 Knowledge gaps and research approach

The study of environmental impacts of ICT end-uses began in the early 2000s; prior work is reviewed in Table 2.1. A majority of studies compare an ICT end-use against a physical counterpart; print and digital media is the most common comparison, appearing in eight studies, additionally reviewed in [116]. Meetings via ICT were compared against physical meetings in four studies; three studies compared the impacts of shipping digital media (CDs and DVDs) via e-commerce networks against other distribution means. In addition, a more recent trend is the comparison of ICT end-uses against other ICT end-uses, including studies of cloud software and digital media consumption in the home. The study in Chapter 5 of this dissertation, which is also listed in Table 2.1 for comparison, falls into this latter category.

Study	End-use	Platforms	Location / data year	Functional units	Impacts	Largest impact
[117]	Phone system	UMTS, GSM	Switzerland, 2004	Gbit; person-yr	GWP, PED, EI	GSM > UMTS
[118]	Meetings	Teleconferencing, travel	USA, 2003?	Meeting	Many	Physical > digital
[119]	Meetings	Videoconferencing, travel	Japan, 2007?	Meeting	GWP	Physical > digital
[44]	Meetings	Videoconferencing, travel	N/S, 2010	Meeting	GWP, PED	Physical > digital
[120]	Meetings	Videoconferencing, travel	Sweden, 2012?	Hr; meeting; company-yr	GWP, PED	Physical > digital
[38]	Books	Print, e-reader	Sweden, 2009	Book	Many	Variable
[121]	Textbooks	Print, e-reader	USA, 2002?	40 textbooks	GWP, ODP, AP	Paper > digital
[122]	Textbooks	Print, online (desktop)	Sweden, 2009?	5000 students / 5 yrs	GWP	Digital ≫ physical
[123]	Magazines	Tablet	Sweden, 2010	Copy; hour	GWP	Few readers > many
[124]	Scholarly journals	Print, online (desktop)	USA, 2001-10	Article	PED	Variable
[125]	E-mail	Desktop, laptop	France, 2012?	1 Mb	Many	Numerical result only
[126]	News	Print, TV, PC	Switzerland, 2001	News item; person-day	EI	Paper > online > TV
[118]	News	Print, PDA	USA, 2003?	Person-yr	Many	Physical > digital
[127]	News	Print, tablet	Sweden, 2007?	Reader-yr	Many	Variable
[41]	News (video, text online)	Desktop, laptop, tablet, smartphone	UK, 2013?	Bit; 10 minutes	Energy	See Ch. 5
[128]	Advertising (online)	Internet	USA, 2006	Impression; US total	GWP, energy	Numerical result only
[42]	Business software	Local data center, cloud	USA, 2013?	US business total	PED	Local > cloud
[129]	Business software	Laptop, tablet; local, cloud	N/S, 2013?	Typical activity	GWP	Variable
[39]	Music (CD, MP3)	Physical retail, shipping, download, CD-R	USA, 2008	Album	GWP, PED	Physical > digital
[130]	Video (DVD)	Physical retail, shipping	USA, 2006?	3 movie rentals	Many	Retail > shipping
[40]	Video (DVD, streaming)	Shipping, PC	USA, 2009	Movie	GWP, PED	Variable
[45]	Video (Broadcast TV, internet VoD)	TV, desktop, laptop	UK, 2009	Viewer-hr; UK total	GWP	Broadcast > VoD
Ch. 5	Video (Broadcast TV, internet VoD, internet video), other internet, offline end-uses	TV, desktop, laptop, tablet, smartphone	US residential, 2012 and 2017	Device-yr; US consumer total	GWP, energy	See Ch. 5

GWP: global warming potential; PED: primary energy demand; ODP: ozone depletion potential; AP: acidification potential; EI: Eco-Indicator points
N/S: not specified; ?: data year not specified, assumed to be year of publication
VoD: Video-on-demand

Table 2.1: Review of studies of ICT end-uses

As with device LCAs, there are many dimensions of variability among these studies, such as choice of end-use and platform, temporal and geographic scope, definition of functional unit, choice of impact dimension and methodology, and others. The majority of studies focus on global warming potential, energy consumption, or primary energy demand as impact dimensions. Unfortunately, due to rapid change in the industry, studies can have a limited window of relevance. E-commerce distribution systems for CDs and DVDs, though a relatively recent development, are in decline in favour of streaming services [131]. Assumptions regarding the impacts due to ICT devices required to pursue and end-use are likewise anchored in a specific time point and may become obsolete; for example, the average impacts of using a PC will have declined significantly since 2000 as the proportion of laptops relative to desktops has grown [5]. Likewise, the rapid rise of smartphones and tablets as media platforms threatens the relevance of studies of end-uses which do not include them. In addition, major categories of ICT end-use have no current coverage in the literature, such as social networking and gaming, while others such as broadcast video and video-on-demand have been studied in limited contexts only.

A majority of the studies in Table 2.1 measure impacts on the functional unit basis, e.g. per book, per article, per hour of use, etc.; only a few include some assessment of overall consumption level in order to assess impacts at an aggregate level. In the context of Equation 2.24, a functional unit assessment measures I/Y, while an aggregate assessment measures I at some level of aggregation. The importance of aggregation is illustrated by two studies of textbooks compared against digital alternatives. The first [121] considered a college context in which students used either an e-reader or used 40 paper textbooks during the course of their degree. The second [122] considered a school system with 5000 students over five years, using either paper books or desktop PCs. The first study found modest environmental benefits to using the e-reader, while the second study found ten to thirty times higher impacts from the desktop PC solution. Impacts from desktop PCs are much higher than e-readers, which in part explains the discrepancy, but in addition, the latter study assumed very high levels of textbook re-use, characteristic of textbooks in a school system, while the former assumed much lower levels of re-use characteristic of college textbooks. In each case, if this research were to support a decision as to which system to adopt, making the correct choice would only be possible by considering levels of consumption in each system.

The study in Ch. 5 of this dissertation considers the impacts of digital media end-uses. One example of a study in this domain considered the impacts of different modes of music delivery, including physical retail, shipping CDs via e-commerce, and digital downloads (optionally with burning to CD-R) [39]. The study concludes that downloading one album is less impactful, but one cannot conclude that the usage of downloading services leads to lower impacts than the usage of physical retail, because consumption of music via each mode may be different, especially given the advent of piracy and streaming music services on the internet which have considerably lowered the barriers to music consumption online. Likewise, a group of studies of online news via text and video delivered to smartphones, tablets, desktops, or laptops [41, 132] considered impacts per bit of data and per 10 minutes of content browsing and of the system as a whole; while this analysis is valuable in highlighting which components of the device, network, and data center systems contribute the most energy towards delivery of these services, it does not assess which end-use/platform uses more energy in aggregate.

The study in Ch. 5 has several complementary aims in order to address several knowledge gaps. First, it compares the impacts of several different categories of end-uses which are defined broadly in order to capture most uses of ICT equipment in the home, thus ensuring that important end-uses are accounted for. Second, it studies each of these end-uses on TVs, PCs, smartphones, and tablets, which gives it significantly broader coverage than the two closest related studies [41, 45], neither of which considers all four of these platforms. Third, it explicitly considers consumption levels at the US aggregate level, which makes it possible to rank end-use/platform combinations in terms of their overall impact. Fourth, using existing industry forecasts and extrapolations of current trends, it estimates impacts forward to 2017, in order to increase the longevity of the study.

Collectively, the studies in Chs. 3, 4, and 5 apply life cycle assessment methods in an integrated context to improve our understanding of the impacts of ICT products and services for use in operational decision-support. Key limitations of the LCA methodology and on the validity of these studies are discussed below.

2.4 Methodological limitations and justification

While the usage of LCA to estimate impacts of devices, systems, and behaviors is a common practice, the methodology does have several important limitations which should be taken into account, which are discussed in this section. In addition, given these limitations, justifications are provided for the use of LCA in this dissertation and in general, and the consequent context in which claims made through the use of LCA can be considered valid.

2.4.1 LCA database and LCIA impact scheme uncertainties

LCAs are integrative models and usually require the use of an industrial database to model upstream processes and flows, such as due to raw materials extraction and processing. Models may be very complex and rely on extensive empirical data, such as the relative mix of energy generation sources used in a regional power grid. Each process modeled in an LCA database may involve dozens or hundreds of emissions to the environment in various forms. The collective environmental impact of these flows is defined in LCA through the use of life cycle impact assessment (LCIA) aggregation schemes, which define characterization factors converting physical flows into damage equivalent units in one of dozens of possible impact categories. Some schemes aggregate in synthetic units, while others aggregate in terms of equivalent units of a reference substance. Both the empirical models in LCA databases and the definition of characterization factors in LCIA schemes are potential sources of error and uncertainty. Each is assessed below.

The ecoinvent V2 database implements 37 different LCIA schemes, each of which contains several impact dimensions. Some dimensions like global warming potential are very commonly assessed in LCA studies of ICT devices, as was shown in Section 2.2.3, while many others are less commonly reported. Table 2.2 shows the output LCIA calculations from the ecoinvent V2 database for selected quantities – 1 kg of steel, 1 kWh of electricity in USA, and one desktop computer. Four impact dimensions are shown: global warming potential, acidification potential, eutrophication potential, and ozone depletion potential; these were selected because they are among the more common impact dimensions in terms of prevalence in LCIA schemes. However, they are not all measured in common units. For those indicators that are measured in common units, we should expect the output results to be equal to one another, because they are based on identical physical models from the ecoinvent database. In order to explore the consistency of categories measures in different units, the ratio of electricity to steel and the desktop computer to steel is calculated as well.

The table shows that the two impact categories calculated in identical units, global warming potential and ozone depletion potential, are mostly numerically stable across several different LCIA schemes; the exception is the TRACI scheme's ozone depletion potential calculation for a desktop computer. Other categories give varying results. Naturally the numeric results differ considerably because they are measured in different units; still, for each of acidification potential and eutrophication potential,

	steel, low-alloyed, at plant (kg)	electricity, high voltage, at grid, US (kWh)	desktop computer, without screen, at plant	Electricity to steel ratio	Desktop to steel ratio
Global warming potential					
IPCC 100-yr [kg CO_2-eq]	1.8	0.76	270	0.43	1.5E+02
CML 2001 100-yr [kg CO_2-eq]	1.8	0.76	270	0.43	1.5E+02
EDIP 2003 100-yr [kg CO_2-eq]	1.8	0.76	270	0.43	1.5E+02
TRACI [kg CO_2-eq]	1.7	0.76	270	0.43	1.6E+02
Acidification potential					
CML 2001 global [kg SO_2-eq]	6.9E-03	5.2E-03	1.8E+00	0.75	3.9E+04
EDIP 2003 [m^2]	1.1E-01	9.4E-02	3.0E+01	0.83	2.4E+03
TRACI [moles H^+-eq]	3.6E-01	2.7E-01	9.3E+01	0.74	7.4E+02
Eutrophication potential					
CML 2001 global [kg PO_4-eq]	3.9E-03	1.4E-03	2.4E+00	0.35	6.9E+04
EDIP 2003 combined [kg NO_3^-]	3.6E-02	1.3E-02	2.2E+01	0.35	7.5E+03
TRACI [kg N]	2.7E-04	9.5E-05	1.2E-01	0.35	1.0E+06
Ozone depletion potential					
CML 2001 [kg CFC-11-eq]	7.5E-08	2.1E-08	2.7E-05	0.28	3.6E+09
EDIP 2003 [kg CFC-11-eq]	7.5E-08	2.1E-08	2.7E-05	0.28	3.6E+09
TRACI [kg CFC-11-eq]	7.1E-08	6.4E-09	2.4E-05	0.09	3.8E+09

Table 2.2: Selected LCIA results for selected processes modeled in ecoinvent V2 database

the relative difference between one desktop computer and one kg of steel can vary by several orders of magnitude across different LCIA schemes. This result suggests that impact scores calculated in one of these dimensions have internal validity only; one cannot compare acidification scores (e.g.) from two different LCIA methodologies even in a relative sense. This is not necessarily problematic, so long as numerical impact scores are used within a consistent framework, but it imposes an additional constraints on the appropriate use of these scores outside of their original source study contexts, and makes such impact dimensions unsuitable for integrative studies which must incorporate LCA results from multiple sources, except in circumstances where the modeling assumptions across sources are guaranteed to be equivalent.

Table 2.3 shows the results of LCIA calculations for select substances for a similar set of impact categories using both the ecoinvent V2 and GaBi 4 databases. The table shows the ratio of the GaBi output to the ecoinvent output; a result of 1.0 indicates the two outputs were identical. GaBi provides large-scale empirically-driven industrial models that are very similar to those of ecoinvent, but it is a competitor product and thus distinct. The substances modeled are nominally equivalent, according to their descriptions, but the internal modeling assumptions and data sources may vary considerably. This comparison shows the degree to which these two databases are internally consistent.

	Electricity	Steel	Passenger car	Circuit board
Global warming potential				
CML 2001 100-yr [kg CO_2-eq]	0.99	1.01	1.04	1.22
EDIP 2003 100-yr [kg CO_2-eq]	0.99	1.03	1.04	1.22
TRACI [kg CO_2-eq]	0.98	1.02	1.04	1.22
Acidification potential				
CML 2001 global [kg SO_2-eq]	1.09	0.74	0.23	1.76
EDIP 2003 [m^2]	1.05	0.69	0.18	0.12
TRACI [moles H^+-eq]	1.08	0.75	0.23	1.76
Eutrophication potential				
CML 2001 global [kg PO_4-eq]	0.03	0.11	0.26	0.14
EDIP 2003 combined [kg NO_3^-]	0.96	0.82	0.63	1.45
TRACI [kg N]	0.01	0.60	0.09	0.71
Ozone depletion potential				
CML 2001 [kg CFC-11-eq]	4.30	0.47	N/A	0.39
EDIP 2003 [kg CFC-11-eq]	3.85	0.47	N/A	0.39
TRACI [kg CFC-11-eq]	4.35	0.56	N/A	0.47
Primary energy demand [MJ]	0.98	0.94	1.05	0.77

Electricity, GaBi: Power grid mix, AC consumption mix, at consumer 230V, Germany [kWh]
Electricity, ecoinvent: electricity, low voltage, at grid, Germany [kWh]
Steel, GaBi: DE: Steel sheet (ECCS) BUWAL [kg]
Steel, ecoinvent: sum of: Steel, low-alloyed, at plant; Sheet rolling [kg]
Passenger car, GaBi: technology mix, gasoline driven, Euro 4, passenger car [vkm]
Passenger car, ecoinvent: operation, passenger car, petrol, EURO4 [vkm]
Circuit board, GaBi: avg. of 4-layer and 8-layer printed wiring board rigid FR4 with HASL finish [m^2]
Circuit board, ecoinvent: avg. of lead-free/leaded printed wiring board, surface mount (6-layer HASL) [m^2]

Table 2.3: Ratio of modeled outputs from GaBi 4 relative to ecoinvent v2, selected processes and impact categories

The first three substances, electricity, steel production, and passenger car transport, are relatively simple and dominated by energy flows, while the fourth, a circuit board, incorporates many components and high-complexity materials; thus modeling uncertainty could be expected to be smaller for the first three substances, which is borne out in most cases. The results for global warming potential are fairly stable, within 5% for the first three substances, and a 22% gap for the circuit board; primary energy demand is similarly stable. Other categories vary widely. The LCIA characterization schemes are supposedly implemented in identical ways, and the underlying models should be very similar, according to the database documentation for each. Nevertheless, in some categories the results differ by an order of magnitude or more. This suggests that the LCIA calculation has a very high sensitivity to perturbations in the underlying input models; the differences between the models is nominally small, but the differences between the results are large. This result may be compared to a study of the uncertainty in calculating device carbon footprints, which used a server as a case study, and compared impacts using process-sum methods based on both ecoinvent and GaBi databases, as above but including a much more detailed adjustment to produce equivalent models [133]. The results of that analysis suggested a 95% confidence interval of $\pm 15\%$ relative to the mean for estimates of global warming potential of the production phase of ICT devices; this range includes model uncertainty relating to data inputs, but excludes truncation error, which is discussed below.

The stability of global warming potential and primary energy demand can be explained by the relative simplicity of these impact categories, as they involve the aggregation of a relatively small number of flows, and possibly by the relatively large amount of physical science and empirical research results relating to these categories. On the basis of these results, the research in this dissertation considers only global warming potential, and in the case of Chapters 3 and 4, primary energy demand. Notwithstanding the relative stability of these categories, care must be taken when integrating results from different studies which may rely on different underlying data sources, especially for complex substances like electronic components.

There are many significant technical issues in LCA regarding the ongoing development of characterization factors, definition of impact categories and aggregation schemes, and linkage of impact scores to downstream damage categories. A summary of technical issues is provided by Reap et al [134, 135]. Given the empirical evidence above that global warming potential and primary energy are relatively stable across different LCIA schemes and modeling databases, this dissertation does not further consider these technical issues.

2.4.2 Truncation error

Process-sum LCA is vulnerable to cut-off or truncation error due to components of the system not included within the study boundary. It is not possible for a process-sum model to precisely include all impacts while maintaining a finite study boundary; thus a fundamental assumption of LCA is that it is possible to define study boundaries such that the study reasonably represents the impacts of the system. A key assumption of most process-sum studies is thus that impacts from outside the study boundary would, if accounted for, not fundamentally change the conclusions of the study. This is more likely to be true if the study attempts to identify an environmentally preferable alternative within a comparative framework, rather than an absolute numerical impact score.

In some cases, it is possible to obtain the impact of a system from the top down, by starting from a larger known impact and determining the share of that impact which should be allocated to the system in question. Economic input-output LCA (EIOLCA) has emerged as a prominent top-down method for LCA which determines allocation according to economic flows (i.e. in monetary units) using economic input-output tables [80, 136]. EIOLCA is a coarse methodology, well-suited to the study of industries and economic sectors but less so to specific devices, but sidesteps the issue of truncation error [79]. Hybrid methods have been developed which begin with a process-sum LCA result and adjust it upwards using economic data to correct for truncation error [137]; these are considered by many experts to be the most accurate means of estimating device footprint [81, 138, 139]. However, they do impose higher data requirements than process-sum LCAs.

Prior work has demonstrated the importance of truncation errors. In particular, when comparing systems which have different value chains involving different industrial mixes, the ranking of those systems in terms of impact may be determined entirely by the study boundaries and corresponding truncation error, rather than by the fundamental physical processes associated with those systems [81, 140]. Past hybrid LCA studies have quantified truncation error as ranging from 20% up to 80%, with most studies reporting results between 30% and 50% [81]. Of the two hybrid LCA studies of ICT equipment, the first, a study of a desktop, estimated that process-sum LCA accounted for 50% to 60% of the total impacts of the production phase [13], while the second, a study of a laptop, estimated that process-sum LCA accounted for 44% of total impacts of the production phase [92]; the remainder of impacts were calculated using an economic correction based on EIOLCA methods. Given the potentially large magnitude of truncation error, LCA studies should use hybrid analysis where possible, and especially when determining numerical impact results which are likely to be applied in contexts external to the study, such as device carbon footprints.

A major barrier to the use of hybrid LCA is the added complexity it brings. The required combinations of process-sum and EIOLCA databases is intricate, and brings added data requirements of component pricing and industrial economic data, to which the output results are sensitive [138]. In the recent hybrid study of a laptop PC, the economic correction was derived using estimates of the value of components and raw materials in the laptop, along with its purchaser price [92]. While this method may correct for truncation error, it introduces new sources of error due to uncertainty in component and product prices, which are typically trade secrets, especially for newer products. Prices can be particularly volatile for rapidly emerging and evolving products.

The study in Ch. 4 considers impact of ICT devices using a process-sum approach, rather than a hybrid approach. Difficulty in obtaining reliable pricing data along with uncertainties related to the intricacy of hybrid LCA was a key consideration in this methodological decision. Of equal importance, however, was the desire to be able to benchmark and compare the results against those of the ecoinvent database, which were derived using process-sum LCA, as well as enabling comparisons with other published LCA studies of ICT devices, the vast majority of which were obtained using process-sum LCA, including Apple's extensive product environmental report dataset. The presence of truncation error in Ch. 4 means its results can be used for internal comparisons between devices only, rather than as device footprints which might be applied outside of the study's modeling framework.

The study in Ch. 5 is not a traditional LCA in that it does not specify device and system inventories, but rather combines existing results using an LCA approach. It is still vulnerable to truncation error which may exist in the integrated studies. However, that error should not greatly affect the conclusions, for two reasons. First, a significant portion of the integrated studies were themselves performed using EIOLCA or similar top-down approaches, and thus should have accounted for truncation error already. Second, the majority of impacts in the systems under study are due to operational electricity use, which are characterized by a grid emissions factor that has been extensively studied and is widely used in many research domains.

2.4.3 Toxicity and environmental health

The framework applied throughout the research in this dissertation is well-suited to a conception of impacts that is quantitative and expressible in units amenable to linear modeling such as greenhouse gas emissions in kg CO_2e. However, some important types of impacts of ICT are less well-suited to quantitative linear modeling, or to quantitative expression in any terms. While these impacts are beyond the scope of the research in this dissertation, they are briefly discussed here for completeness.

ICT devices can contain toxic substances which may be harmful to humans and ecosystems. Life cycle assessment can be used to assess relative human health and ecosystem damage potentials, but LCA models are designed to estimate average potential impacts of typical processes at large scales, e.g. continental or global scales in the case of the USEtox model which underpins many LCA impact aggregation schemes [141]. Informal e-waste recycling operations in lower-income countries have been shown to result in release of toxic substances, including heavy metals, leading to environmental contamination and adverse human health outcomes [142, 143, 144, 145, 146, 147, 148, 149, 150]; these acute, localized impacts are primarily assessed through the use of field measurements and are not incorporated into current LCA models.

Impacts due to toxic substances in electronics have been conceptualized using a red-list approach, exemplified by the EU's Restriction of Hazardous Substances (RoHS) Directive [151] which restricts the use of lead, mercury, cadmium, hexavalent chromium, polybrominated biphenlys, and polybrominated diphenyl ether; similarly, the EPEAT voluntary labeling scheme that assigns points for elimination of the same list of substances [35]. In addition, e-waste management schemes, exemplified by the EU Waste Electrical and Electronic Equipment (WEEE) Directive [152] which sets targets for collection and recycling of waste electronics in the EU, are a key mitigation strategy for reducing opportunities of toxic releases. There remains an ongoing need for primary research to identify high-priority toxic substances, alongside regulatory structures to encourage the elimination of such substances from electronics devices and to reduce the risk of release of toxic substances to environment through improved waste management.

2.4.4 General bounds on LCA results

LCA studies rely on models of technological and natural processes to approximate the potential environmental impacts of a device or system. There are a few caveats when considering the validity and interpretation of these results. First, unless specifically otherwise modeled, models of upstream processes are intended to be representative of typical or average industrial conditions. Obtaining actual emissions flows from specific physical facilities is beyond the scope of most LCAs, especially if LCA databases are used. Thus, the impact scores should be thought of as average representational impacts, rather than specific physical impacts. For this reason, the impact dimensions represent potential impacts (e.g. global warming potential), rather than physical emissions. Scientific consensus defines these potential scores to be meaningful and reasonable expressions of likely impacts, but they are synthetic, not empirical, and only as accurate and meaningful as the underlying models and data.

In addition, the methods discussed thus far have followed the attributional style of LCA, which is useful for defining the impacts arising from industrial processes related to a device or system. Broader impacts on society, such as changes in consumption patterns, are not captured in attributional LCA. There are other methods available, such as consequential LCA, which can measure the effects of large scale industrial changes, e.g. due to a policy; these involve economic frameworks and have very different data requirements and methods [79]. Consequential LCA is not used in this dissertation or in any existing LCA studies of the impacts of ICT devices and services. One should not attempt to infer large scale societal changes from attributional LCA alone.

Finally, notwithstanding the apparent numerical instability of impact models for dimensions other than global warming potential and primary energy demand, restricting the definition of impact to those two dimensions is potentially problematic, as they may not capture many important impacts. For example, the global warming potential of the end-of-life phase of electronics is very small [1], but e-waste landfill and recycling operations may be very damaging to environment and human health, especially in a lower-income informal context. A lower GWP score does not necessarily mean a lower environmental impact; it only means a lower impact in terms of global warming potential.

2.4.5 Alternative approaches

LCA is one of a family of quantitative approaches towards environmental impact assessment. Other methodologies exist, such as ecological footprint analysis, which aggregates impacts in terms of equivalent land area usage [153]; ecosystem services assessment, which aggregates impacts according to their effect on valuable properties of ecosystems, e.g. their ability to provide clean air and water; and material/substance flow analysis [154] and structural path analysis [155], which quantify stocks and flows of materials through economies and ecosystems. Each methodology comes with its own set of limitations and challenges; none of them have seen any appreciable use in the context of studying environmental impacts of ICT devices and services.

One possible approach towards simplified analysis of ICT devices and services is to consider operational energy use alone. There is considerable value in understanding the way energy is used, for example in order to aid the design of policies to encourage demand-side reductions in energy use, and there is a rich history of literature regarding the energy usage of ICTs (see Section 2.2.1). Some studies of ICT services have chosen to study operational energy only [41], or global warming potential due to operational energy only [45], excluding embodied impacts due to devices and infrastructure. This greatly simplifies the analysis, but of course significantly narrows the scope of the study as well; the appropriateness of this decision depends on the research goals of the study.

2.5 Chapter summary

Regarding environmental impacts of ICT, knowledge gaps have arisen due to rapid change in the industry, such as the introduction of new devices enabled by Moore's Law, convergence in broadcast TV / internet services, roll-out of high bandwidth mobile networks, and growth of cloud computing services. LCA and operational energy accounting were identified as useful methodologies for estimating such impacts using quantitative linear models; both have seen substantial use in existing literature. Specific knowledge gaps addressed in this dissertation are ambiguity in the existing literature of LCAs of desktop PCs (Chapter 3), lack of coverage regarding impacts of newer devices along with high time and data costs of conducting LCAs for such devices (Chapter 4), and lack of high-level forward-looking integrated views of modern network-enabled services (Chapter 5). Impact dimensions were limited to GHG emissions and primary energy demand due to apparent numerical instability of models of other impact dimensions.

Chapter 3

Meta-analysis of LCAs of desktop PCs

3.1 Introduction

Information and Communication Technology (ICT) equipment has come under scrutiny in the past decade due to rising concern over their environmental impacts. According to the best recent estimates, the global ICT sector is responsible for about 2% of global anthropogenic greenhouse gas emissions; half of these emissions are due to Personal Computers (PCs) and peripherals [30]. Quantifying the environmental impacts of PCs is important in order to understand both the aggregate impacts of the industry, and the relative share of the impacts from residences and offices that can be attributed to PCs.

Several life cycle assessment studies have focused on consumer electronics including PCs. Unfortunately, the results of these studies are not consistent with one-another, with significant variation in both the absolute impact reported, and the life cycle phase that dominates the impact, which is either the manufacturing or use phase. This literature has been recently reviewed by several authors including James and Hopkinson [156], Malmodin et al [25], Yao et al. [20], and, most thoroughly, Andrae and Andersen [19]. Each review noted the lack of consensus in the literature, but none attempted to provide a systematic and rigorous exploration of the source of the disagreement, or to identify which (if any) of the reviewed studies might be the most accurate, a task which is undertaken here. Focusing specifically on desktop PCs without displays in order to limit variation, existing LCA studies are disaggregated into impact assessments for each life cycle phase; data sources used to assess for each phase were identified. The validity of all reported data sources and modeling assumptions is assessed. This work has a significantly narrower scope than Andrae and Andersen and so allows for greater depth in order to improve understanding the results of existing studies of desktop PC impacts. Associated literature is also surveyed which helps contextualize and interpret these results.

First, relevant studies are summarized in order to show their reported results in terms of total environmental impact, and relative impact by life cycle phase, and to identify which components of the desktop PC's life cycle inventory are the largest contributors to the total impact of each life cycle phase. The study then addresses the following two questions:

1. To what extent and for what reasons do estimates from different studies disagree with one another?
2. Given the uncertainties in estimates for the environmental impacts of a desktop PC, and in light of the various studies, what are the best guess estimates or ranges for evaluating the impacts of desktop PCs?

The study's approach to structuring the analysis and answering these questions is described in the following section.

3.2 Approach

Meta-analysis of LCA studies is challenging, because studies can differ in terms of unit of analysis, temporal and geographic scope, inventory data, impact factor data, and impact characterization scheme. These differences each add variation to the numerical result and must be accounted for where possible in order to facilitate a valid comparison.

3.2.1 Scope and unit of analysis

The study focuses on desktop PCs, excluding other electronic devices like laptops and cell phones, because desktops have received the most attention to date from LCA researchers, and because they represent a relatively large share of the total impact of the ICT sector. Desktop PCs typically include a CRT or LCD display, peripherals such as a keyboard, mouse, and printer, and a central unit, often called the control unit. The scope of comparison in this study is restricted to control units only, excluding displays and peripherals. Displays in particular are known to represent a significant component of the total impact of a desktop PC system, but they are not treated consistently in the literature, with some studies assuming CRT displays, some assuming LCDs, many assuming a mixture of the two, and some excluding displays altogether. An accurate comparison of these studies would have to separate the display and control unit and compare them independently, and while a comparison of LCA estimates of displays would be valuable, such an analysis is not performed here in order to limit the scope and complexity of this study. As such, when the study refers to desktop PCs, this should be understood to refer to the control unit only. Desktop PCs come in different sizes and with different features, but most studies aim to measure a PC with characteristics representative of an average or typical product within this category; this study follows the same approach.

Geographic scope does vary from study to study; manufacturing impacts usually occur in southeast Asia, but use-phase impacts depend on the local electricity generation mix. To correct for this source of variation, use-phase impacts are compared in terms of kWh of electricity used rather than endpoint impacts. Temporal scope also varies; results are reported according to their year of publication with a slight preference given to more recent studies when weighing evidence, as they are more likely to be representative of modern products.

3.2.2 Definition of environmental impact

Impact can be measured in many different ways depending on the life cycle impact assessment (LCIA) method chosen by the practitioner. Two categories, global warming potential (GWP100, in kg CO_2e, per the Intergovernmental Panel on Climate Change (IPCC) standard) and cumulative primary energy demand (CED, in MJ), were used in a large number of studies. Some categories like ecotoxicity and eutrophication potential were used only in a few studies, and in some cases were measured with different units, making a comparison across studies in these categories much more difficult. This study therefore reviews reported impact measurements in both global warming potential and primary energy demand.

3.2.3 Analytical approach

The central challenge is judging the quality of the LCA studies and commenting on their reasonableness. This study's strategy for doing so is decomposition: reported results are split first into component life cycle phases; second, into the largest sources of impacts for each phase (that is, decomposing the manufacturing phase into a listing of key modules such as mainboard, integrated circuits, and so on); and third, into an inventory listing of items, in kg for material parts and kWh for electricity, and a corresponding impact factor, in MJ per item unit and kg CO_2e per item unit. Assumptions in each study are compared at this fine-grained level, highlighting key differences that are obscured in the total result.

In judging reasonableness, a non-quantitative weight-of-evidence approach is employed. It is often very difficult to independently verify reported results of life cycle assessments, but some aspects of the desktop PC life cycle, notably use-phase electricity usage and product lifespan, have been studied outside the body of LCA studies surveyed here. This study surveys this literature as well, assigns a data quality score to each study, and assumes that reasonable representative values lie towards the middle of the range reported by the highest-quality evidence; comparing against this broader context allows for a rough judgment as to whether the LCA studies make reasonable assumptions. For parts of the desktop PC life cycle without a large ancillary literature, it is more difficult to judge reasonableness; instead the study identifies clear outliers or errors, and suggests that more weight should be given to higher-quality studies, as demonstrated by thorough reporting of methods, data sources, and results. Recognizing the limitations of this approach, the study draws only cautious conclusions in such cases. In all cases, data heterogeneity precludes a rigorous statistical aggregation with probability distributions. Instead, the study assigns reasonable upper and lower bounds on impact measurements.

In answering these questions, the study attempts to mitigate some of the uncertainty surrounding desktop PC LCAs, and provide the reader with appropriate information and context needed to evaluate such efforts, and to accurately interpret their results.

3.3 List of studies and their overall results

LCA studies of desktop PCs were identified through literature searches of Google Scholar and a number of academic databases, and through citations in other published studies and reviews. A 1993 study is excluded due to its age [157], and one study [158] because the same results were re-published in another [159]; to our knowledge, all other published LCAs of desktop PCs are included in this review. Details about the scopes and methodologies of these studies used for this work are as follows, with the studies identified by their authors:

- Tekawa et al, published in 1997 [160], is a process-sum study, based in Japan, which focuses on desktop and laptop PCs and reports several types of impacts, but includes minimal information about the unit of analysis and does not provide a bill of materials. There is not enough information to separate the CRT display impacts from the control unit impact, so the total impacts in this study include the display.

- Atlantic Consulting, published in 1998 [161], was a major process-sum study for the European Union's EcoLabel scheme and provides a full listing of impacts, though the bill of materials is not fully specified, making it impossible to split the impact into components.

- Williams, published in 2004 [13], uses a hybrid economic input-output LCA methodology, with the intention of correcting for truncation errors inherent in process-sum methods relating to manufacturing impacts.

- Masanet et al., published in 2005 [162], from Lawrence Berkeley National Laboratories and prepared for the California Energy Commission, calculates impacts for desktops manufactured and used in California using an EIOLCA approach. Manufacturing data is adapted from earlier studies from Williams [13, 163], and energy data is taken from Kawamoto et al. [164].

- Hikwama, published in 2005 [165], is an undergraduate thesis from the University of Southern Queensland. Characterization factors are taken from a proprietary database, but the study contributes an inventory which was created through disassembly and manual weighings. The inventory was adapted for use by Eugster et al. [158] and Duan et al. [159].

- Kemna, published in 2005 [166], known as the Methodology Study for Eco-design of Energy-using Products, or MEEUP, was conducted for the European Commission by VHK and studied a number of energy-using electrical products, including computers, using a process-sum approach. The study contains a detailed inventory and a particularly strong meta-analysis assessing use-phase energy consumption.

- Choi et al., published in 2006 [167], based in Korea, examined several different impact categories and focused in-depth on the influence of recycling on total impact, but provides minimal information regarding the inventory or impact factors assumed in the analysis.

- Braune and Held, published in 2006 [168], known as the Development of Environmental Performance Indicators or EPIC-ICT project, conducted for the European Commission and co-ordinated by researchers at IKP Universität Stuttgart, contains detailed case study process-sum LCAs of desktop PCs, but does not provide the full inventories or the absolute impact results; instead the project focused on identifying areas of leverage for future eco-design initiatives.

- Hischier et al., published in 2007 [95], describes the studies in the ecoinvent database, which is available in the unit process titled “Desktop computer, without screen, at plant/GLU U”. This is the most transparent of the surveyed studies. The desktop PC data comes from a mixture of primary measurements and imported results from Kemna [166] and Braune and Held [168]. Primary energy and GWP results were obtained from the ecoinvent database using the IMPACT2002+ methodology.

- IVF, published in 2007 [169], was conducted for the European Commission’s Energy Using Products (EuP) program, and focused on identifying eco-design requirements. Like the MEEUP project, this report contains a strong review of previous literature. The LCA study within is quite transparent and contains a full bill of materials and listing of impacts.

- Duan et al., published in 2009 [159] is apparently a re-publication of results also available in Eugster at al [158]); both studies examine the life cycle impacts of a PC manufactured and used in China, partially adapting data from the ecoinvent database and from Hikwama [165]. Results are provided as aggregated Eco-Indicator points which unfortunately makes it difficult to determine how the results were obtained or how they might compare with other studies.

- Apple product environmental reports, published in 2010 [170, 171], are environmental declarations for the Mac Mini and Mac Pro, respectively, publicly available on Apple’s corporate website. These studies provide estimates of the global warming potential of each product disaggregated by life cycle phase, but provide no methodological details as to how the figures were reached.

Results of studies included in this synthesis are shown in Figure 3.1, where the left-most axes show the relative impacts of each phase of the life cycle, and the right-most axes show absolute impacts, where available. Numerical data tables for this and other figures are in Appendix A. Studies that measured impact in terms of cumulative primary energy demand in MJ are on the top; studies that measured global warming potential in kg CO_2e are on the bottom. Where possible, the results have been adjusted to exclude displays. Only one study, Tekawa et al [160], did not provide enough information to do so; its results thus include a CRT monitor. All other studies report the desktop PC control unit only.

The relative impacts on the left side of the figure suggest that the use phase is the dominant component in total impact, according to most studies. The studies measuring primary energy on average report

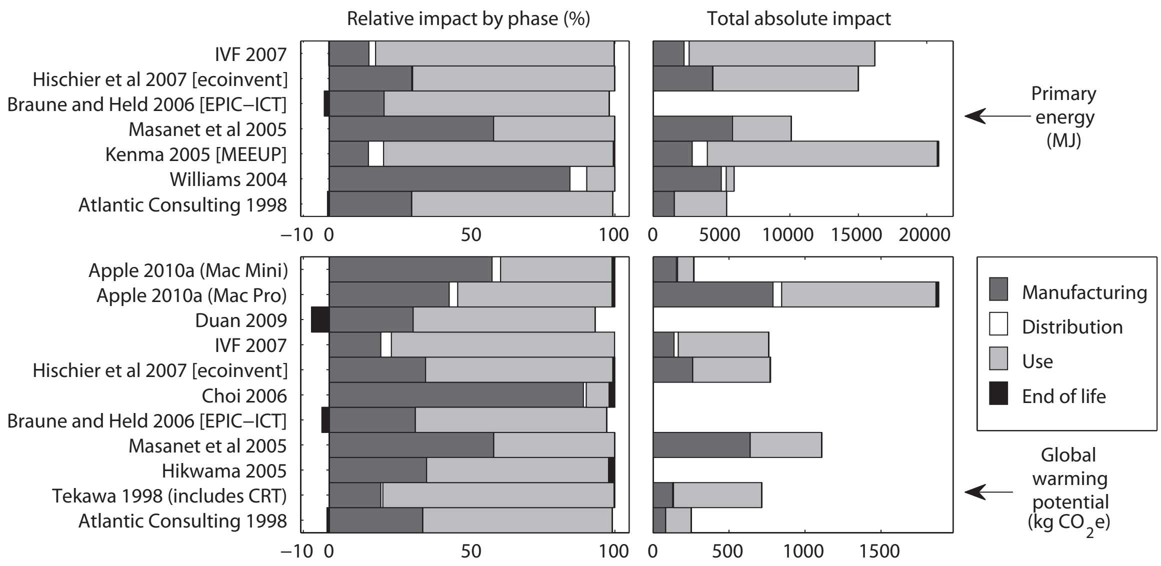


Figure 3.1: Summary of LCA studies showing breakdown of life cycle energy use and carbon equivalent impacts

use phase impacts of 62% of the total, with 35% due to manufacturing and very small portions for distribution and end-of-life. Studies measuring global warming potential similarly report an average of 58% for use phase, 39% for manufacturing phase, and very small portions for distribution and end-of-life.

End-of-life and distribution are not considered in this analysis because of their relatively small impacts in terms of MJ and kg CO_2e. Small impacts in terms of primary energy and global warming potential should not however be taken as indications that the end-of-life life-cycle phase is environmentally benign, as impact categories relevant to toxic releases may show higher scores for the end-of-life phase. In particular, informal recycling in lower-income countries is not captured in LCA databases and is difficult to accurately characterize, but has been shown to have significant negative health impacts on workers and local residents due to environmental contamination; see [21] for a review on this topic.

The remainder of this study focuses on the manufacturing and use phases, and attempts to deduce the reasons underlying the disagreements across the studies shown in Figure 3.1. In particular, the study focuses on understanding why studies that report dominant impacts from the manufacturing phase, namely those of Williams [13], Masanet et al [162], and Choi et al [167], disagree with the majority of the LCA studies that show the use-phase as dominant.

3.4 Manufacturing and production phases

The manufacturing phase of the life cycle, which includes material extraction and processing, subassembly production, and final assembly, is particularly difficult to analyze because of the large number of highly complex processes involved. The analysis can nonetheless be made tractable by examining the impacts of a relatively small number of component categories. Figure 3.2 shows the results of an initial review, in which the impacts have been divided into component categories: mainboard-integrated circuits (ICs), mainboard-other, power supply, hard drives and disk drives, and the metal or plastic casing. Graphics cards and other internal circuit-board-based peripherals are grouped with the mainboard. All additional items are grouped as “other”. For details on how the source study’s results were adjusted in order to fit into these component categories, see Appendix A.

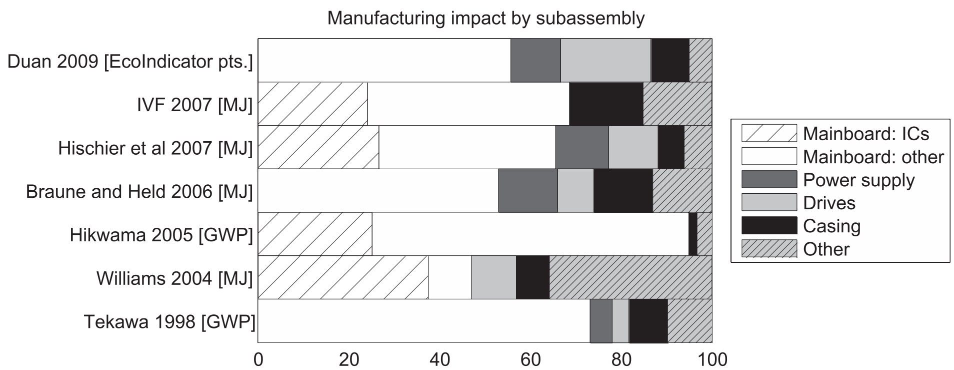


Figure 3.2: Manufacturing impacts of desktop control unit components (relative)

The study goal, to identify the quantity and impact per quantity unit of each component category, is challenged by a lack of published complete bills of materials or complete listings of impact factors, and by differences in the way the respective authors structure their analyses. For example, some studies consider ICs separately and others lump them in with the mainboard. Nevertheless, as shown in Figure 3.2, it is possible to make observations about relative impacts of component categories: the mainboard including ICs is responsible for the largest impact, accounting for more than 50% of the impacts in all but one study, with the other components constituting small but non-negligible proportions of the remainder. The proportions vary considerably, as do the absolute totals of the production phase visible on the right half of Figure 3.1; in order to explore the sources of this variation, the quantity and impact of each component category is identified in the following sections.

3.4.1 Component-level impacts

The study's approach here is to identify the quantity, in kg, of each component category, and its impact, in terms of primary energy, in MJ per kg of component, and global warming potential, in kg CO_2e per kg of component. Figure 3.3 shows results of our survey. Integrated circuits are excluded from this figure because they have very high impacts and negligibly small mass, making a comparison inappropriate; they are examined separately in the following section. Product packaging such as cardboard or polystyrene foam is excluded from the total product mass. Note that only four full inventories for component categories were available – Williams [13], IVF [169], Hischier [95], and Hikawama [165]. The study by Williams does not provide global warming potential; the study by Hikwama provides neither global warming potential nor primary energy.

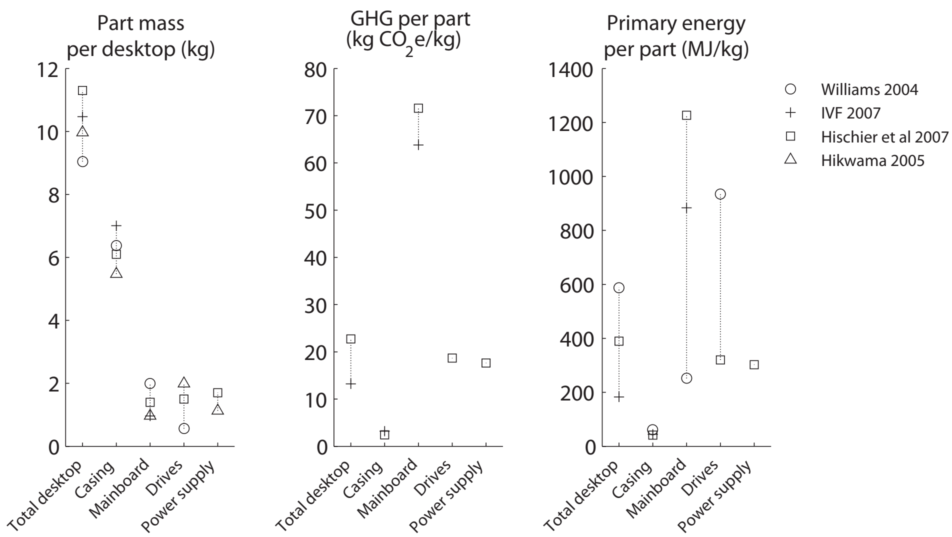


Figure 3.3: Mass and impacts of desktop PC components (excluding mainboard ICs)

The studies roughly agree over the mass of the components, with no obvious outliers; yet they disagree on the impacts per part. Hischier's results are consistently much larger than IVF's, roughly by a factor of two. Thus, for apparently similar inventories, the two studies report significantly different final results. The primary energy impacts from Williams vary significantly from both of these studies. With a limited number of data points no specific conclusions can be drawn except that the impacts may lie in the range shown on these graphs. Ideally it would be possible to benchmark these results against other external studies, as is done later in this study for use-phase energy consumption, but we are not aware of any such studies focusing on these particular component categories. Fortunately, the literature for integrated circuits is slightly richer, which is drawn upon in the next section.

3.4.2 Integrated circuits

The LCA studies measure semiconductor content in three ways: in area of input silicon wafer; area of finished silicon die; and mass of packaged chip. In the latter case, a mass ratio of finished silicon die relative to the mass of the packaged chip is assumed. It is possible to convert between these units by making a few assumptions; calculations described Appendix A result in a silicon wafer input of roughly 1.67 cm^2/cm^2 finished die, and a mass of 0.2 g/cm^2 finished die. Table 3.1 shows the semiconductor content per desktop according to each of the studies that reported it. The area of the table labeled "adjusted inventory" shows this study's estimates of the total mass and area of finished die given the reported inventories and these calculated conversion factors.

	Williams (2004)	Yao et al. (2010)	Hischier et al. (2007)	Kemna (2005)	IVF (2007)	Williams et al. (2002)	Krishnan et al. (2008)	Boyd et al. (2009)	Andrae and Anderson (2010)
Reported inventory									
Input wafer (cm^2/desktop)	110	–	–	–	–	–	–	–	–
Finished die (cm^2/desktop)	–	12	–	–	–	–	–	–	–
Packaged chip, 0.9% Si (g/desktop)	–	–	30	–	–	–	–	–	–
Packaged chip, 1% Si (g/desktop)	–	–	–	–	95.5	–	–	–	–
Packaged chip, 2% Si (g/desktop)	–	–	59	–	–	–	–	–	–
Packaged chip, 5% Si (g/desktop)	–	–	–	100.4	69	–	–	–	–
IC primary energy (MJ/desktop)	1992	99	1175	–	463.6	–	–	–	–
IC global warming (kg/desktop)	–	–	72.4	–	34.8	–	–	–	–
Adjusted inventory									
Si mass (g/desktop)	13.2	2.4	3.9	5	4.4	–	–	–	–
Finished die (cm^2/desktop)	66	12	19.4	25.1	22	–	–	–	–
Impacts per finished die area									
Primary energy (MJ/cm^2)	30.2	8.3	60.6	–	21	31	33	81	–
Global warming ($kg\,CO_2e/cm^2$)	–	–	3.7	–	1.6	–	–	5.5	7

Table 3.1: IC inventories and impacts per desktop mainboard, with originally reported inventory and adjusted inventory assuming 0.2g/cm^2 finished die

The table also shows the impacts per finished die area, measured in MJ/cm^2 and $kg\,CO_2e/cm^2$. For the five LCA studies, the figure is obtained by dividing the total reported IC impact, where available, by the adjusted finished die area. In addition, three studies were identified that assessed the life cycle impacts of semiconductors alone; these results are included on the right side of the table. The latter, from Boyd [172], reports a total of 91 MJ per die and 6 kg CO_2e per die for all production phases, which corresponds to 81 MJ/cm^2 and 5.5 kg CO_2e/cm^2 assuming an average 1.11 cm^2 die in a 45 nm process, according to their data. Likewise, an algorithm from Andrae and Anderson [93], based in part on Boyd's work, estimates 34.7 kg CO_2e/g of die, which would be 7.0 kg CO_2e/cm^2 assuming this study's estimated conversion rate of 0.2 g/cm^2.

Overall, the finished die area ranges from 12 cm^2 to 66 cm^2 per desktop PC - though the latter figure was criticized by Yao as being an overestimate [20] - with a median of 22cm^2. There is evidence that Yao's impact estimate is too low due to an apparent misapplication of Williams' methods, and Hischier's is too low due to an apparent error in calculating the die area of a packaged chip; see Appendix A for details. Discarding these, reported primary impact estimates range from is 21 to 81 MJ/cm^2, and global warming impact estimates range from 1.6 to 7.0 kg CO_2e/cm^2. Boyd's study [172], which reported impacts at the upper end of these ranges, is the most thorough and up-to-date LCA of semiconductor manufacturing, which suggests that other studies may be underestimating impacts due to semiconductors. Establishment of standard impact factors and inventory reporting schemes would help a great deal in removing some of this uncertainty.

3.4.3 Total manufacturing impact: analysis

Studies at the level of component categories disagree significantly. For the component categories shown in Figure 3.3, inventories are relatively consistent, indicating that much of the variation is due to different assumptions regarding the impacts of the various components, especially the mainboard and ICs. For integrated circuits, both inventory and impacts were highly variable. Using the data from Figure 3.3, there is a range of total desktop mass from 9.0 to 11 kg; a global warming potential ranging from 13 to 23 kg CO_2e/kg desktop, and a primary energy consumption ranging from 180 to 590 MJ/kg desktop.

The data is not sufficient to determine a plausible range for the manufacturing impacts of a desktop PC. The data can be summarized by assuming that both total desktop mass and impacts per desktop mass may fall within the ranges reported in Figure 3.3; thus by multiplying these ranges together, the total global warming potential could vary from an estimated 120 to 250 kg CO_2e/desktop, and the total primary energy consumption could vary from 1600 to 6500 MJ.

3.5 Use phase

The use phase is responsible for the highest impact according to a majority of studies as shown in Figure 3.1. Impacts due to the use phase are simpler to measure and quantify than impacts in the manufacturing phase, as the only impacts are due to electricity consumed by the device during its lifespan. Nevertheless, the LCA studies vary to a surprising degree, with estimates of lifespan primary energy consumption due to the use phase ranging from a low of 580 MJ (Williams [13]), to a high of 16800 MJ (Kemna [166]), which is a 30-fold variation.

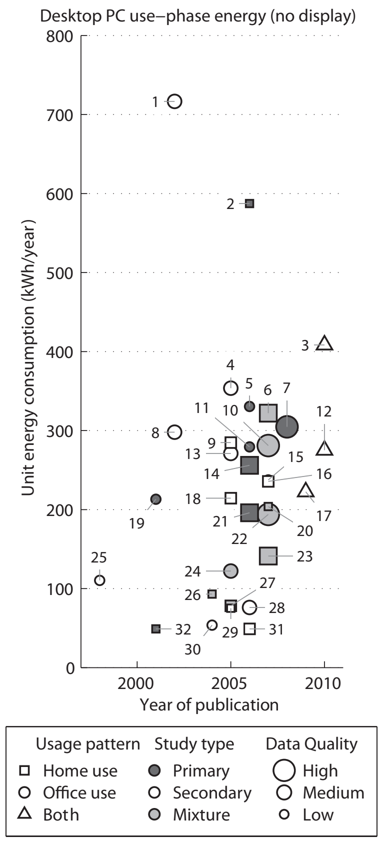
Total use-phase electricity consumption is a function of the power demand of the device, patterns of usage, and the lifespan of the device. Most devices have several different operating modes, such as active, standby, or off, which have different power demands. Using methods described by Roth et al. [82] and Kawamoto et al. [164], given a set of power modes PM such that, for mode $i \in PM$, if the average power draw in mode i is P_i, and the average time spent in mode i is t_i, then the total lifespan energy consumption can be found using the following equation:

$$\text{Lifetime energy[kWh]} = \text{Lifespan[years]} \cdot \sum_{i \in PM} P_i[\text{kW}] \cdot t_i \left[\frac{\text{hours}}{\text{year}}\right] \tag{3.1}$$

The total of the summation on the right side of the equation is sometimes called the Unit Energy Consumption (UEC), measured in kWh/year. Variation between studies occurs due to differing estimates for the lifespan, power draws, and time share which cause variation in the UEC. In addition, when energy consumption is converted to an impact such as global warming potential or primary energy demand, assumptions regarding the characterization factors may vary across studies as well. Each of these causes of variation is analyzed in turn below.

3.5.1 Unit energy consumption

In addition to the LCA studies already introduced, a significant body of literature has assessed the energy consumption of consumer electronics. Results from these studies are summarized in Figure 3.4, with the annual unit energy consumption in kWh/year on the y-axis (desktop control unit only, no display), and the year of publication on the x-axis. Studies have been assigned a data-quality score, with large-n primary studies and meta-analyses marked “high”, smaller or less rigorous studies marked “medium”, and $n = 1$ studies or assumptions marked “low”; the size of the marker corresponds to the data quality. The marker shape indicates whether the study measured use in a home setting (square), an office setting (circle), or both/not specified (triangle). Primary studies are shaded dark.



1 [82] Roth et al. (2002) (high-power PC): Secondary data
2 [168] Braune (2006) [EPIC-ICT] (gamer PC): Dell data
3 [173] US EPA (2010) [Energy Star, baseline]: Secondary data
4 [174] US EPA (2005) [Energy Star, baseline]: Secondary data
5 [168] Braune (2006) [EPIC-ICT]: US EPA data
6 [166] Kemna (2005) [MEEUP]: Meta-analysis of prior studies
7 [175] Moorefield (2008): California plug-load audits
8 [82] Roth (2002): Secondary data
9 [174] US EPA (2005) [Energy Star, baseline]: Secondary data
10 [166] Kemna (2005) [MEEUP]: Meta-analysis of prior studies
11 [168] Braune (2006) [EPIC-ICT]: Dell data
12 [173] US EPA (2010) [Energy Star, certified]: Secondary data
13 [174] US EPA (2005) [Energy Star, certified]: Secondary data
14 [176] Porter (2006): California plug-load measurements
15 [95] Hischier (2007) [ecoinvent]: Secondary data
16 [4] Roth (2007): Phone survey, secondary data
17 [159] Duan (2009): ecoinvent; China statistics
18 [174] US EPA (2005) [Energy Star, certified]: Secondary data
19 [164] Kawamoto (2001): Small-scale measurements
20 [95] Hischier (2007) [ecoinvent]: Secondary data
21 [177] MTP (2006): Measurements and secondary data
22 [169] IVF (2007): Meta-analysis of prior studies
23 [169] IVF (2007): Meta-analysis of prior studies
24 [178] Schlomann (2005): Measurements and secondary data
25 [161] Atlantic Consulting (1998): Secondary data
26 [179] Nordman (2004): Estimates based on prior studies
27 [178] Schlomann (2005): Measurements and secondary data
28 [167] Choi (2006): Korea statistics
29 [165] Hikwama (2005): Secondary data
30 [13] Williams (2004): Secondary data
31 [167] Choi (2006): Korea statistics
32 [164] Kawamoto (2001): Small-scale measurements

Figure 3.4: Review of unit energy consumption of desktop PCs

The visual presentation of the data is illuminating; most studies are clustered between 100 and 350 kWh/year, with an approximate average of 225 kWh/year. The highest data points are case studies of a high-performance office workstation and a high-performance home gaming PC, highlighting the wide range of possible direct measurement results and thus the need for a large n if a study is to be representative of a typical PC. The lower outliers all tended to make questionable assumptions regarding power consumption; for example, Kawamoto et al. [164] assumed that residential PCs are off 91% of the time, but plug-load measurements by Porter et al. [176] show this figure to be closer to 60%. Likewise, Williams [13] assumed 3h of daily use for a residential computer, but Porter et al. [176] measured almost 8h of daily use. Note that studies which report dominant impacts from the production phase rather than the use phase - Williams [13] and Choi [167] - both report use-phase consumption at the low end of this range, suggesting that differing assumptions are largely behind the disagreement. Consumption of 50 to 100 kWh/year as these studies assumed is not implausible for low-power desktops or for computers that are used infrequently, but seems to be well below the representative range of a typical desktop under typical usage patterns.

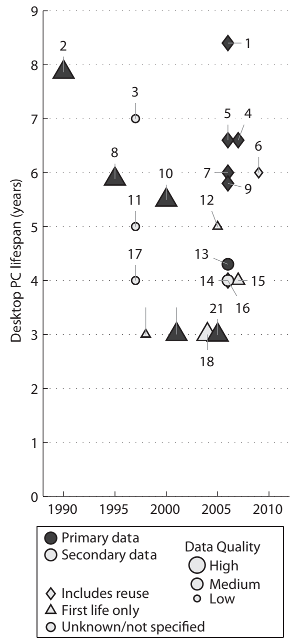
3.5.2 Product lifespan

The lifespan of the product, multiplied by its annual energy consumption, determines the total energy consumed in the use phase of a product. Measuring average product lifespan is deceptively difficult, because computers can sit in storage for years after their useful life is over, and sometimes enjoy continued use in the secondary market. The latter activity should be included in the total lifespan, as the product is still consuming energy, but the former should not. Techniques to measure lifespan, which may include customer surveys, waste stream monitoring, or purchase monitoring, may not always be able to identify storage and re-use, leading to variation in lifespan estimates.

Studies measuring lifespan, and the estimates used in LCA studies, are shown in Figure 3.5. The shape of the markers indicate whether the study was measuring first life only, or included re-use, or did not specify whether or not re-use was included. The most persuasive study of lifespan to date is from Babbitt et al. [180], which calculated product lifespan based on 20 years of procurement data in a university setting (n $>$ 2000 per year), and documented a steadily declining trend in lifespan; the last reliable data was for purchases made in 2000, when the average lifespan was 5.5 years. Other reported results came from a survey of consumer purchases in Japan [181], a Gartner survey [182], and a series of studies in Japan [183, 184, 185], originally cited in studies by Yoshida [186, 187][1]. Studies have been assigned a data quality rating, with larger primary studies ranking higher than secondary data, and direct measurements such as through a procurement database as in [180] ranking higher than surveys. Notably, several life cycle assessments rely on unreferenced assumptions.

As shown in Figure 3.5, estimates for PC lifespan range from three years to more than eight. The best-quality study, from Babbit et al [180], is probably close to an upper bound on first lifespan because it tracked computers on an academic campus with significant internal re-use. Downward trends in that dataset suggest an average lifespan of 5 years in the present day. The smaller result from Gartner [182],

[1]The original papers, in Japanese, were not available to us, so we could not confirm these figures.



1 [183] JEITA (2006) (Home): Japan study, cited in [187]
2 [180] Babbitt et al. (2009) (1990 purchases): Procurement database
3 [160] Tekawa et al. (1997) (Office): Unreferenced assumption
4 [169] IVF (2007): Survey of computer vendors, n = 6
5 [184] Oguchi et al. (2006): Japan study, cited in [187]
6 [159] Duan et al. (2009): Unreferenced assumption
7 [166] Kemna (2005): Consumer survey
8 [180] Babbitt et al. (2009) (1995 purchases): Procurement database
9 [183] JEITA (2006) (Office): Japan study, cited in [187]
10 [180] Babbitt et al. (2009) (2000 purchases): Procurement database
11 [160] Tekawa et al. (1997) (Home): Assumption
12 [165] Hikwama (2005): Assumption based on depreciation
13 [185] ESRI (2007): Japan study, cited in [186]
14 [168] Braune and Held (2006) [EPIC-ICT]: US EPA data
15 [95] Hischier et al. (2007) [ecoinvent]: Secondary data
16 [167] Choi et al. (2006): From [188]
17 [162] Masanet et al. (2005): Aassumption
18 [13] Williams (2004): From Williams and Hatanaka (2005) [181]
19 [161] Atlantic Consulting (1998): Assumption based on depreciation
20 [182] Smulders (2001): Gartner survey
21 [181] Williams and Hatanaka (2005): Home survey, Japan

Figure 3.5: Review of lifespan of desktop PCs

a 3 year lifespan, was conducted in a business context which likely featured higher replacement frequencies than an academic context. Second lives due to reuse will increase the average lifespan. According to Yoshida et al [186], the establishment of take-back recycling schemes increased re-use rates such that in 2004, about 37% of discarded PCs in Japan were re-used domestically, and an additional 25% were exported, though re-use rates are likely to be lower in jurisdictions like the USA which do not have well-established recycling programs. The prevalence of re-use and the length of any secondary life are additional sources of uncertainty; very little high-quality data assessing these factors is available. Given the available evidence, lifespans between three and six years seem to be reasonable estimates, depending on the context of use and the availability of infrastructure to support re-use.

3.5.3 Total use phase impact: analysis

The impacts due to electricity consumption can be measured in MJ primary energy or kg CO_2e by multiplying kWh of electricity by the appropriate impact characterization factors. Not all studies actually report the emissions factors used, but in some cases they can be derived by identifying reported total use-phase impact, in MJ energy or kg CO_2e, and dividing by total reported lifespan electricity consumption in kWh. These impact factors are shown in Figure 3.6, alongside emissions factors for various electricity grids from the ecoinvent database [189], obtained using low-voltage at-grid supply data with cumulative energy demand (CED) and IPCC GWP100 LCIA schemes.

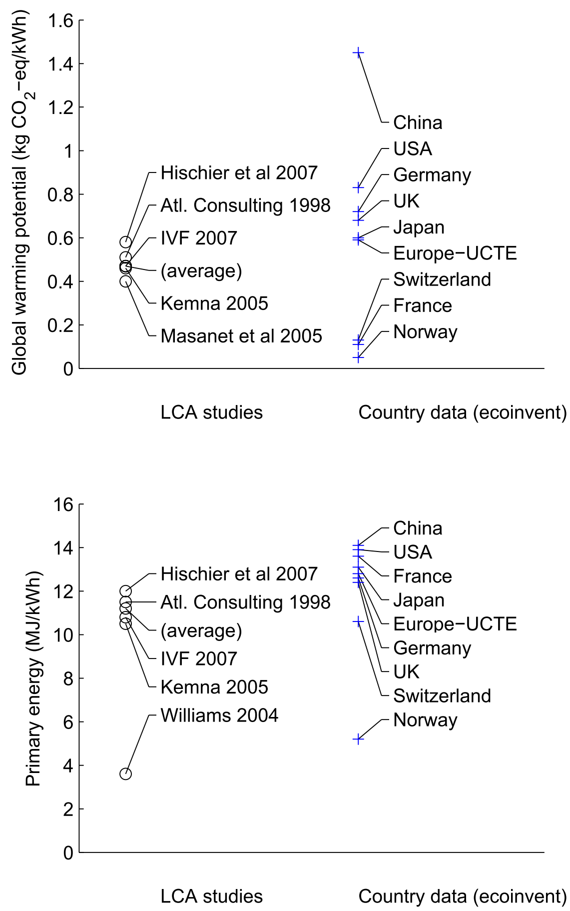


Figure 3.6: Impact factors for electricity from LCA studies and ecoinvent database

Most studies assume 1 kWh electricity is equivalent to between 10 and 12 MJ of primary energy in order to account for losses in electricity generation. Williams' study is an exception, accounting only for direct electricity consumption in the use phase (1 kWh electricity = 3.6 MJ primary energy) [13], which is a questionable assumption. Likewise, emissions factors are usually between 0.4 and 0.6 kg CO_2e per kWh. Both of these figures are intended to encapsulate the impacts of the electricity generation infrastructure at whatever geographic locale is appropriate for the study, so some variation is to be expected. In order to remove this variation from results in this study, constant factors of 11 MJ/kWh and 0.5 kg CO_2e/kWh are applied, which are the averages of the reported factors, excluding those of Williams. Note that these are slightly lower than most impact factors in ecoinvent; unfortunately, rationale for impact factor choice is usually not presented in these studies, so it is difficult to determine why they were chosen. The large spread in country data shows that the geographic location of product use is an important determinant of the total impact of the product; for example, global warming impacts due to use phase will be thirty times higher in China than in Norway, as China's electricity system is coal-based and Norway's relies almost exclusively on hydropower. This information is not unknown to LCA practitioners, of course, but is not always clearly communicated in the presentation of results.

The data in the previous sections suggest that plausible estimates for UEC range from 100 to 350 kWh/year, and lifespan ranges from 3 to 6 years. Multiplying UEC and lifespan together gives a possible range from 300 kWh to 2100 kWh. Converted to primary energy using the average emissions factors reported by the studies, this yields a range from 3300 MJ to 23100 MJ; in global warming potential, impacts range from 150 to 1050 kg CO_2e. Absolute rather than probabilistic bounds are defined because the ranges are defined by qualitative assessment of the data rather than rigorous statistical aggregation, the latter approach being inappropriate due to the heterogeneity of the data. Consequently, the ranges are relatively large. The implications of this result, and the result of the analysis for the manufacturing phase, are examined in the next section.

3.6 Analysis of overall impact

Figure 3.7 shows the ranges identified in the previous two sections and their overall impact in terms of primary energy demand and global warming potential; also plotted are the results from other available studies. In interpreting these data, the weight of evidence suggests that the use phase impacts of a typical desktop PC are more likely to occur at the middle of the range, seen in Figure 3.7, and less likely to occur at the fringes. Studies that lie towards the bottom of the range, including Williams [13], Atlantic Consulting [161], Masanet [162], and Apple [170], have therefore calculated use-phase impacts which are likely well below those of a typical desktop PC, though the Apple study examined a compact Mac Mini system. The other Apple study [171] is well above typical, and examined a high-powered workstation (the Mac Pro); neither the Mac Mini nor Mac Pro are intended to be representative of a typical desktop PC. It is unfortunate that no methodological details are available for these studies as this prevents any evaluation of their quality or reasonableness. Nevertheless, the very wide variation in overall impact for these two studies is intriguing; if the methods are at least internally consistent, then internal variation within the product category of desktop PCs may itself be large enough to overwhelm any methodological or impact-data-related variation.

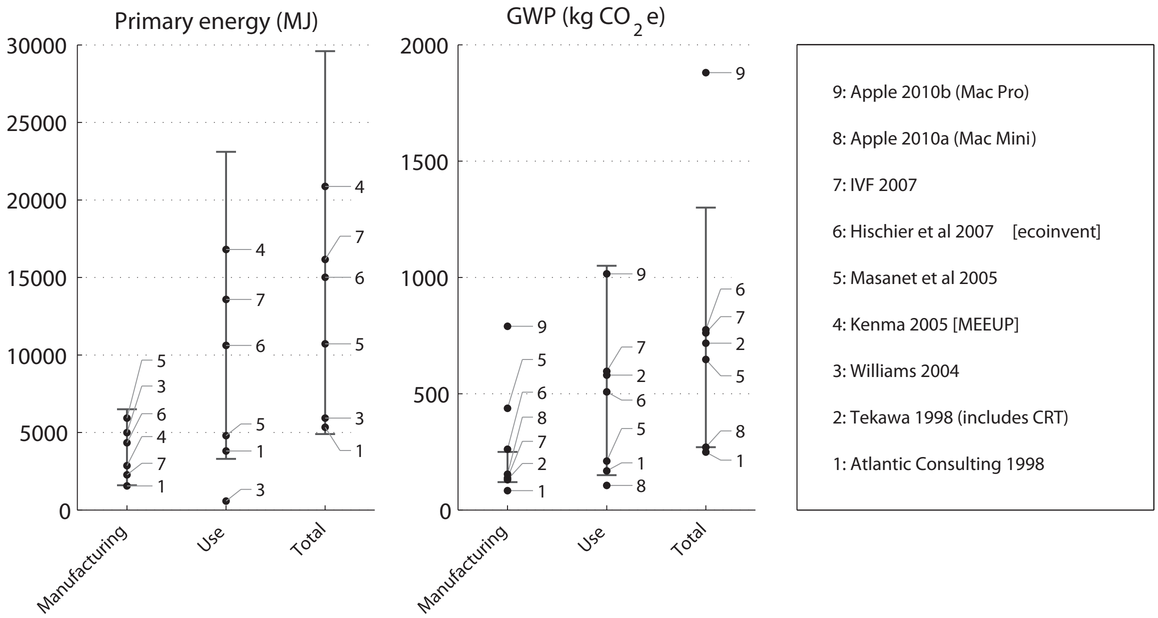


Figure 3.7: Overall primary energy and global warming potential, showing prior results and this study's estimates of reasonable ranges for a typical desktop PC without display

The emissions factors for use-phase electricity consumption used in this figure are slightly below the average of the impact factors of European UCTE country electricity grids according to the ecoinvent database. Use-phase impacts will proportionally increase or decrease according to the impact characteristics of the local grid where consumption occurs. In very low-carbon jurisdictions like Norway, manufacturing impacts (which occur in southeast Asia) will far outweigh use-phase impacts.

The collective evidence for impacts due to manufacturing is less conclusive. This study's analysis identified significant variation in impact factors of subcomponents, especially mainboards and ICs, which were a substantial source of variation in the overall impact due to manufacturing, but there was not enough evidence to identify a reasonable range for these impact factors. Methodological differences add more uncertainty: Masanet [162] used a top-down input output method which is not easily comparable to those studies previously analyzed; the Apple studies [170, 171] did not report any methodological details. The complexity of the underlying methods and data makes independent verification of any of these studies very difficult. Reasonable ranges of manufacturing impacts are defined to span the range defined by those studies analyzed in Section 3.4, on the basis that they provide the most detail, making an assumption that detail is correlated with quality and accuracy. Outlier studies could expand the range of reasonable results only if they are comparable in observable quality. This line of reasoning is admittedly somewhat speculative, but until standardization efforts reduce or eliminate uncertainty in product inventories and impact factors, accepting all high-quality studies as reasonable seems to be the only defensible option.

3.7 Conclusion

When measuring primary energy consumption and global warming potential, the impacts due to use phase energy consumption of a typical desktop PC without display are the dominant impact in the product life-cycle, except in areas with very low-impact electricity grids; manufacturing impacts are smaller, but still significant, and distribution and end-of-life are both negligible (note, however, that end-of-life activities can cause significant damage to environment and human health not captured in these two impact dimensions). A few studies have reported that manufacturing impacts exceed use-phase impacts, but these studies each reported use-phase energy consumption at or below the low end of a reasonable assessment of a typical PC's energy consumption, which ranges from about 100 to 350 kWh/year for a lifetime of 3 to 6 years. Manufacturing impacts exhibit a particularly high variability, most of which is due to disagreement about the impacts per unit of the various components inside the PC, especially mainboards and semiconductors. Estimates of the physical contents of a PC by mass vary as well, but less so. Total impact, summarized in Figure 3.7, might be expected to range from 270 to 1300 kg CO_2e and from 4900 to 39100 MJ of primary energy, with the most likely result towards the middle of these ranges. The use-phase primary energy consumption and greenhouse has emissions are strongly dependent on the local electricity grid where the product is used. In addition, variation of the functional unit, such as choosing a lightweight low-power computer or a high-performance workstation, can have a dominating effect on the value of the impact, making it important for researchers to either conduct studies with a larger sample of products in order to smooth out this variation, or to explicitly limit the scope of their assessments to a specific sub-category. The latter approach has become increasingly important with new products being introduced and the desktop PC category broadening.

This exercise uncovered several inaccurate assumptions in published studies and highlights a general problem with life cycle assessments: they are very difficult to evaluate, even for an experienced practitioner, as a full listing of data, methods, and assumptions used is rarely available, often for reasons of industrial confidentiality or proprietary data, and the correctness of the data may itself be difficult to determine. A tendency for data re-use is noted as newer studies build on older studies, but as the pool of primary research is small and difficult to verify, errors may have been propagating through the literature undetected, creating a risk that erroneous results may become established. Data on electronics manufacturing, especially for less-frequently researched components and processes, is particularly vulnerable to undetected errors, and current reported results are of an unknown quality.

Data quality issues will diminish when standardized impact-reporting systems with participation from electronics manufacturers are in place. Until such time, practitioners should use caution when adapting results from previous studies and critically evaluate such results regardless of their prominence and apparent acceptance by other researchers. Rich opportunities remain for future research to reduce uncertainty in life cycle assessments of electronics.

Chapter 4

Embodied emissions of ICT devices

4.1 Introduction

The global share of worldwide greenhouse gas (GHG) emissions from information and communications technology (ICT) is substantial and rising; computers and electronics are a significant source of household electricity consumption [190]. In the personal computing (PC) sector, operational impacts are estimated to account for roughly 60% of greenhouse gas emissions, with the remaining 40% due to manufacturing [25]. The latter, also referred to as embodied emissions, is difficult to estimate, and there is a need for both additional and improved estimates of embodied emissions of ICT products, and for heuristic methods to enable faster and easier first-order estimation.

Current literature examining the embodied impacts of ICT equipment suffers from three important shortcomings: disagreement across studies regarding the magnitude of impacts of ICT products [1, 19, 20]; lack of coverage for newer products; and lack of transparency in studies, particularly due to confidential input data, which hampers reproducibility and cross-study comparisons. Using primary data from hand disassembly and the ecoinvent v.2.2 database [191] for upstream process data, this study quantifies the embodied greenhouse gas (GHG) emissions of 11 ICT products, most of which were manufactured in 2009 or later. This work represents the first peer-reviewed examination of the embodied impacts of a small-form-factor desktop PC, netbook-style laptop, thin client device, Apple iPad, Apple iPod Touch, and Amazon Kindle. An additional study of three older ICT products from the ecoinvent database [95] was reformulated using this study's framework so that all 14 products could be compared. A full listing of the products analyzed and the results recorded is in Table 4.1. By using a consistent framework, product emissions estimates can be compared against one another with some confidence, avoiding the problems of different modeling assumptions or different upstream data sources that arise when comparing results from independent studies. This framework is used to develop first-order linear models for estimating embodied emissions using a small set of product characteristics. Findings are also compared against a dataset published by Apple (described in Appendix B) that provides life cycle assessments (LCAs) of its entire product line [46].

Product category	Model (year of manufacture)	Mass [kg]	GHG [kg CO_2e]
Desktop PC	[ei] Typical desktop (2002)	11.1	322
	Dell Optiplex 780 mini tower (2010)	10.7	164
	Dell Optiplex 780 ultra-small form factor (2010)	3	73.5
	Dell FX-100 zero client (2009)	1.3	33.6
Laptop PC	[ei] 12.1" HP Omnibook with dock (2003)	3.3	256
	HP 530 laptop, 16" (2009)	2.8	108
	HP Mini 110-1030 CA Netbook, 10" (2009)	1.3	62.2
LCD display	[ei] Typical 17" (2004)	5.1	297
	Samsung Syncmaster 2243 21" (2009)	5.1	168
Mobile electronics	Apple iPad 8 GB Wi-Fi 1st gen (2009)	0.78	25.5
	Apple iPod Touch 8 GB 3rd gen (2009)	0.2	7.5
	Amazon Kindle Wi-Fi 3rd gen (2010)	0.31	13.3
Server and network	Dell PowerEdge EMU3710P71 rack server (2005)	15.5	383
	3Com 24-port Superstack 3 10/100 Ethernet switch (2003)	2.1	91.8

[ei]: Adjusted version of study originally published in ecoinvent [95]
Mass includes power supplies; desktop PCs exclude display
GHG: embodied emissions derived in this study

Table 4.1: Products analyzed in this study

The broad goal of this work is to make LCA results for ICT products easier to derive and more useful in supporting decisions, both by contributing a new primary dataset of product inventories and impact estimates, and by exploring linear regression-based models that could approximate impact assessment using a limited set of easily collected inputs. Similar linear regression-based methods being developed by the PAIA project [192] and by iNEMI [193] are aimed at enabling impact estimation using product characteristics (e.g. screen area, amount of RAM, hard drive size, etc.). The dataset produced by this study could be adapted to use these tools and methods once they become publicly available.

4.2 Methodology

The process-LCA methods applied here have been used in many studies of ICT equipment, such as the adapted ecoinvent studies [95], the EPIC-ICT project [168], the EU energy-using-product studies [166, 169], and others. The ecoinvent database has been described as the "most complete and transparent process-LCA database" [81] and is used for upstream data in one LCA study of a desktop PC [159] and as the process component in several hybrid-LCA studies [92, 138]. However, the limitations of this methodology must be stressed. Process-LCA accounts for only those impacts that are specified in product inventories and underlying process databases; truncation error due to activities not modeled in these databases can be significant. Large sectors of the economy, especially service sectors, are not modeled by the ecoinvent database at all [81]. Top-down methods, such as economic input-output LCA, do not suffer from truncation error, but have a limited ability to distinguish between similar products due to the coarseness of economic data. Hybrid-LCA methods attempt to achieve a balance by merging top-down economic data with process-LCA results. Two hybrid-LCA studies of a desktop PC [13] and laptop PC [92] found that the economic correction respectively accounts for 51% and 40% to 56% of total impacts in the production phase, respectively. Likewise, in a comparison of LCA methods for ICT products [138], the original process-LCA estimate accounted for only 37% of the emissions estimated by a top-down input-output LCA. Accordingly, hybrid analysis is recommended by several researchers as the best means to produce accurate estimates of emissions in absolute terms [81, 138, 139].

The scope of this study is limited to comparing the embodied impacts that can be identified using process-LCA methods with the ecoinvent database. This limitation is imposed because the strengths and weaknesses of this framework are relatively well understood, which allows for increased confidence that the relative differences in the product impacts that the analysis identifies are not methodological artifacts. The process-sum method introduces significant truncation error such that this study's results underestimate the absolute impact; the use of economic data to correct for truncation error would improve accuracy, but such a correction would require pricing data which are largely unavailable. Accordingly, these results should be interpreted as a comparison between products, and not as a calculation of product carbon footprints that could be used in contexts external to this study. Future work to produce product carbon footprints should address this truncation error, as well as the use phase and end-of-life phase which are not included in this study.

A number of standards for LCA of ICT equipment have recently been published or proposed by the ETSI [194], ITU [195], IEC [196], and GHG Protocol [197], coordinated in part by the European Commission's Information Society department [198]. This study was conducted prior to the publication of these standards, and thus is not compliant with any of them, though compliance could be achieved with some additional effort. The use of standards, especially the ETSI standard which is the most thorough and rigorous of the above, would greatly improve transparency and comparability across compliant studies, and should be encouraged.

This study focuses on embodied impacts, in terms of global warming potential, using the IPCC 100-year characterization; primary energy demand is calculated as well in Appendix B. Raw material extraction, processing, final assembly, and transport are included. Modeling assumptions are equivalent to those used in previous ecoinvent studies [95]. In particular, the ecoinvent database supplies data for all electronic component manufacturing, processing, assembly, and transport data and assumptions, with the exception of silicon die, for which an updated study is used [172].

Bills of materials were constructed via hand disassembly and weighing. Product packaging and extra parts, including manuals, software, and extra cables and adapters, are excluded, as this information is not available for all products and tends to represent a small share of the impacts for ICT products. Some other components, such as flame retardant coatings, are not detectable via weighing and were thus excluded. The ecoinvent models for silicon die content in packaged integrated circuits (ICs) contain a calculation error (identified in other studies [1, 133]) that leads to an underestimate of silicon die content. In order to develop more accurate estimates of silicon die content in packaged ICs, a selection of packaged ICs were X-rayed and their die areas measured. Silicon die content is modeled as a linear function of packaged IC area for large ICs and of mass for smaller ICs, which were weighed in bulk. An additional correction was made for stacked ICs in the Apple iPad and iPod Touch.

Appendix B contains full details regarding modeling assumptions; the mapping of bills of materials entries to ecoinvent processes; experimental data and calculations for the silicon die ratios; and a discussion of stacked ICs. Full bills of materials for all products analyzed are provided in the Supporting Information of the published study available online [2], but omitted from this dissertation due to their length.

4.3 Results

Two sets of results are presented: the mass composition of each product as determined through hand disassembly (Figure 4.1a), and estimated embodied GHG emissions calculated with ecoinvent impact data (Figure 4.1b). Data tables for the graphs are available in Appendix B.

4.3.1 Product composition by mass

Circuit boards account for between 5% and 20% of product mass across most products. Casing, typically metal or plastic, represents roughly half of the mass in large desktop and rack servers, each of which weigh more than 10 kg. In mobile devices, casing is only about one quarter of the mass due to the extra mass of batteries and displays.

The three studies adapted from the ecoinvent database model a desktop PC, manufactured in 2002; a 17” LCD monitor from 2004; and a 12.1” laptop (with dock) from 2003. Comparable products in this study, all manufactured in 2009 or 2010, are significantly lighter. The 21.5” monitor studied here is comparable in mass to the 17” monitor modeled in ecoinvent, despite the former’s larger screen size, because the latter was significantly thicker and had a much heavier frame, likely because LCD technology was relatively new and less compact in 2004. This information constitutes evidence that electronics products are becoming more materially efficient over time.

In terms of both IC mass and die area, modern devices show significantly less material usage for integrated circuits when compared to the older products modeled in ecoinvent. That is likely due to higher levels of miniaturization available in modern packaging technologies (as described in another study [93]), as well as reduced numbers of ICs per product due to increased integration of functionality.

4.3.2 Embodied emissions

Circuit boards including ICs are responsible for the majority of embodied GHG emissions in most devices. Product casing in this study is modeled as aluminum, steel, or plastic, all of which have relatively low emissions per unit mass, so the overall impact of casing is small. One exception is the laptop modeled in the ecoinvent database for which the casing includes a higher-emissions magnesium alloy. Integrated circuits have high impacts despite their very small mass; silicon dies alone are responsible for about 20% of product embodied emissions on average.

The results suggest a strong link between product mass and embodied emissions, with heavier or

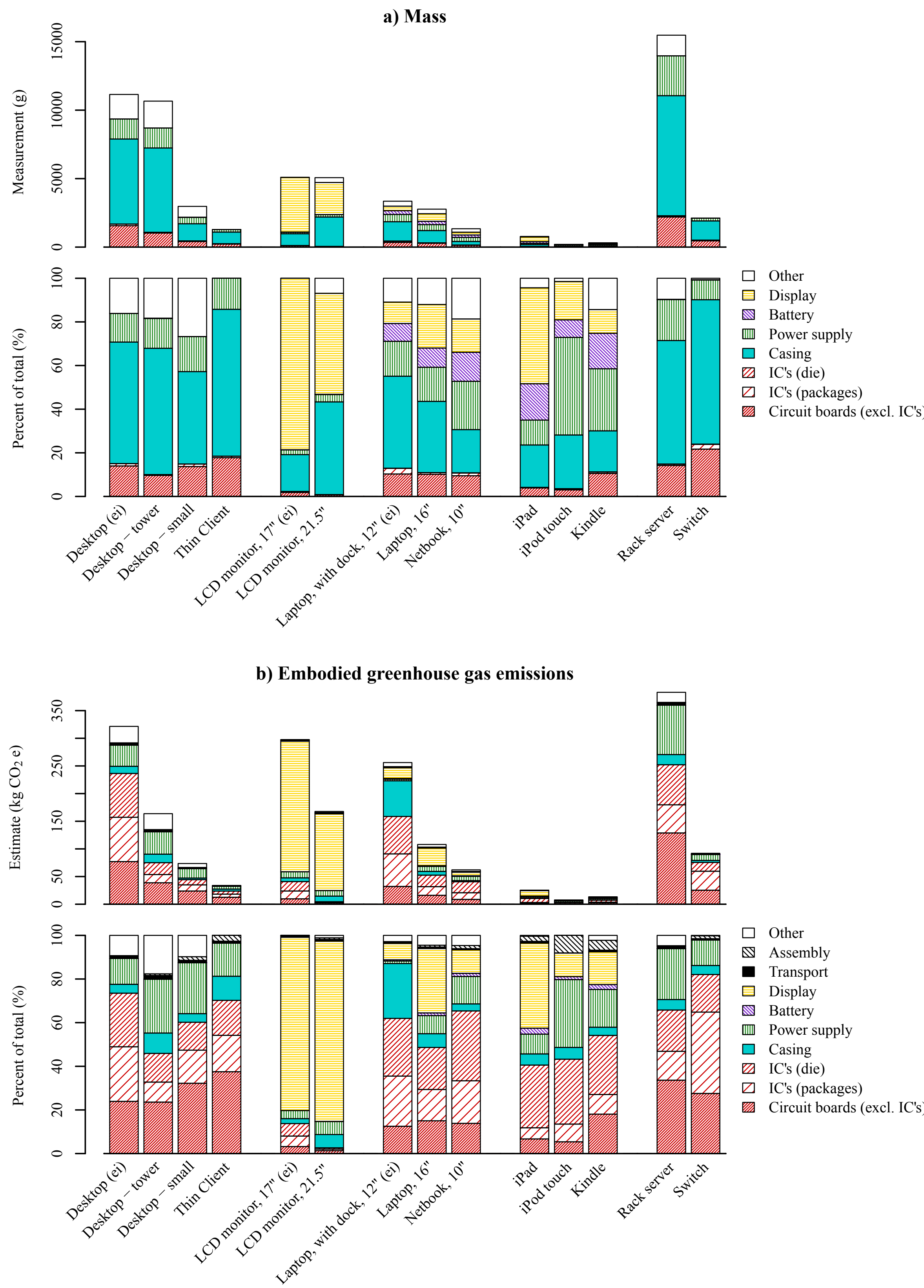


Figure 4.1: Results showing product mass (a) and embodied emissions (b). (ei) denotes adjusted studies from ecoinvent database.

larger products having higher emissions; the following section explores this relationship in more detail. The older devices modeled in ecoinvent (desktop, laptop, monitor) have significantly higher emissions than modern devices with similar functionality. Since the modeling framework and data sources are identical in this study and in the ecoinvent study, aside from some minor adjustments discussed in Appendix B, the differences can be ascribed to changes in the material composition of the products themselves: modern devices have fewer integrated circuits and circuit boards, certainly a consequence of higher levels of on-chip integration enabled by Moore's Law. When modern devices are compared to other modern devices from the same product category, smaller form factors have smaller impacts: the 10" netbook's embodied emissions are about 40% lower than those of a similar 16" laptop, while the small desktop's emissions are about 50% lower than a comparable minitower from the same product line. The embodied GHG emissions of mobile devices are very small compared to laptops, desktops, and monitors.

4.3.3 Comparison with other studies

This study's output estimates for the adjusted ecoinvent studies are very similar to those from the original ecoinvent studies, suggesting that the framework has been accurately reproduced; differences due to this study's adjustments are explained in Appendix B. Compared to recent studies of similar equipment published within the last five years, this study's results are mostly similar. This study's emissions estimate for a rack server, 360 kg CO_2e, is comparable to a recent study's estimate of 380 kg CO_2e [133], while this study's result for the Dell Optiplex 780 tower desktop, 161 kg CO_2e, is comparable to Dell's estimate of 120 to 180 kg CO_2e for the same product [199]. Dell's study of a 14" laptop estimates emissions to be 160 kg CO_2e [200], larger than this study's estimate of 106 kg for a 16" HP laptop. In this case, differences occur primarily in casing (25 kg CO_2e in Dell's study vs. 6 kg CO_2e in this study), mainboard (72 kg CO_2e vs. 52 kg CO_2e), and battery (9 kg CO_2e vs. 1.3 kg CO_2e). The latter study is the only example from a manufacturer in which emissions are specified at a component level that allows a detailed comparison. A recent hybrid-LCA study of a 15" laptop manufactured in 2001 found GHG emissions from manufacturing to be between 227 and 270 kg CO_2e; of that amount, 93 to 136 kg CO_2e were accounted for via bottom-up process LCA, comparable to our estimate of 106 kg CO_2e for a 16" laptop using similar methods, with the remaining 134 kg CO_2e due to the top-down economic correction.

There is one study of an e-book reader, and it identifies 40 kg CO_2e for a 2007 Sony PRS 505 [201], higher than this study's estimate of 13 kg CO_2e for a 2010 Amazon Kindle. That study also uses the ecoinvent dataset, but identifies 31 g of packaged ICs compared to 2 g in this study, implying that the difference is due to physical variation between products. Two studies of mobile phones report 20 kg CO_2e [202] and 30 kg CO_2e [203], higher than this study's estimate of 7 kg CO_2e for an iPod Touch. The mobile phone in the latter study had a mass of 250 g, which may or may not include an external charger, whereas the iPod Touch has a mass of 109 g, while its charger's mass is an additional 89 g. Given the tendency for the newer products in this study to use fewer integrated circuits compared to older products in the ecoinvent database, we speculate that the older mobile phones in those two studies likely contained more ICs, which could account for some of the difference between these results.

Apple's dataset of 22 products [46][1] shows results that are considerably higher than this study's estimates for similar products. This study's estimates of the manufacturing emissions of a laptop, netbook, iPad, and iPod touch are 106, 62, 22, and 6.7 kg CO_2e, respectively; comparable products in the Apple product environmental reports, a 15" Macbook Pro, 11" Macbook Air, iPad 2, and iPod touch, are estimated to have embodied emissions of 290, 162, 25, and 15 kg CO_2e, respectively. The author of Apple's reports indicates that a different impact database, i.e. not ecoinvent, was used by Apple, and notes that the casing materials were modeled in more detail and were not classified simply as aluminum or steel, but as rather more complex materials, though the methodologies are otherwise comparable[2]. A lack of transparency and access to the details of Apple's study prevents definitive identification of the source of the variation.

Overall, when compared against other studies, this study's results are roughly comparable for large products and lower for smaller mobile products. In some cases, the variation may be a consequence of the more recent vintage of products analyzed here relative to other studies, since newer products tend to have fewer integrated circuits. Additional variation may be caused by different underlying models for some parts (such as casing and battery) and/or different modeling assumptions. It must be stressed that this study is replicating the modeling assumptions of the ecoinvent database. Agreement between this study's results and those of other studies is not a guarantee of accuracy, which is a function of the underlying source data and methods. Such agreement does, however, suggest that this study's methods

[1] This study considers a historical snapshot of Apple's product environmental reports as of September 2011, when the study was conducted; environmental reports released or updated after that time are not accounted for.

[2] Personal communication, 2011

and data are in-line with standard practices. To the extent that these practices are valid, the relative differences in our estimates of embodied emissions for different products arise due to differences in the products being analyzed, as intended.

4.3.4 Data quality and uncertainty

The ecoinvent database uses a semi-quantitative uncertainty model based on "pedigree" matrices in which each inventory item is assigned a probability distribution based entirely on the quality of the data as estimated by experts [191]. These scores are intended to account for mismatches between the ecoinvent technological processes and the physical real-world processes they model. The same method is applied here in order to enable comparisons with other studies that use the ecoinvent database and uncertainty method, using Monte Carlo analysis with 100 trials per product. Details about the probability distributions used are discussed in Appendix B; results are shown in Figure 4.2. The distributions have standard deviations ranging from 10% (several products) to 18% (LCD monitor) of their respective means.

This uncertainty model has some advantages in that it is quantitative, consistent, and tractable, but it relies on expert judgment and is prone to errors related to that approach [204]. In particular, the pedigree approach produces artificial probability distributions that have no empirical basis and represent only expert judgments of data quality, and in addition only capture uncertainty which is internal to the ecoinvent modeling framework. Structural uncertainties due to truncation errors are not included; neither are uncertainties in emissions characterization factors. The actual bounds on the results will be larger than those shown in Figure 4.2 and are not precisely quantifiable using this method.

4.4 Analysis

The data in Figure 4.1 suggest the presence of a linear relationship between embodied emissions and product mass. This trend also appears in Apple's dataset (n=22). These datasets could be used to estimate embodied emissions for ICT products based on easily measurable physical characteristics such as total mass and volume. Differences in the underlying modeling frameworks mean that this study's dataset and Apple's cannot be combined in such an analysis. However, it is possible to develop a linear model that adequately describes both datasets, tuning the coefficients independently to produce one set of coefficients for each dataset.

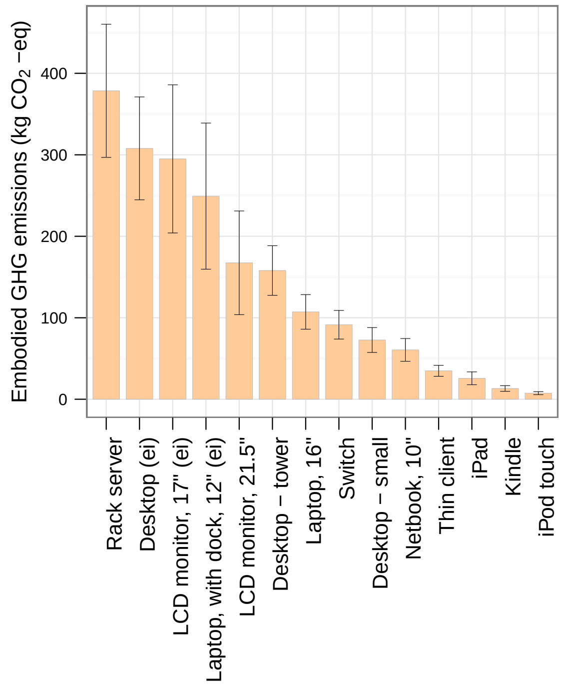


Figure 4.2: Monte Carlo results: mean embodied GHG emissions with error bars showing $\pm$ two standard deviations, using data quality pedigree matrix approach

Apple provides a breakdown of the material composition of its products by mass. By arranging the data from this study's disassembly analysis into the same categories as Apple, six possible predictors of embodied GHG emissions are yielded: circuit board mass, display mass, battery mass, casing mass, power supply mass, and other mass. Two additional predictors that describe overall product characteristics are included: product mass and product volume. Using combinations of these eight predictors, many possible linear regression models were examined, each of which was independently fit to both datasets to produce a set of coefficients that could be used to predict a product's emissions. Model robustness was evaluated using leave-one-out cross-validation in order to obtain the cross-validated residual sum of squares statistic (cvss), which is intended to quantify how well the model can predict output values for data points not in the training set. Each candidate model is assigned two scores, cvss_1 and cvss_2, which are equal to the cvss for this study's dataset and for Apple's dataset, respectively. A combined score for both models is generated by summing $\text{cvss}_1^2 + \text{cvss}_2^2$; the sum of squares is used to penalize models that fit one dataset well and the other poorly, since the goal is to find a model that fits both datasets well. The linear model that has mass as its only predictor is used as a benchmark against which other scores are normalized.

Three of these models are shown below in detail; more model results are in Appendix B. The first, 'mass only', which is the benchmark model, treats emissions as a linear function of product mass. The second model, 'pcb+disp+batt', uses three internal predictors (i.e. $\text{Emissions} = \alpha_1 \cdot \text{mass}_{\text{circuit board}} + \alpha_2 \cdot \text{mass}_{\text{display}} + \alpha_3 \cdot \text{mass}_{\text{battery}}$). The third, 'all internal', uses all six internal predictors (circuit board, display, battery, casing, power supply, and other). All models are constrained to pass through the origin; adding an intercept does not improve the fit. For each model, the fitted results for both datasets are shown in Figure 4.3 and the coefficients and diagnostics in Table 4.2. In the figure, the x-axis represents the actual estimate for embodied emissions for each product in the dataset, while the y-axis shows the residual; a perfect model would have each point along the $y = 0$ line.

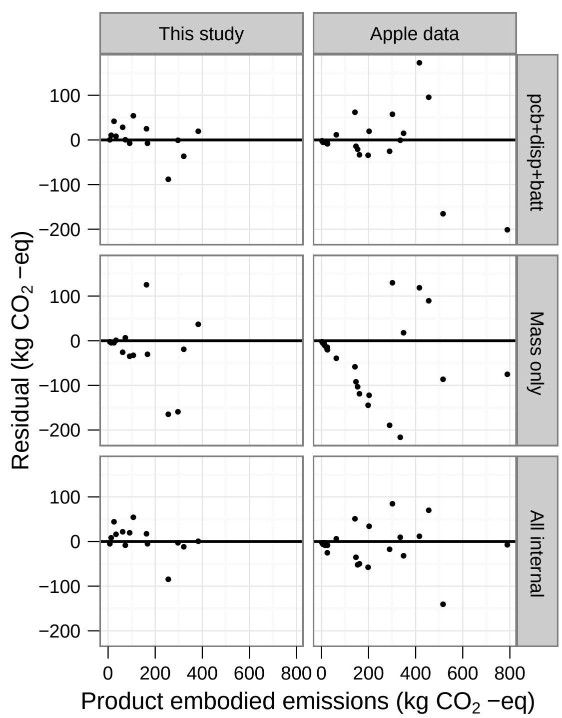


Figure 4.3: Residuals from model selection

The 'mass-only' model has the best cross-validated score of the dozens of models that were compared, while the 'pcb+disp+batt' model is only slightly worse. Figure 4.3 shows that the mass-only model systematically underestimates emissions for light products, especially in the Apple dataset; that

	Model coefficient [kg CO_2e per g] *p-value*											
	'pcb+disp+batt' model				'mass only' model				'all internal' model			
Predictor	This study		Apple data		This study		Apple data		This study		Apple data	
Mass					0.027	*<0.01*	0.039	*<0.01*				
pcb	0.18	*<0.01*	0.37	*<0.01*					0.24	*<0.01*	0.48	*<0.01*
casing									0.012	*0.49*	-0.1	*0.23*
batt	0.30	*<0.01*	0.36	*<0.01*					0.36	*0.02*	0.41	*<0.01*
disp	0.065	*<0.01*	0.052	*<0.01*					0.062	*<0.01*	0.066	*<0.01*
psu									-0.079	*0.97*	0.53	*0.02*
Other									-0.012	*0.41*	0.1	*<0.01*
cvss	0.42		1.4		1.0		1.0		0.45		2.8	
Score	2.1		2.1		2.0		2.0		7.9		7.9	
R^2	0.97		0.94		0.85		0.89		0.97		0.97	
Adj.R^2	0.96		0.93		0.84		0.88		0.95		0.96	

Table 4.2: Coefficients and statistics from model fitting

occurs because the masses of heavier products are dominated by casing, which has a much lower emissions-per-unit-mass than electronic components. A linear-mass model is not sufficiently sophisticated to account for the different composition of light and heavy products. The 'pcb+disp+batt' model appears to be unbiased, and has a comparable cross-validation score, meaning it is a better fit overall, though it requires more data inputs than the mass-only model. The 'all-internal' model illustrates the effect of including additional predictors: the residuals are smaller, but the model is overly tuned to the dataset and does not accurately predict emissions, as shown by its poor cross-validation score. Some coefficients for this model are negative, indicating non-physical results and double-counting from correlated predictors.

The two best models - 'mass only', and 'pcb+disp+batt' – both produce good results and coefficients that are physically reasonable and fairly consistent numerically across the two datasets. Ideally, the analysis could be repeated with a wider dataset, perhaps including multiple specimens from each product category, and should incorporate newer process data when available. Nevertheless, the strength of the linear relationships uncovered in both this study's dataset and Apple's dataset is encouraging, and suggests that linear models based on a limited number of product characteristics could reasonably approximate the results of using full process-sum LCA to estimate manufacturing emissions.

4.5 Discussion

This work compares modern ICT products to those originally modeled almost a decade ago in the ecoinvent database. In all three cases, the newer products' embodied GHG emissions are an estimated 50% to 60% lower than those of the corresponding older products. This decrease is mainly caused by a reduction in total mass and a proportional decrease in integrated circuits and circuit boards, the result of systems becoming more highly integrated and thus using fewer ICs. These products were chosen to be roughly representative of typical products within their respective categories, so it can reasonably be inferred that over time ICT products are getting lighter, becoming more integrated, and having a reduced impact. However, efficiency trends in ICT products are counteracted by increased growth in the installed base of existing products and the emergence of new complementary products; the overall impact of the ICT industry, or of a consumer's personal collection of ICT products, depends on the relative strength of these competing trends, which are not analyzed here.

Embodied impacts identified in this study are roughly linear with respect to mass, with a coefficient of 27 kg CO_2e per kg of product using this study's data and 39 kg CO_2e per kg of product using Apple's data, but this model tends to underestimate impacts of lighter products. If the masses of printed circuit board (including ICs), battery, and display can be obtained, then emissions can be calculated as $0.18 \cdot \text{mass}_{pcb} + 0.30 \cdot \text{mass}_{battery} + 0.065 \cdot \text{mass}_{display}$ (using this study's data), or as $0.37 \cdot \text{mass}_{pcb} + 0.36 \cdot \text{mass}_{battery} + 0.052 \cdot \text{mass}_{display}$ (using Apple's data), with masses in grams and coefficients in kg CO_2e per gram. These results do not account for truncation error and exclude the use phase and end-of-life phase; they therefore should not be taken as product footprint benchmarks. More sophisticated linear models could be constructed, but the benefits of doing so appear small.

The relatively good fit of these models suggests that linear regressions based on product characteristics may be a promising avenue of exploration for first-order life cycle assessments. Further investigation could determine the stability of these findings over a wider range of product categories, as well as over variation within a product category; for example, by assessing several monitors with different screen sizes, as in the PAIA project [205], or by examining the effects of using alternative materials (e.g. for casing) that may have considerably higher impacts per unit mass than the materials used here. In addition, the effect of imposing a top-down economic correction on the results could be explored. Finally, the necessity to re-tune the model depending on the underlying framework and data is problematic; enforcing compliance with the aforementioned ETSI standard [194] (or others) could enable standardized models for simplified LCA, which would help achieve the broad goal of a more practical and useful methodology to support decisions.

Chapter 5

Emissions due to connected media

5.1 Introduction

Information and communications technologies (ICTs) represent a small but growing share of the global energy and CO2 burden, accounting for roughly 2 to 3% of global anthropogenic greenhouse gas (GHG) emissions and 4 to 6% of global electricity consumption [25]. Growing convergence between television sets and personal electronic devices, alongside a shift from traditional broadcast media distribution forms to on-demand streaming over the internet, blurs the boundary between the formerly distinct categories of ICT and consumer electronics (CE). When these two categories are grouped, they account for about 12.5% of combined residential and commercial building energy consumption in the US [26]; this total does not include most datacenters, which themselves account for about 2% of US electricity consumption [23]. Overall energy consumption due to ICT/CE devices in the home and due to network and datacenter infrastructure are well-known through prior studies, especially in a US context [5, 206, 207, 208]. However, connected media platforms such as the tablet, smartphone, and connected TV account for a growing share of consumer time spent with digital media [98, 209] which complicated the relationship between end-uses, such as watching video on a device, and energy consumed in the provision of that end-use.

ICT/CE devices have many end-uses, such as watching video, consuming online content, and others. Greenhouse gas emissions due to such end-uses may be assessed with a life cycle assessment (LCA) approach, which tabulates all emissions associated with operation of electronic devices and infrastructure which services the end-use, as well as all embodied emissions which occur during the production, assembly, transportation, and disposal of all devices and infrastructure involved in servicing the end-use. Previous life cycle environmental impacts of individual ICT products have not included the energy or emissions due to services typically accessed on those devices. Such work has focused on desktop PCs [1], laptops PC [210], mobile phones [211], and other devices to a lesser degree such as televisions and servers [2, 19, 91, 212]. Studies of the impacts of ICT-enabled behaviors have drawn wider boundaries, such as comparing changes in travel impacts due e-commerce [130, 213] or telework/telecommuting [44, 68, 214], or comparing the impacts of physical media against online textbooks [121], e-books [38], online journals [124], online news [118, 126], digital music [39], and streaming video [40]. The studies have varying goals, but each tests the impact of a relatively new ICT-enabled behavior, and each includes a comparison to a functionally similar non-ICT behavior. However, comparisons of physical and digital end-uses are prone to large uncertainties since they entail comparisons of systems with vastly different characteristics.

More recently, researchers have begun to examine the impacts of ICT/CE end-uses in absolute terms and in comparison with other ICT/CE end-uses. Study topics include broadcast TV compared with on-demand video [45]; impacts of video and text online news delivery on different platforms [41]; comparisons of business productivity software with "cloud"-hosted alternatives [42, 129]; a comparison of access network, core network, and datacenter energy for wireless cloud applications [43]; and a forecast of total global ICT/CE energy through 2017 [215]. In contrast to previous studies, these studies do not compare against non-ICT behaviors; rather they seek to better understand the relative impacts of different behaviors, often by taking a national or global approach; to identify environmentally preferable or non-preferable behaviors; and to identify the most impactful components of ICT/CE systems so that future impact reduction efforts may be effectively targeted. This approach allows for the development of higher-quality models and data inputs given the more focused scope; in addition, it enables linkages between well-established estimates of aggregate ICT/CE energy, and the behaviors that are driving it.

This work continues along this approach by focusing on digital media end-uses in the home across four prominent media platforms, in order to better understand how consumer digital media consumption habits relate to overall ICT/CE emissions. The remainder of this paper is organized as follows. Section 5.1.1 outlines the study boundaries and the scope of this work. Section 5.2 describes the modeling methodology which is used to evaluate energy use and GHG emissions relating specific end-uses (e.g. video, browsing, etc) to device, network, and datacenter combinations. Section 5.3 describes model inputs estimated from US data. Section 5.4 presents energy use and GHG emissions by device types (5.4.1), end uses (5.4.2), and presents an uncertainty analysis (5.4.3). The study also compares ICT uses in the home to those from other household appliances (5.4.4) and concludes by summarizing the implications of this study's findings for future research in Section 5.5.

5.1.1 Study scope and boundary

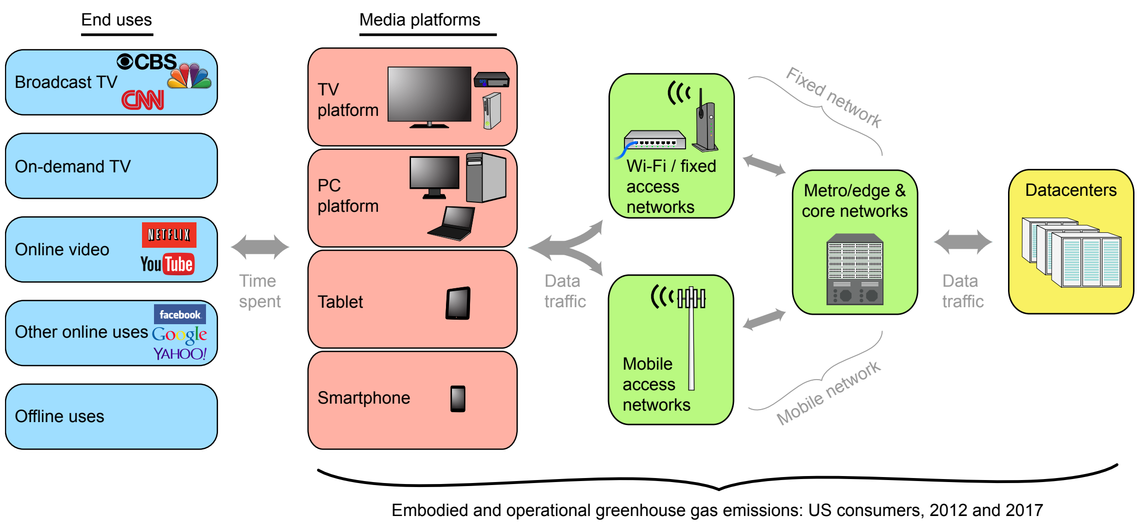


Figure 5.1: Block diagram showing study scope and boundary

Figure 5.1 shows the study scope and boundary. The study estimates the embodied and operational greenhouse gas emissions of five broadly defined end-uses using four ICT/CE platforms among US consumers in 2012 and 2017. The study applies a top-down methodology using secondary data to establish emissions intensities (i.e. emissions per unit of data transfer) for networks and datacenters. Forecasts to 2017 derived based on best available secondary data sources were used to show the effects of continuing growth in data traffic alongside continual improvement in network and datacenter efficiency, both of which are changing rapidly. The time horizon of 2017 was chosen to coincide with the horizon of the Cisco VNI data traffic forecast [103], a major data source for this study, as well as horizons of other data sources regarding energy consumption and installed base. A key contribution of this study is the development of an integrated end-use time and traffic model that allows for calculation of greenhouse gas emissions of each end-use on each platform. The model uses a compilation of appropriate data inputs, relying primarily on data from market research and technology company reports; it is transparent and could be easily applied to other contexts with different intensity estimates.

Five end-uses are modeled: (1) broadcast television, i.e. TV programs delivered via aerial broadcast or over cable or satellite networks; (2) IP video-on-demand, i.e. TV programs delivered to connected televisions over managed IP networks, usually through a service managed by a cable or satellite provider; (3) online video, also known as "over-the-top" video, which includes Youtube, Netflix, Hulu and all other internet video services; (4) other online uses, such as online gaming, streaming music, and social network; and (5) all offline uses including word processing, DVD watching, offline gaming, and other uses which do not involve network data transfer. These categories of end-use were chosen so that they reasonably encompass the majority of ICT/CE behaviors. Four device platforms are considered: TVs, PCs, tablets, and smartphones. Networks are modeled as a combination of fixed access networks, which include customer premises equipment (e.g. routers) and customer access equipment run by telecommunication operators; mobile access networks, including cellular base station for all networks in operation; and core IP networks, which includes all metro, edge, and core network equipment. A synthetic "fixed network" is defined to facilitate model calculations. It includes a fixed access network and that portion of core IP networks which carry data traffic that arrived via fixed access networks; a "mobile network" is similarly defined. Datacenters include all servers and storage equipment as well as cooling, power distribution, and other overhead. This network model is simplified; the intent is to be as inclusive as possible when accounting for energy and emissions.

5.2 Methodology

Devices that are used in conjunction with one another to perform end-uses are grouped together as "device platforms". Tablets and smartphones are each platforms which consist of one device only – the tablet device and smartphone devices themselves. The TV platform includes a number of peripheral devices: set-top boxes, game consoles, DVD/Blu-ray players, and A/V receivers, as well as the TV set itself. Because not all of these devices will be present in each case, an average TV platform is defined which contains one TV set and a fraction of each peripheral according to the relative installed base, with impacts scaled accordingly; for example, if there are 0.6 set-top boxes per TV set, then the emissions of using the TV platform include the emissions of the TV set plus 60% of the emissions of one set-top-box. Other platforms defined in this study are the desktop PC platform, which includes LCD monitors; the laptop PC platform, which also includes LCD monitors but in a smaller proportion; and the average PC platform, which includes a mix of desktop PCs, laptop PCs, and LCD monitors. Other peripherals are excluded on the basis that their aggregate energy consumption is relatively small [5]. Platform definitions follow in Section 5.3.

Greenhouse gas emissions are assessed using a life cycle assessment (LCA) approach with impacts tabulated in terms of $\mathrm{kg\,CO_2e/yr}$. An end-use, EU, such as watching online video, is undertaken through the use of a platform P, which consists of one of more devices D. The emissions of performing end-use EU on platform P at time t are defined as $G_{EU,P}(t)$. Total US emissions are determined by the platform installed base, as follows:

$$G_{EU,P,\text{total}}(t)\left[\frac{\mathrm{kg\,CO_2e}}{\mathrm{yr}}\right] = I_P[\text{platforms}] \cdot G_{EU,P}(t)\left[\frac{\mathrm{kg\,CO_2e}}{\text{platform}\cdot\mathrm{yr}}\right] \tag{5.1}$$

Emissions $G_{EU,P}(t)$ are the sum of emissions due to devices, networks, and datacenters. Each is discussed in turn below.

5.2.1 Device emissions

For a given device, D, emissions due to end-use EU are specified as $G_{EU,D}$. Emissions at the device level are allocated according to the amount of time spent pursuing the end-use on the associated platform, $T_{EU,P}$, relative to the total amount of time spent actively using the platform for all end-uses, $T_{\text{total},P}$. The time share given by $T_{EU,P}/T_{\text{total},P}$ is applied to annual device emissions, as follows:

$$G_{EU,D}(t) = \frac{T_{EU,P}}{T_{\text{total},P}}\left(\frac{G_{D,emb.}(t)}{L_D(t)}\left[\frac{\mathrm{kg\,CO_2e}}{\text{device}\cdot\mathrm{yr}}\right] + E_D(t)\left[\frac{\mathrm{kWh}}{\text{device}\cdot\mathrm{yr}}\right]\cdot EF\left[\frac{\mathrm{kg\,CO_2e}}{\mathrm{kWh}}\right]\right) \tag{5.2}$$

Device emissions are calculated as the sum of annualized embodied emissions, equal to overall embodied emissions per device $G_{D,emb.}$ divided by average device lifespan L_D, plus annual operational emissions, equal to device annual operational energy use $E_D(t)$ multiplied by a grid emissions factor EF. Throughout this analysis, a US average grid emissions factor of $0.6\,\mathrm{kg\,CO_2e/kWh}$ is applied [216]. The rightmost factor thus represents the annualized GHG footprint of the device, accounting for embodied and operational emissions, while the left factor is a percentage share allocated according to time spent. The two factors are related through the total amount of time spent which influences overall power consumption, but the annualized footprint is defined to include energy consumed while the device is idle, while $T_{\text{total},P}$ includes only time spent pursuing an active end-use. As such, overhead emissions are proportionally allocated to active end uses, on the basis that the device was purchased and turned on in order to pursue these end-uses. This is done to ensure that all emissions are accounted for.

The emissions from all of the devices D which are part of platform P are combined as follows:

$$G_{EU,P,\text{devices}}(t) = \sum_{D \in P} \frac{I_D}{I_P} G_{EU,D}(t) \tag{5.3}$$

Here I_D is the installed base of the device, and I_P is the installed base of the platform, so that emissions due to devices which are part of platforms are scaled according to their prevalence. In other words, a platform is made up of a weighted sum of devices with the weights determined by relative installed base.

5.2.2 Network emissions

Two types of networks are modeled: fixed, and mobile. G_{EU,P,N_F} is the emissions due to fixed network infrastructure, including fixed access networks and core IP networks, due to performing the end use on one instance of platform P; likewise G_{EU,P,N_M} is the emissions due to mobile network infrastructure, including mobile access networks and core IP networks. Network emissions are allocated according to the amount of data traffic generated by the end-use. The total amount of traffic generated by end-use EU on platform P is defined as $D_{EU,P}$, measured in gigabytes (GB) per year, which is divided into data traffic on fixed and mobile networks:

$$D_{EU,P}\left[\frac{\text{GB}}{\text{platform} \cdot \text{yr}}\right] = D_{EU,P,N_F} + D_{EU,P,N_M} \tag{5.4}$$

Assuming fixed networks carry total data traffic of D_{N_F} GB/yr, emissions due to fixed network infrastructure are calculated as follows:

$$G_{EU,P,N_F}(t) = \frac{D_{EU,P,N_F}(t)}{D_{N_F}(t)}\left(G_{N_F,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right] + G_{N_F,op.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right]\right) \tag{5.5}$$

$$= \frac{D_{EU,P,N_F}(t)}{D_{N_F}(t)}\left(G_{N_F,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right] + E_{N_F}(t)\left[\frac{\text{kWh}}{\text{yr}}\right]\cdot EF\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{kWh}}\right]\right) \tag{5.6}$$

$$= D_{EU,P,N_F}(t)\left[\frac{\text{GB}}{\text{platform}\cdot\text{yr}}\right]\cdot \left(GI_{N_F,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{GB}}\right] + EI_{N_F}(t)\left[\frac{\text{kWh}}{\text{GB}}\right]\cdot EF\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{kWh}}\right]\right) \tag{5.7}$$

Again, the equation describes an allocation share, based on data traffic in this case, multiplied by an annualized GHG footprint, considering the entire fixed internet. Embodied emissions, $G_{N_F,emb.}$, are annualized and include all life cycle emissions aside from operational emissions, $G_{N_F,op.}$, which arise from use energy, E_{N_F}. Because a data transfer over a fixed network crosses both fixed access networks and core IP networks, fixed network emissions (both operational and embodied) are defined to be the sum of fixed access network emissions, and core IP network emissions; modeling details are provided in Appendix C. The total data traffic carried by fixed networks, D_{N_F}, is multiplied through; the ratio of annualized embodied emissions to data traffic is called the *embodied GHG intensity*, $GI_{N_F,emb.}$, measured in $\text{kg}\,\text{CO}_2\text{e}/\text{GB}$, while the ratio of annual use energy to data traffic is called the *energy intensity*, EI_{N_F}, measured in kWh/GB. Total emissions due to an end-use may thus be obtained by multiplying data traffic generated by that end-use, in GB, by these intensities.

Mobile network emissions follow a similar approach to that of fixed networks: emissions from mobile networks G_{EU,P,N_M} due to end-use EU on platform P may be calculated as follows, where D_{EU,P,N_M} is the annual traffic generated by the end-use that travels on mobile networks:

$$G_{EU,P,N_M}(t) = \frac{D_{EU,P,N_M}(t)}{D_{N_M}(t)}\left(G_{N_M,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right] + G_{N_M,op.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right]\right) \tag{5.8}$$

$$G_{EU,P,N_M}(t) = D_{EU,P,N_M}(t)\left[\frac{\text{GB}}{\text{platform}\cdot\text{yr}}\right]\cdot \left(GI_{N_M,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{GB}}\right] + EI_{N_M}(t)\left[\frac{\text{kWh}}{\text{GB}}\right]\cdot EF\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{kWh}}\right]\right) \tag{5.9}$$

5.2.3 Datacenter emissions

Datacenter allocation is performed on the basis of network traffic generated, though this metric is a proxy; ideally datacenter impact of an end-use would be estimated by tabulating the number of datacenters, servers, or server workloads employed in servicing that end-use, but current limitations in data availability make this approach impractical; data-based allocation does have precedence in other studies [41]. The amount of data traffic entering datacenters due to the end-use, $D_{EU,P,DC}$, is assumed to be equivalent to the amount generated by the platform (see Appendix Cfor justification). Thus:

$$D_{EU,P}\left[\frac{\text{GB}}{\text{platform}\cdot\text{year}}\right] = D_{EU,P,DC} \tag{5.10}$$

Emissions due to datacenters $G_{EU,P,DC}$ are therefore calculated as follows:

$$G_{EU,P,DC}(t) = \frac{D_{EU,P,DC}(t)}{D_{DC}(t)}\left(G_{DC,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right] + G_{DC,op.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{yr}}\right]\right) \tag{5.11}$$

$$G_{EU,P,DC}(t) = D_{EU,P,DC}(t)\left[\frac{\text{GB}}{\text{platform}\cdot\text{yr}}\right]\cdot \left(GI_{DC,emb.}(t)\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{GB}}\right] + EI_{DC}(t)\left[\frac{\text{kWh}}{\text{GB}}\right]\cdot EF\left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{kWh}}\right]\right) \tag{5.12}$$

5.2.4 Overall emissions

Considering device, fixed network, mobile network, and datacenter emissions, overall emissions are defined as follows:

$$G_{EU,P}(t) = \sum_{D\in P}\frac{I_D}{I_P}G_{EU,D}(t) + G_{EU,P,N_F}(t) + G_{EU,P,N_M}(t) + G_{EU,P,DC}(t)\ \left[\frac{\text{kg}\,\text{CO}_2\text{e}}{\text{platform}\cdot\text{yr}}\right] \tag{5.13}$$

The model is straightforward, but requires significant empirical data inputs. In order to calculate network and datacenter impacts, it is necessary to determine energy and embodied GHG intensities of these systems, which require estimates of total traffic, energy consumption, and embodied GHG emissions. Device impacts require estimates of embodied emissions and unit energy consumption, as well as installed base. Allocation shares for an end-use require an estimate of the typical annual time spent on a platform performing the end-use, as well as the typical data traffic generated by that end-use on that platform. All of these data inputs are compiled in this study from secondary sources.

5.3 Model inputs

Required model inputs can be grouped into three categories, as follows: device and platform characteristics, including operational energy use, embodied emissions, and installed base; network and datacenter characteristics, including operational energy, embodied emissions, and total data traffic; and end-use parameters, including data traffic generated and time spent for each platform and end-use.

5.3.1 Device and platform characteristics

	Operational energy [kWh/yr]		Embodied GHG [kg CO_2e/yr]		Installed base (MM)	
	2012	2017	2012	2017	2012	2017
Devices						
Desktop PC	212	193	39	36	103	90
Laptop PC	61	56	19	18	130	126
LCD Monitor	100	109	9	8	132	120
Game Console	149	190	8	7	111	115
Set top box	136	136	8	7	227	235
TV set	173	152	23	21	358	371
DVD / Blu-ray player	25	18	2	2	238	247
AV receiver	65	65	2	2	100	104
Tablets	12	12	60	55	60	120
Smartphones	3	3	14	13	121	207
Platforms						
TV platform	340	326	32	30	358	371
Tablet	12	12	60	55	60	120
Smartphone	3	3	14	13	121	207
Desktop PC platform	308	298	47	43	103	90
Laptop PC platform	87	84	22	20	130	126
Average PC platform	187	173	33	30	232	217

Table 5.1: Device and platform assumptions for operational energy, embodied GHG emissions, and US consumer installed base

Device and platform parameters are shown in Table 5.1. Operational energy use, E_D, is primarily obtained from a Consumer Electronics Association survey [5] and laboratory measurements [217]. Device embodied GHG emissions per product $G_{D,emb.}$ and device lifespan L_D, which together determine annual device embodied GHG emissions, are based on a review of prior LCA results developed researchers at LBNL [42]. Installed base estimates I_D are based on Consumer Electronics Association estimates from 2010 [5], while forecasts to 2017 for PCs, smartphones, and tablets are based on forecasts from IDC [218], Forrester [111], and eMarketer [112], respectively; for all remaining devices, installed base is assumed to scale with population, i.e. penetration rates are fixed. Calculation details including basis for forecasts to 2017 are in Appendix C. Platforms are defined as follows. The TV platform contains one TV set and a proportion of set top boxes, game consoles, DVD/Blu-ray players, and A/V receivers; the installed base of the TV platform is equal to the number of TV sets. The Desktop PC platform is assumed to include one desktop PC and 0.97 LCD monitors, while the laptop PC platform is assumed to include one laptop PC and 0.26 LCD monitors, using results from CEA [5]. The average PC platform is weighted sum of all desktop PCs, laptop PCs, and LCD monitors; its installed base is equal to the combined installed base of desktop and laptop PCs.

5.3.2 Network and datacenter characteristics

For each of fixed networks, mobile networks, and datacenters, the model requires energy intensity EI in kWh/GB and embodied GHG intensity $GI_{emb.}$ in kg CO_2e/GB for each of 2012 and 2017; intensities are calculated by dividing total embodied GHGs $G_{emb.}$ and total energy $E(t)$ by total data traffic; traffic on fixed networks D_F and mobile networks D_M is obtained from the Cisco Visual Networking Index [103], a major data source for this study.

The use of energy intensity as an impact factor for network data transfer was pioneered by Koomey in 2004 [97] and is now widespread. Energy intensity is a useful metric, but it is fast-moving; Taylor and Koomey showed an order-of-magnitude reduction in internet energy intensity from 2000 to 2006 [128]. It is thus of critical importance to ensure temporal consistency when comparing energy and data factors. In addition, the top-down method used by Koomey and applied here, in which total internet energy is divided by total internet traffic, is by necessity coarse; energy intensity may also be calculated from the bottom up, by tabulating the energy per unit of traffic in smaller systems of equipment (e.g. collections of routers and servers), but this can lead to much smaller intensity estimates. This study's estimates are compared against others in Appendix C; see also a recent review [72].

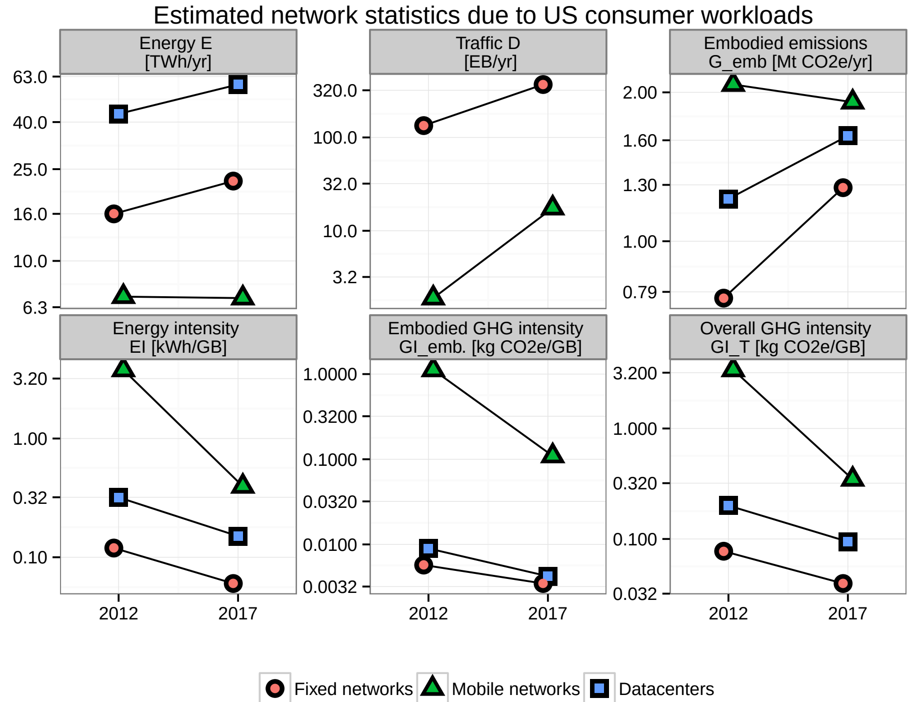


Figure 5.2: Network and datacenter energy, emissions, and intensities (note log scales).

Total embodied energy and total energy are derived from several sources discussed in Appendix C. Figure 5.2 shows the calculated energy, emissions, and intensities for each of mobile networks, fixed networks, and datacenters; an additional parameter, GI_T, the overall GHG intensity, is obtained by adding embodied GHG intensity to the product of energy intensity and grid emissions factor.

The above inputs allow for estimation of US network and datacenter intensities for 2012 and 2017. Declining trends are evident: mobile network electricity intensity drops from 3.8 kWh/GB in 2012 to 0.40 kWh/GB in 2017, while fixed network electricity intensity drops from 0.12 kWh/GB in 2012 to 0.060 kWh/GB in 2017, and datacenter electricity intensity similarly drops from 0.32 kWh/GB to 0.15 kWh/GB. The order of magnitude gap between mobile and fixed network electricity intensities is consistent with other findings [219] and will imply higher environmental emissions from end-uses that use mobile networks for data transfer, especially in 2012; next-generation mobile networks are much less energy intense per unit of data, so the gap between mobile and fixed networks shrinks by 2017. Previous top-down estimates of network energy intensity have been higher than the results reported here, such as 1.8 kWh/GB in 2008 [220], or 7 kWh/GB in 2008 including end-devices [39]; this is to be expected as energy intensity has declined over time. Bottom-up estimates tend to be smaller, since the system boundary is more precisely drawn and will exclude some energy is included in this study's top-down approach; recent estimates ranging from 0.05 kWh/GB [41] to 0.2 kWh/GB [221] have been reported, with the variation due to differences in system boundary and data year [72]. The very steep decline in energy intensity between 2012 and 2017 shown here serves as a caution to researchers to ensure that energy and emissions estimates are temporally consistent with data flows when calculating impacts due to network end-uses.

5.3.3 End-use data traffic and time spent

Data traffic generated by each platform is derived from the Cisco VNI [103], shown below in Table 5.2. The platforms are disaggregated according to connection type, as there will be different network emissions for an end-use depending on whether the platform has a mobile network connection or not. Total monthly traffic for a platform is assumed to be equivalent regardless of connection type, i.e. all connection-platform combinations generate the same amount of monthly traffic in total, though the distribution across fixed and mobile networks may differ. All platforms are assumed to have a connection to fixed networks, either via wired or Wi-Fi links. All smartphones are assumed to have access to mobile networks in addition to Wi-Fi. About 40% of tablets in 2012 possessed both mobile and Wi-Fi radios, while the remainder were Wi-Fi only. Finally, a small number of laptop PCs have access to mobile connections via USB radio devices. Detailed calculations of data traffic for each platform, including relative installed base of the different connection types, are in Appendix C.

Data traffic is further disaggregated into traffic due to online video, and due to other online uses, using data from Cisco [103], with these results shown in Table 5.3. In circumstances where platforms generate traffic on both fixed and mobile networks, the traffic shares are assumed to be consistent across all end-uses; i.e., if 60% the average smartphone's traffic is transmitted via mobile networks, then 60% of smartphone online video traffic and 60% of smartphone other online traffic is also assumed to be transmitted via mobile networks. With these assumptions and data, it is possible to calculate data traffic on fixed and mobile networks, D_{EU,P,N_F} and D_{EU,P,N_M}, for each end-use and platform.

Time spent on each end-use on each platform is also shown in Table 5.3, in hours per month. Time estimates for online video were derived from online video traffic estimates along with assumptions about typical data traffic rates. Time spent online is derived from a range of market research reports,

	Data traffic, 2012 $\left[\frac{\text{GB}}{\text{month}}\right]$			Data traffic, 2017 $\left[\frac{\text{GB}}{\text{month}}\right]$		
	Fixed	Mobile	Total	Fixed	Mobile	Total
TV platform	16.3	-	16.3	40	-	40
PC platform, mobile-connected	17.1	4.9	22	30.1	9.1	39.3
PC platform, fixed/Wi-Fi only	22	-	22	39.3	-	39.3
PC platform, average	21.7	0.3	22	38.4	0.9	39.3
Tablet, mobile-connected	3.6	1.1	4.7	29.9	8.4	38.8
Tablet, fixed/Wi-Fi only	4.7	-	4.7	38.8	-	38.8
Tablet, average	4.4	0.3	4.7	35.4	2.9	38.8
Smartphone	0.6	0.8	1.4	5.8	3.3	9.1

Table 5.2: Estimated US monthly consumer data traffic per platform instance across fixed and mobile networks.

	$D_{EU,P}$ $\left[\frac{\text{GB}}{\text{month}}\right]$		$T_{EU,P}$ $\left[\frac{\text{Hrs}}{\text{month}}\right]$	
Platform / end-use	2012	2017	2012	2017
PC platform				
Offline	0	0	27.2	8.4
Online video	14.9	29.3	14.5	19.4
Other online	7.1	9.9	48.9	56.6
Smartphone				
Offline	0	0	25.8	7.7
Online video	0.9	6.4	2.6	9.3
Other online	0.6	2.7	36.1	60.3
Tablet				
Offline	0	0	23.9	7.2
Online video	3.1	28.3	10.2	36.6
Other online	1.6	9.9	25.7	28
TV platform				
Broadcast TV	0	0	137.2	123.9
IP video on demand	14.5	33.4	18	27.7
Offline	0	0	3.3	3.3
Online video	1.2	5	1.6	4.9
Other online	0.6	1.7	1.6	1.6

Table 5.3: Estimated monthly data traffic $D_{EU,P}$ and time spent $T_{EU,P}$ per platform instance, for each end-use and platform.

notably studies from Nielsen [98], eMarketer [112], and comScore [222]; however, results from such studies vary widely, likely due to differences in scope and assumptions. Time estimates for all end-uses were tuned to be as consistent as possible with best available data sources; full calculation details are in Appendix C. The end-uses above encompass all active end-uses for each platform, so that for each platform P listed in Table 5.3, $T_{total,P}$ is the sum of the time spent on all listed end-uses.

5.4 Analysis

The above model inputs make it possible to calculate GHG emissions due to device, network, and datacenter for each of the study's platforms and end-uses. The analysis proceeds by first considering impacts at a platform level, for all end-uses combined, using the monthly data traffic results in Table 5.2 to calculate network and datacenter emissions. These results are then disaggregated into emissions due to specific end-uses by applying time and data traffic amounts in Table 5.3. The results of the model, which give emissions estimates for each end-use on each platform at each level (device, network, and datacenter), are aggregated and presented in several different ways in order to identify the overriding characteristics of US consumer ICT usage.

5.4.1 Emissions by platform

Figure 5.3 shows the total GHG emissions per year of using each platform in total, on a per-platform basis and accounting for all US consumers. The graphs are colour-coded by the location to which emissions are attributed, which is either in the devices, in mobile networks, fixed networks, datacenters, or broadcast TV networks. All emissions include both operational and embodied emissions, except broadcast TV networks which exclude embodied emissions as they are expected to be negligible. Emissions per platform are highest for televisions, desktop PCs, and mobile-connected laptops; the latter is particularly high in 2012 because mobile-connected PCs generate greater amounts of mobile traffic than mobile-connected tablets and smartphones [103], and mobile networks are much more energy intensive than fixed networks. Forecast declines in mobile network energy and GHG intensity by 2017 reduce the environmental penalty of mobile-connected devices relative to fixed/Wi-Fi–only devices. Overall emissions among US consumers are dominated by emissions due to TV platforms, due to their relatively large unit emissions and very large prevalence, with most of these due to devices in consumer homes, though average device emissions are expected to decline slightly through 2017 as more energy-efficient

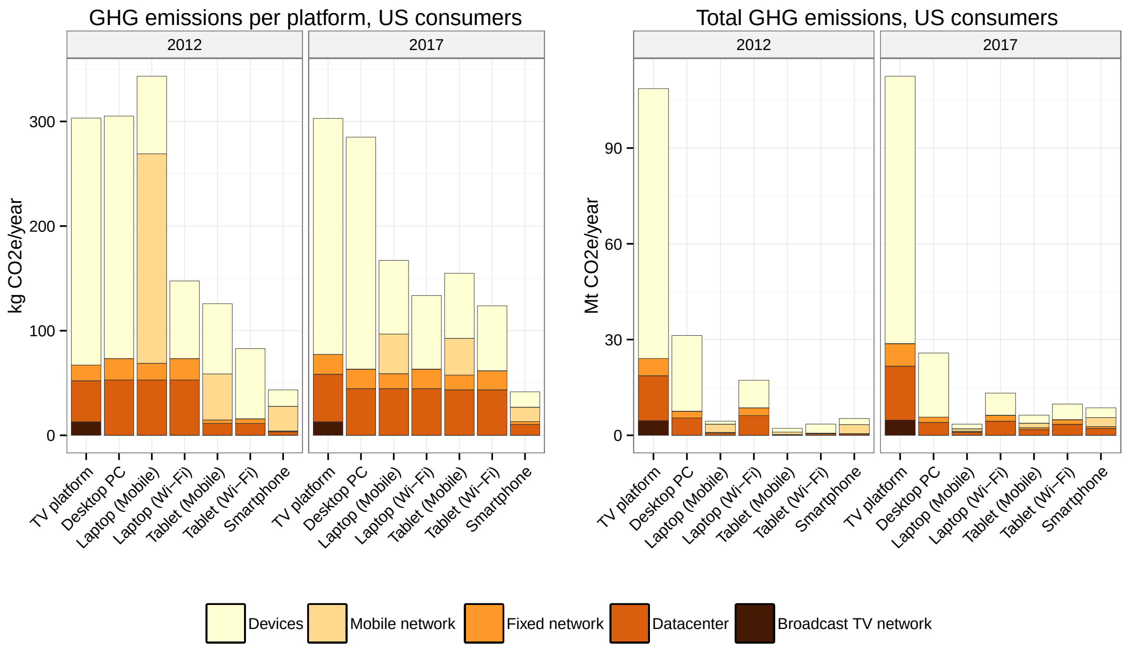


Figure 5.3: Emissions per platform and US consumer total, for all platforms, including devices, networks, and datacenters

LCD televisions gain higher market share [5].

5.4.2 Emissions by end-use

Figure 5.4 shows a disaggregation of emissions data from Figure 5.3 according to end-use. In 2012, about 70% of emissions on the TV platform can be attributed to consumption of broadcast television; of these, 93% arise due to on the devices in the home. IP video on demand accounts for 25% of TV platform emissions, but this rises to 30% in 2017, with total emissions due to IP video on demand growing by 30% in that time; for this end-use, device emissions account for only 30% to 40% of emissions, with the remainder due to network and datacenters. All devices show network and datacenter emissions exceeding device emissions for online video; all devices likewise show the opposite for other online activities. Impacts per tablet platform are forecast to increase by about 50% by 2017, with the majority of that growth due to network and datacenter emissions due to online video.

Emissions across all platforms and end-uses are summed in Figure 5.5, which shows the location of emissions for each end-use across all platforms, and in Figure 5.6, which the relative overall emissions of each end-use, including device, networks, and datacenters, on each platform. Figure 5.5 demonstrates

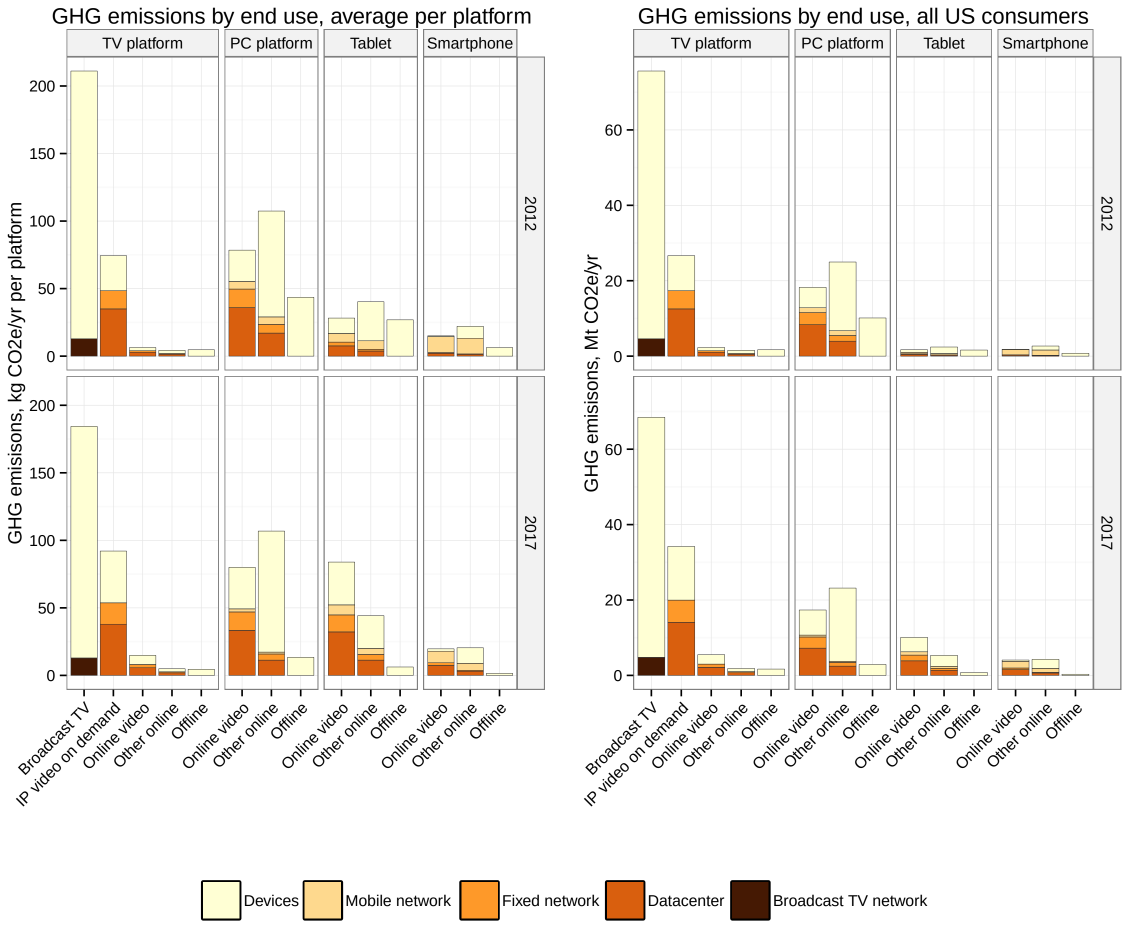


Figure 5.4: Emissions per platform, by end-use

that the majority of US consumer emissions due to digital media end-uses arise due to devices in the home. Overall emissions grow slightly by 2017, led by an expansion in emissions due to online video and IP video on demand, most of which arises in networks and datacenters. Emissions due to broadcast TV are expected decline slightly following a transfer of viewing time away from broadcast TV in favour of IP video on demand and online video.

5.4.3 Uncertainty analysis

Several types of uncertainty are inherent in the model. First, the model structure is dictated by several modeling assumptions, such as the allocation approach, to which the output results are sensitive. Second, each model input parameter is an estimate; while every effort has been made to obtain accurate estimates for each parameter and confirm their accuracy against other data sources, in some cases

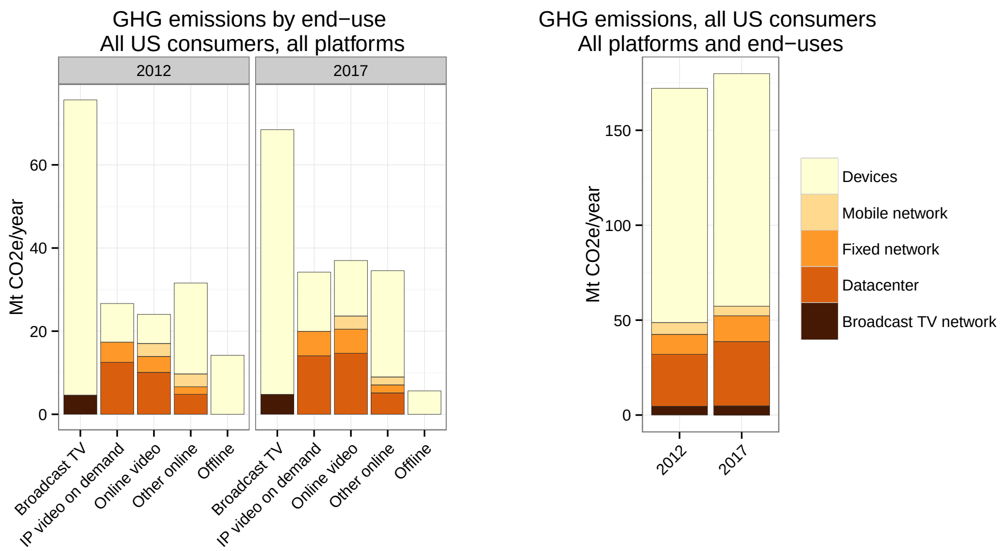


Figure 5.5: Emissions across all platforms, by end-use and overall, US consumer total

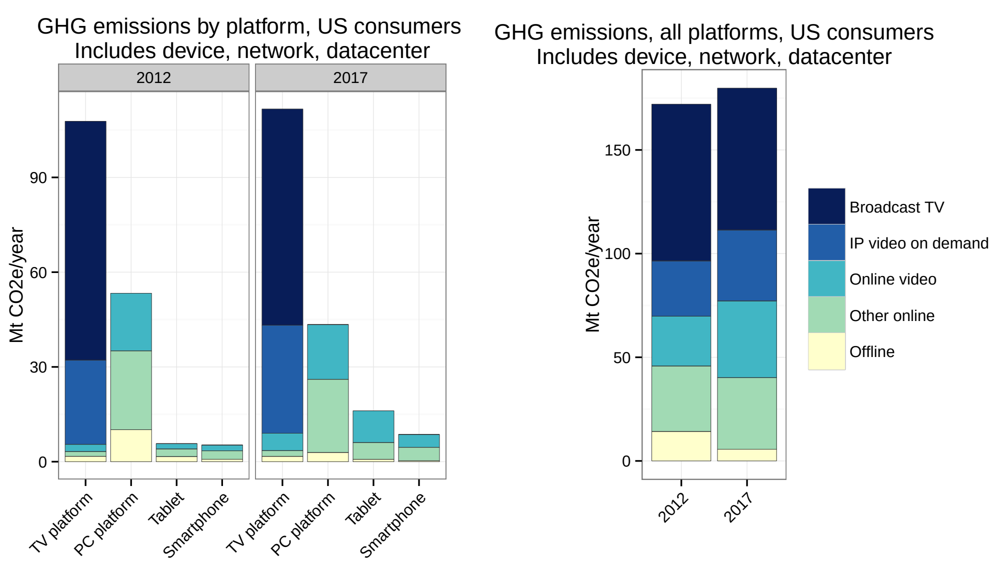


Figure 5.6: Emissions across all end-uses, by platform and overall, US consumer total

due to poor data availability the accuracy of each input parameter is difficult to assess. Third, model parameters estimate empirical quantities to varying degrees of precision. Structural uncertainty is discussed with a comparison to other studies, with suggestions for future studies to explore alternative models. Scenario analysis is employed to explore the sensitivity of the model to a large change in one input parameter. Finally, probability distributions are imposed on the model parameters to estimate their precision according to our subjective judgment; precision of model outputs is obtained through Monte Carlo simulation, assuming that the model structure and nominal parameter values are fixed.

Structural uncertainty

Studies which make different modeling assumptions may have significantly different results. The most closely related study [41], estimates that consuming 10 minutes of video content at a bit rate of 2.25 Gbps (corresponding to data transfer of about 170MB) would require about 3 Wh of energy due to servers plus 6 Wh if transferred via Wi-Fi or 40 Wh if transferred via 3G. According to our model, such a data transfer in the US in 2012 would incur 54 Wh due to servers plus 20 Wh due to fixed/Wi-Fi data transfer or 640 kWh due to data transfer via mobile networks, though these numbers respectively decline to 25 Wh, 10 Wh, and 67 Wh by 2017. Both studies agree on the relatively high impact of data transfer via mobile networks, but the magnitude of the estimates differ considerably, largely because that study's bottom-up methodology results in smaller estimates for energy intensity than those derived here (see derivation of each input parameter in Appendix C, including comparison to [41]). Appropriateness of modeling assumptions depends on study goals; our study is focused on characterizing aggregate US consumer emissions and thus draws an wide boundary which may be more inclusive than those of bottom-up studies of specific services.

This study applies a US average grid emissions factor to all operational energy consumption, which does not capture regional variation in emissions factors that can significantly change the emissions due to a particular datacenter [223]. Some firms attempt to preferentially incorporate renewable energy sources into their datacenter energy mix, such as Google who report their average emissions factor to be 0.34 $\mathrm{kg\,CO_2e/kWh}$ [224], about 45% less than the US average. Analysis of specific services tied to specific datacenters should consider the local emissions factor and efficiency of those datacenters. However, given this study's aggregate focus, the three connected end-uses – IP video on demand, online video, and other online – were assumed to be equivalent in terms of datacenter emissions intensity, all using the US average. More detailed analysis identifying the characteristics of specific services and datacenters which service these end-uses would reduce uncertainty regarding their emissions.

In addition, this study applies a US average approach for calculating and allocating emissions which obscures significant heterogeneity in both use behavior and deployed infrastructure. Considering datacenters, data traffic is used as a proxy for datacenter usage, on the assumption that traffic generated by an end-use is correlated to energy consumed in servicing that end-use. A more direct allocation, such as number of servers and storage devices used, or number of server workloads required, would be preferred, if data inputs were available to support such an approach, and could conceivably alter the results. In particular, because video end-uses dominate total network traffic, they also dominate datacenter emissions under a data allocation model, but it is not known if the majority of datacenter emissions are actually dedicated towards servicing video. If the relationship between data traffic and datacenter energy is not linear, then this study could overestimate the datacenter component of emissions due to video, and underestimate impacts due to other online services. It is also possible that some ICT applications, which may or may not fall within the categories assessed in this study, require highly disproportionate datacenter resources relative to network traffic generation. Further research is required to better understand these relationships. In the mean time, a simple sensitivity analysis is performed below.

Parameter accuracy

Datacenter energy intensity was difficult to assess due to lack of data as discussed in Appendix C. A sector-wide intensity of 0.32 kWh/GB in 2012 and 0.15 kWh/GB in 2017 was applied in this study, but Google's self-reported datacenter energy in 2012 was 0.08 kWh/GB [224]. While the average datacenter will be less efficient than Google's, which are among the industry's most efficient, it is possible this study overestimates average datacenter energy of consumer ICT services. Accordingly, an "efficient datacenter" scenario was created which applies Google's datacenter energy intensity uniformly, assuming it declines to 0.04 kWh/GB in 2017. The implications of this analysis, shown in Figure 5.7, are straightforward; a 75% reduction in datacenter energy intensity results in a corresponding 75% reduction in datacenter emissions.

Because the model is linear and multiplicative, sensitivity analysis is straightforward; for example, a 10% change in network energy intensity would result in a 10% change in network energy consumption of an end-use. The model specification and input parameters provided in Sections 5.2 and 5.3 fully

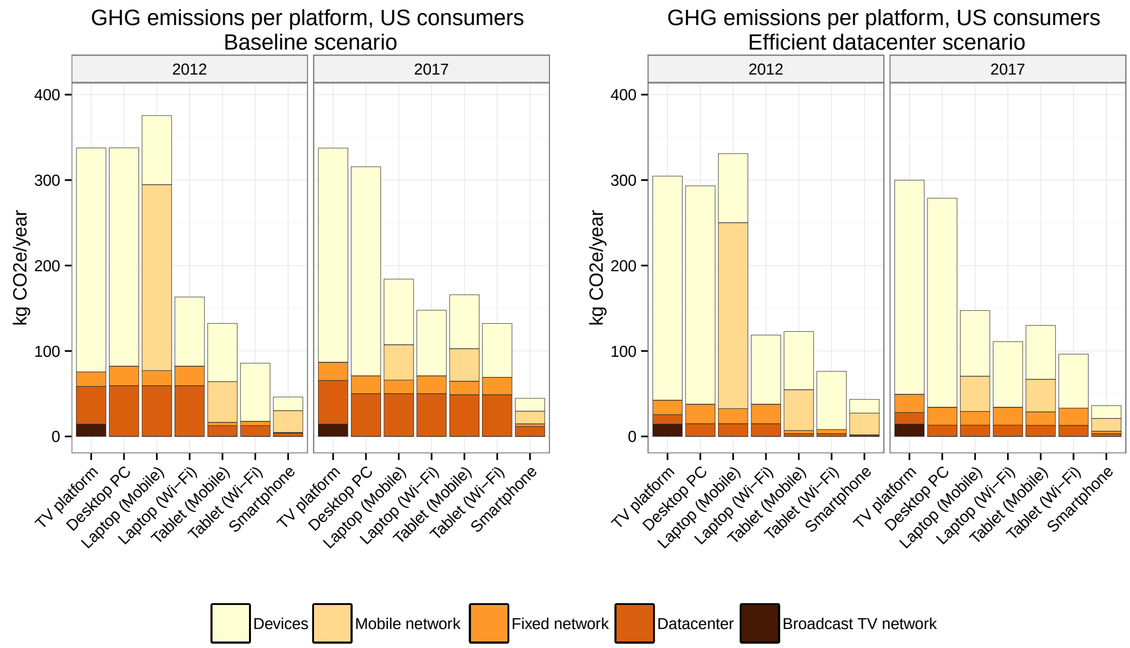


Figure 5.7: Emissions per platform and US consumer total, baseline and efficient datacenter scenarios.

describe the model, such that it may adapted for use in other contexts in which the values of some input parameters may change.

Parameter precision

Model precision is assessed assuming that all modeling assumptions are fixed; i.e. all of the assumptions which were used in calculating model input parameters are assumed to be appropriate. Approximate confidence intervals are applied on each empirical input parameter to express the range within the true value lies, in our best subjective judgment, taking into account the expected precision of the underlying data sources. Many parameters describe populations with high variability or heterogeneity, such as annual energy consumption of a desktop PC among US consumers; because the study is concerned with aggregate impacts, the parameters are estimates of the population mean. As such the confidence intervals do not capture the significant variability within the population. Consequently, the average emissions per device reported in this study apply to a fictitious average consumer and may be unrepresentative for many categories of consumer with behavior far from the mean; future work could explore how variability among consumer usage patterns affects emissions, perhaps stratifying the population into light, medium, and heavy users of a particular platform or service. Such a study would require behavioral data at a finer level of disaggregation than the sources applied here. Table 5.4 shows the 95% confidence intervals which were applied to each input parameter; justifications are in Appendix C. To illustrate the impacts of uncertainty on model outputs, a 1000-trial Monte Carlo simulation was performed, assuming normal distributions on each model input, with resulting error bars shown in Figure 5.8, where the error bars span $\pm$ two standard deviations from the nominal output.

	95% C.I.	
	2012	2017
Network and datacenter energy intensities, EI	$\pm$20%	$\pm$40%
Network and datacenter embodied GHG intensity, $GI_{emb.}$	$\pm$30%	$\pm$50%
Device energy E_D	$\pm$20%	$\pm$30%
Device embodied emissions $G_{D,emb.}$	$\pm$20%	$\pm$30%
Device installed base I_D	$\pm$5%	$\pm$10%
Time share per end-use on each platform $T_{EU,P}$	$\pm$15%	$\pm$30%
Traffic per end-use on each device $D_{EU,P}$	$\pm$10%	$\pm$20%

Table 5.4: Estimated confidence intervals on model input parameters.

It is possible to conclude that emissions due to devices significantly exceed those due to networks and datacenters, but the distinction between datacenter, fixed network, and mobile network emissions is less strong, especially in 2017, and particularly if one accounts for the possible differences in modeling assumptions such as the efficient datacenter scenario discussed above. Likewise, it possible to conclude that emissions due to broadcast TV are largest, and that emissions due to the three video end-uses (broadcast TV, IP video on demand, and online video) significantly exceed remaining emissions, but the differences between IP video-on-demand, online video, and other online end-uses are not significant. By 2017, the lower-range of the confidence interval for broadcast TV emissions overlaps with the upper range of emissions estimates for other end-uses, reflecting uncertainty in usage patterns looking forward, though the most likely outcome is that broadcast TV emissions will remain the largest. Improved precision would require higher-quality data sources regarding user behavior with respect to time spent and data traffic generated due to each end-use. Finer-grained disaggregation into a larger number of end-uses would likely be challenged by additional uncertainty caused by the incorporation of new data sources.

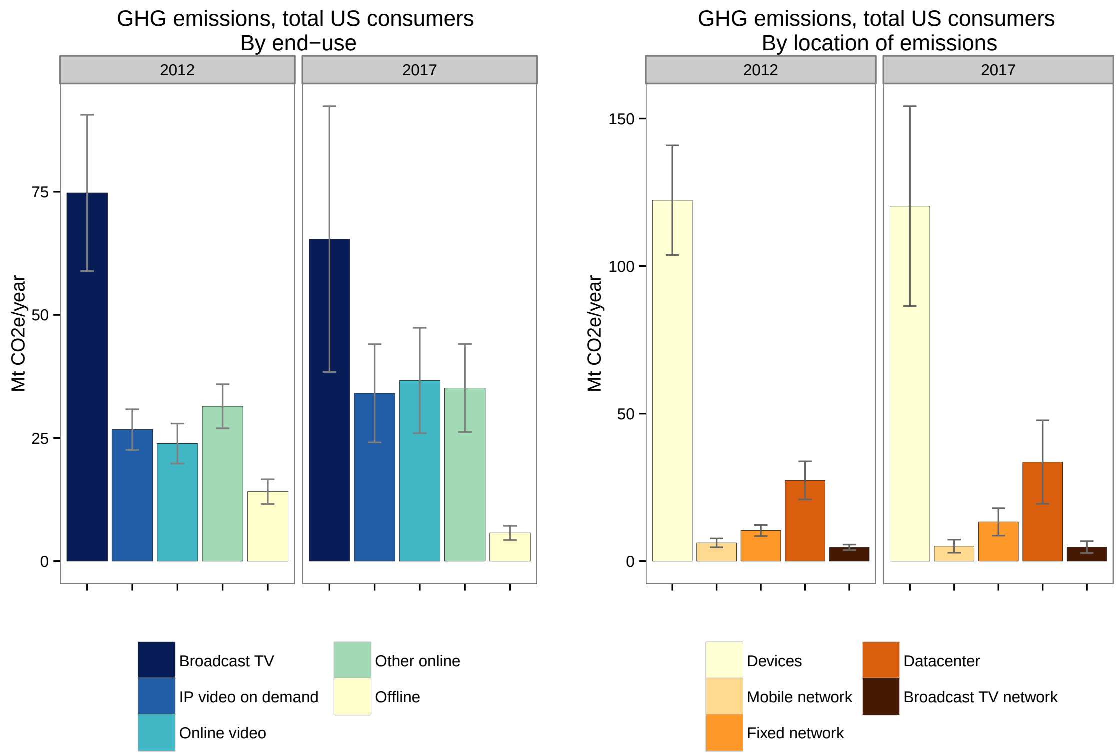


Figure 5.8: Monte Carlo results showing uncertainty range for GHG emissions, US consumer total; error bars span $\pm$ two standard deviations.

5.4.4 Energy comparison to household appliances

In Figure 5.9, the operational energy only in kWh/year of using each platform is compared to the annual consumption of various electric household appliances according to DoE data [225]; network and datacenter energy use are grouped together. A recent controversial report published online by Mills claimed that network and datacenter energy due to an iPhone could exceed that of a refrigerator [226], though this was refuted online by Koomey [227]. Our model suggests that a smartphone operated in the US consumes at most about 36 kWh/year in 2012 and about 39 kWh/year in 2017, including network and datacenter energy, which is about 5% of a typical refrigerator's annual usage of 620 kWh/year. The annual energy use of a tablet is higher, at about 37 kWh/year (Wi-Fi) and 110 kWh/year (mobile) in 2012, growing to 84 kWh/year (Wi-Fi) and 143 kWh/year (mobile) in 2017, the vast majority of which occurs in networks and datacenters. These levels of combined device and network energy consumption place tablets in a similar category as some appliances like microwaves and dishwashers, but still far below desktop PCs and TV platforms.

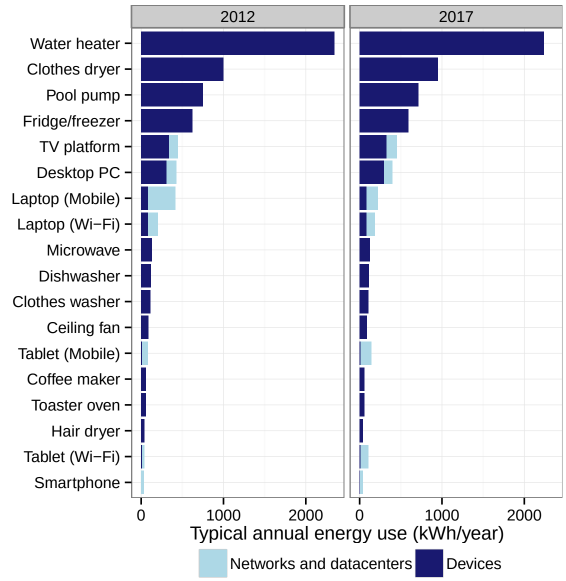


Figure 5.9: Comparison of ICT energy use against other electric household appliances

5.5 Implications

Life cycle GHG emissions due to digital media end-uses across different platforms were calculated using estimates of network and datacenter energy and embodied GHG intensities, which were applied to a model of data traffic and time spent on each end-use and platform for 2012 and 2017 in a US consumer context. Among end-uses, broadcast television is the largest contributor to emissions, accounting for 42% of total US consumer emissions due to ICT end-uses in 2012 and 34% in 2017, the vast majority of which occur due to devices in the home. IP video-on-demand, another end-use which is consumed on the TV platform exclusively, represents a further 16% in 2012 and 19% in 2017; in contrast to broadcast television, the majority of emissions due to IP video-on-demand occur due to network and datacenter infrastructure, largely because this delivery mechanism requires a high amount of traffic to individual subscribers, unlike broadcast television which spreads the infrastructure burden over many more viewers, confirming results in a BBC study [45].

Viewing of video content on a TV platform is currently the most popular consumer ICT end-use in terms of hours spent, and this seems likely to continue; due to the relatively high energy use of TV sets and associated peripherals and their popularity, along with the relatively high data traffic rates required to deliver video, video on TV platforms is expected to remain the largest contributor to emissions through 2017. The potentially disruptive traffic burden due to an ongoing transition from broadcast to on-demand has already been noted [100], but this transition will have an impact on emissions as well, in effect increasing the network and datacenter burden of consuming TV content. The effect, though modest under this study's assumptions, is proportional to the degree of substitution of video on-demand for broadcast TV, which could grow substantially over time. The best opportunities for reducing impacts are thus reducing the impacts of the TV platform, especially the energy consumed by televisions,set-top-boxes, and game consoles, reducing the network load required to deliver on-demand video content. Network operators already have strong market incentives to meet to latter objective; the former can be targeted through policy initiatives such as ENERGY STAR. In addition, the next-highest portion of overall emissions after TV platforms is due to desktop PC devices. According to a 2010 plug-load audit, two-thirds of desktop PCs are left on overnight or for large periods of time, despite the availability of sleep or hibernation modes which were often turned off and which could cut aggregate desktop PC energy use in half if widely used [228]. These findings are not new; energy researchers have previously identified the prominent energy consumption of TV sets, set-top boxes, and desktop PCs in the home [229] and the energy savings opportunities of power management on these devices [228]. Our study suggests that this energy consumption remains of primary importance even when network and datacenter emissions are taken into account.

Despite this finding, there is value in accounting for network and datacenter emissions, especially for devices with lower operational energy consumption. A life cycle assessment of a tablet device that does not consider network or datacenter impact would account for only 30% to 50% of the emissions that arise due to end-uses performed on the device. However, reports that an iPhone's energy use including networks and datacenters could be comparable to that of a refrigerator [226] are not supported by our study. Emissions due to mobile networks from mobile-connected devices were particularly high in 2012, especially for mobile-connected laptops which generated large amounts of mobile traffic, but the ongoing shift toward next-generation networks will greatly improve mobile network emissions intensity allowing emissions due to mobile networks to decline.

Emissions due to network-enabled ICT end-uses are a moving target. While network and datacenter efficiencies do improve dramatically over time, total traffic demand also grows at a comparable rate, leading to a modest net gain in emissions due to networks and datacenters. The emissions due to some end-uses may decrease over time on a functional unit basis, such as the emissions due to downloading an hour's worth of music, which would decline over time so long as the data rate of the music stays constant. However, expected 280% growth in total US consumer data traffic from 2012 to 2017 [103] indicates some combination of increasing consumption of end-uses, increasing data rates of end-uses (e.g. higher quality video), and/or emergence of new end-uses (e.g. ambient video streams) during that time. It is difficult to draw any general conclusions about the broader impacts of ICT without considering these trends. Future research on this topic will depend on the continuing availability of frequently refreshed data sources describing device installed base, energy consumption and emissions; network and datacenter energy and emissions intensities; and user behavior with respect to end-uses. Further disaggregation into more detailed end-uses such as social networking, email, e-book reading etc. would be possible with better data sources indicating time spent and data traffic generated by these end-uses; market research reports can be a valuable data source for understanding user behavior, but are often not freely available, and may not fully report study assumptions leading to unexplainable disagreements with other studies.

Overall, video is the dominant category of ICT end-use among US consumers, accounting for about three-quarters of total emissions, including broadcast television, IP video on demand, and online video across all platforms. Because of its high data rates, video traffic represents about 80% of total IP traffic according to Cisco [103], and thus accounts for about 80% of network and datacenter emissions under a data-based allocation model; it accounts for a large share of emissions due to electronics in the home as well primarily due to the large impacts of TV sets and associated peripherals. Thus, understanding consumer behavior with regards to video is of critical importance toward understanding emissions due to consumer use of ICT.

Chapter 6

Conclusion

This chapter contains a summary of specific findings from each of the previous three chapters; a discussion of the limitations of the research; suggested future work, both in terms of methodological improvement and study topic; recommendations for practical application of this work; and commentary about broader issues in the domain of ICT and environment.

6.1 Specific findings and significance

Specific conclusions from each of the studies in Chs. 3, 4, and 5 are summarized below. In addition, the significance of each study is discussed in relation to existing published research in this domain.

6.1.1 Life cycle assessments of desktop PCs

The meta-analysis of previous LCA studies of desktop PCs resolved some previous ambiguities in this literature, most notable a disagreement regarding which phase of the product life cycle was dominant in terms of energy and GHG emissions – production, or operation. Through a thorough review of prior studies of operational energy consumption of desktop PCs, including field measurements, surveys, and data from ENERGY STAR, the study established that a reasonable range for operational energy consumption of a desktop PC was between 100 and 350 kWh/yr, with overall mean energy consumption likely towards the middle of that range. Two of the studies which showed higher energy and emissions due to production rather than operation made unrealistically low assumptions of operational energy consumption, namely, 54 kWh/yr for Williams [13] and 49 kWh/yr for Choi et al [167]; Williams also estimated PC lifespan to be 3 years, which is on the lower end of the range used by other studies, and accounted for only use electricity rather than primary energy due to electricity. Taking these disagreements into account, the study concludes that under typical, average usage conditions, energy and emissions due to operation of a desktop PC usually exceeds those due to its production, and that the studies which reached the opposite conclusion did so after making unreasonably low assumptions regarding operational impacts. In addition, the study showed that differences in product from factor, e.g. between a large workstation-class desktop and a small integrated desktop, could be a dominant factor influencing the study result.

The study highlights the difficulty in assessing and comparing published LCA studies which do not provide full details of modeling assumptions and source data, as only a small number of studies could be decomposed in sufficient detail to allow for comparisons of modeling assumptions; others were completely non-reproducible, which is troubling. The comparison showed that studies were sensitive to assumptions regarding operational behavior among end-users, as well as to differences in product inventory and source data, much of which is not provided in many studies. As such it is difficult to know that the results of any LCA study in particular are valid, or the circumstances under which they may be valid, aside through processes of extensive meta-analysis as I demonstrate in this study.

6.1.2 Embodied emissions of electronics

Study of the embodied emissions of 11 electronic device specimens yielded three primary conclusions. First, modern desktop, laptop, and LCD monitor specimens had embodied GHG emissions about 50% to 60% lower than those of earlier-generation products originally modeled in ecoinvent, which can primarily be attributed to reduced usage by mass of circuit boards and integrated circuits; this is a consequence of Moore's Law, which has allowed for higher levels of functionality to be achieved on fewer integrated circuits. Second, embodied emissions showed a roughly linear trend with respect to mass: to first order, heavier products had higher levels of embodied emissions, a trend which was also observed in Apple's product environmental reports [212]. Third, a statistical model was developed which enabled first-order emissions estimation using only product mass, i.e. 27 $\mathrm{kg\,CO_2e/kg}$ if the model is fit using my study's data, or 37 $\mathrm{kg\,CO_2e/kg}$ if the model is fit using Apple's data; a more sophisticated model using the masses of the display, circuit board, and battery was also developed and produces better results, especially for lower-mass products.

The study is unique in its scope; aside from the Apple product environmental reports, which are not peer-reviewed, no other study has included a comparison of this number of products. The integrated approach of modeling all products within a consistent framework allows us to draw general conclusions about the characteristics of electronics products, i.e. that embodied emissions are lower for compact, lightweight models, which can be used as heuristics for decision-making. The statistical modeling approach towards impact estimation, though in need of further validation and development, may offer a means of characterizing environmental impacts of a wide range of products without need for individual detailed LCA studies of each.

6.1.3 Emissions of connected media

A model of GHG emissions due to end-uses in the home showed that video was the dominant end-use from an emissions perspective, both in the home due to high energy use from TV sets and related devices, and in networks and datacenters due to high amounts of data traffic attributable to video. The network and datacenter components of emissions (collectively, the 'network emissions') were smaller than device emissions overall. On mobile devices, network emissions far exceed device emissions, especially when consuming video content, and thus significantly enlarge the GHG footprint of using the devices. However, even considering network emissions, the overall emissions due to mobile products are dwarfed by those of larger devices like desktop PCs and televisions, for which the majority of emissions arise due to devices. Conjecture that an iPhone's network emissions could exceed the emissions of operating a refrigerator was not supported. Aggregate emissions due to consumer ICT use in the US is expected to remain relatively stable into 2017, though total emissions due to devices are forecast to decline slightly (by about 10%) while network emissions grow slightly during that time.

The integrated, top-level approach of this study is unique, as is its breadth; no other study has compared the impacts of broadcast TV, video-on-demand, and other online and offline end-uses, and no other study has compared the impacts of end-uses using TVs against those using PCs, tablets, and smartphones. The most closely related work, by Schien et al [41, 132] examined a subset of these end-uses and devices, and estimated aggregate impacts of one service only, namely online news delivery. The integration of behavioral data from market research firms was a key innovation in the study in Chapter 5 enabling aggregate estimates of multiple end-uses. The study helps us understand the impacts of connected media consumption in many different forms, and provides a template for characterizing the impacts of cloud services which are growing to dominate the ICT landscape.

These conclusions should be considered alongside the methodological limitations of the study, which are outlined in the following section.

6.2 Limitations

The research in this dissertation is constrained by some general limitations, discussed below. In addition, each of the three studies has unique issues related to methodology and approach, which are outlined in turn. These limitations motivate a discussion of future research needs which follows in the next section.

6.2.1 General limitations

The studies are constrained by the limitations of LCA in general, which were discussed in Section 2.4. The studies rely on average data and models, especially for upstream industrial processes; and they are sensitive to modeling assumptions, input data source, and aggregation methodology. The tension between results obtained from process-sum LCA, hybrid LCA, and EIOLCA was not directly confronted in this research program. Because of this limitation, the research in this dissertation focus on comparisons within a framework, rather than the reporting of absolute numbers.

The studies consider impacts only in terms of GHG emissions and (in some cases) primary energy demand, and focus primarily on operational and manufacturing phases which dominate in those impact dimensions. While these are operationally useful dimensions of impact, they do not capture many other important forms of environmental impact which are not considered in this dissertation. Thus, when the study results discuss lower-impact products or behaviors, this must be understood to refer only to those impact dimensions specified.

In addition, the studies all considered a US context exclusively, with a US grid mix. Other geographic jurisdictions would naturally have different grid emissions factors, which would affect the operational impacts. Because ICT is a highly commodified industry, production emissions of ICT devices identified through LCA can be considered to be a global average, and thus not affected by study geographic scope. However, behavioral patterns in non-US contexts may differ considerably, as could penetration rates for different devices, especially in less-developed countries; network energy and emissions intensity may differ as well.

6.2.2 LCA meta-analysis

The study in Chapter 3 attempted to draw conclusions about the GHG emissions of a typical desktop PC under typical operating conditions in the US, but this is a simplification which obscures the high amounts of variation possible both in product form and function, and patterns of usage; the study's conclusion, that operational emissions usually exceed emissions due to manufacturing, will not hold for all types of desktop or pattern of usage. In addition, the conclusions regarding plausible ranges for a desktop PC's GHG emissions due to manufacturing are tentative, based on the very small pool of studies from which they were derived.

6.2.3 Product LCA and embodied emissions

Truncation error is a particular issue in the study in Ch. 4, which is a likely contributing reason as to why it reports significantly lower GHG emissions than those reported by Apple for comparable products. Some substances were not easy identifiable using the teardown method employed in Ch. 4, such as coatings, metallic alloys, or blended plastics, and would have thus been excluded. Since Apple's analysts had access to proprietary industrial data including full bills of materials of each products, I would consider their numerical results to be more accurate than those reported in Ch. 4. However, trends between products were consistent in both datasets, as was the linear relationship between product characteristics and embodied emissions; only the numerical values of the coefficients differed. Further truncation error due to upstream economic sectors not accounted for in Apple's dataset may exist, since those results were produced using a process-sum methodology according to their analyst [1]; there is not enough information to analyze or bound this error, since the study details are not public. I consider Apple's reports to be the best currently available data source regarding the impacts of their products, but caution must still be exercised when applying these results outside their original context.

The study in Chapter 4 considered only embodied emissions, rather than the full product life cycle which would include operational emissions. The study's conclusion that lighter, smaller products have fewer embodied GHG emissions than heavier products, should hold in terms of operational emissions as well, since mobile products tend to be very power-efficient, but the study did not assess this explicitly.

[1] Personal communication, 2013

6.2.4 Connected media

The study in Ch. 5 applied US consumer averages in all consideration of behavior and impacts, primarily due to limited data availability. This approach is well-suited towards consideration of aggregate behavior, which was the study's focus, but it does not capture the wide variability of many of the study model's inputs, which may have highly skewed and/or multimodal distributions. Thus, some of the study's primary conclusions – e.g., that most emissions are due to TV sets and related equipment – may not hold for some categories of individuals, such as very heavy consumers of internet video on PCs. The study could be extended to include more fine-grained groupings of consumers, with the availability of higher-resolution data sources.

Likewise, the study in Ch. 5 grouped all internet services together and considered internet-wide averages of energy and GHG emissions. Again, this framing is useful for considering aggregate impacts, but presents a simplified picture. Data center allocation was performed according to network data traffic, which has precedence in other studies but is a simplification; ideally, the number of datacenter workloads attributable to each class of service would be known, which would enable more accurate allocation. There are significant structural uncertainties in the allocation methods which suggest that the estimates of end-use emissions should be taken as first-order estimates. The estimates of platform emissions which are not disaggregated by end-use are more certain.

6.3 Future research needs

This dissertation suggests several important areas of future research, which are grouped into three categories: methodological issues relating to the application of LCA to ICT products and services; knowledge gaps relating to ICT products; and knowledge gaps relating to ICT services and infrastructure.

6.3.1 Methods

The influence of truncation error on LCA results and the use of hybrid methods continues to be an important research frontier. The surprisingly high magnitude of the economic correction obtained through hybrid LCA in this domain is problematic, as it means that results obtained from process-sum LCA, which includes the vast majority of published work on ICT, may significantly underestimate emissions. Better data is needed regarding upstream process models for manufacturing and end-of-life, and further exploration of truncation error and hybrid LCA, in order to improve our understanding of device impacts through LCA.

The continued use of process-sum LCA in spite of its potential weakness may be attributed in part to its relative simplicity. As many LCAs come from industrial practitioners who tend to be resource-constrained, there is a need for streamlined, simplified tools; an increase in complexity towards hybrid LCA may improve accuracy while simultaneously reducing the accessibility of the method. Thus, continuing fundamental research into hybrid LCA should aim to identify simplified tools and rules-of-thumb which are accessible to the practitioner community.

Significant differences were identified between top-down and bottom-up estimates of the GHG emissions of ICT end-uses, especially considering emissions due to the internet. The top-down energy and emissions intensities derived in Ch. 5 used an inclusive approach based on best available data sources to estimate overall energy and emissions and data traffic. The appropriate methodological choice might depend on the study goal; a study attempting to estimate aggregate GHGs as in Ch. 5 should use a top-down approach in order to avoid truncation error, while a bottom-up method might be more appropriate for detailed study of specific end-uses or systems in order to identify emissions hotspots. Still, there remains an unresolved question as to the source of the disagreement between the two methods which should be explored.

6.3.2 ICT products

New products continue to emerge on the market, including smart glasses, smart watches, and connected sensors in the home; existing products continue to evolve through new technological advances such as ultra-high-resolution displays which appear to bring a significant emissions premium according to Apple's latest product environmental reports [212]. Continuing primary research regarding the composition, upstream manufacturing processes, and overall emissions of these products will be needed.

When considering impacts of devices, point estimates are less reliable than integrated analyses or meta-analyses. In particular, for estimates of operational energy consumption of ICT devices, researchers should make use of empirical data which exists from large-scale studies of user behavior, as discussed in Ch. 3. Likewise, given the large number of devices currently on the market, including variations in form factor within a given product category, and hybrid devices which span formerly distinct product categories, point estimates of the impacts of one device are of declining utility. The study in Ch. 4 argues for a shift towards broader frameworks considering the impacts of multiple products simultaneously. In addition, the statistical analysis in Ch. 4, though simple in its construction, suggests the possibility of specifying device impacts in terms of product characteristics using simple linear equations, which could expand the breadth of product LCA studies.

The GHG emissions due to networks and datacenters arising from connected end-uses on ICT devices can be significantly larger than those due to the devices themselves in the case of small mobile devices like smartphones, tablets, and to some extend, laptop PCs. Since normal operation of these devices includes extensive use of connected services, a reasonable assessment of the impacts arising from the operation of these devices should include the impacts due to networks and datacenters, likely using an approach similar to that developed in Ch. 5.

6.3.3 ICT services and infrastructure

Assessment of impacts of ICT services requires high-quality models of networks and datacenters, including information regarding their operational energy consumption and embodied emissions. The energy and emissions intensities developed in Ch. 5 are coarse and rely on simplified infrastructure models, and would be improved by more focused study, especially empirical assessments of energy consumption. In addition, the relationship between ICT services and datacenter resources is poorly understood and modeled only in aggregate in Ch. 5; new data sources offering a more detailed mapping of services to resources would enable studies of specific ICT services (e.g. Netflix, Facebook) rather than aggregate categories. Collecting such data will be hampered by their proprietary nature. However, sustainability reporting from firms such as Google and Facebook has shed at least some light on industry practice that were hitherto opaque, as has some pioneering research by Greenpeace [223]; continuing research and data disclosure could enable more accurate and higher-resolution estimation of the impacts of ICT services, which would support environmentally conscious decision-making by consumers of those services.

The market research data used in Ch. 5 was an invaluable data source, but these studies report only limited modeling details which makes it challenging to resolve disagreements across studies. It seems unlikely that peer-reviewed academic studies will be able to research emerging products and behaviors at a speed comparable to market research firms; thus, future research of ICT services will likely depend on market research. Accordingly, research is needed to validate and calibrate these data sources, perhaps through academic-industry partnerships.

Because of rapid change in user behavior as well as technological improvements in network and datacenter efficiency, point estimates of the emissions of a specific end-use are of declining utility, echoing a finding above relating to device emissions; many of the studies reviewed in Ch. 2 analyze end-uses which are already in rapid decline. In order to produce meaningful research with some longevity, researchers should move past snapshot views and consider longer-term trends. An interesting observation is that while the collection of end-uses for which devices are used changes very rapidly, device annual energy consumption as reviewed in Ch. 5 changes relatively slowly. By tracking device installed base and total device energy consumption instead of specific end-uses, studies may achieve higher relevance for a longer period of time. This will come at the cost of some precision, but I would argue there is limited value in achieving high levels of precision when analyzing such a fast-moving industry. High-level integrated frameworks are a useful approach which should be considered in future studies.

6.4 Implications

The research was designed to support green decision-making among ICT-using firms and organizations, as well as to inform policy-makers who are attempting to reduce emissions due to ICT. Specific recommendations to these actors are outlined below. In the following section, commentary is offered regarding the ICT/environment research field in general.

6.4.1 Recommendations

For **ICT-using firms**, office workers should be given compact desktops, thin client devices, laptops, or tablet PCs where possible, rather than larger desktop PCs, as this results in a significant decrease in embodied GHG emissions; operational energy consumption of these devices in an office context was not explicitly studied in this dissertation, but compact and mobile devices tend to use significantly less operational energy as well. Power-savings features should be activated for all devices, but especially desktop PCs and large displays, which in a consumer context are dominant energy consumers; these devices should be turned off or in a low-power state when not in use. ICT services in an office setting were not studied in this work, but a different study has shown that offices should prefer cloud services rather than custom-hosted software running on dedicated servers [42], which leads to reduced network and datacenter emissions of running office productivity software.

For **ICT-using individuals**, media consumed on mobile devices will lead to lower emissions than if consumed via televisions or desktop PCs; the use of Wi-Fi connections will lead to less emissions that the use of mobile connections. Individuals should ensure power management features are in use on all large energy-using devices, including television sets, game consoles, set-top boxes, and desktop PCs, and especially that these devices are turned off or in a low-power sleep mode when not in use. Where possible, individuals should preferentially purchase energy-efficient devices.

For **labelling authorities** such as the Green Electronics Council (responsible for EPEAT) and the US EPA (responsible for ENERGY STAR), when calculating product impacts, consider incorporating an estimate of the network and datacenter impacts attributable to the product under typical operating conditions. Once the research has advanced sufficiently, labelling authorities should consider adopting empirically-derived statistical models of product GHG emissions in order to quantify emissions of a wide range of products.

For **regulatory agencies** addressing the broader impacts of ICT usage, consider enforcing efficiency standards on heavy energy-using products, similar to the California Energy Commission's regulations specifying maximum power consumption ranges for televisions sold in that state [230]. Televisions, set-top boxes, game consoles, and desktop PCs are of particular importance, even when network and datacenter energy consumption is accounted for. Procurement directives for government agencies should preferentially support laptops, lightweight desktops, thin clients, and tablets over desktop PCs.

6.4.2 Commentary

Though not specifically discussed within the scope of the research in this dissertation, I offer the following commentary and conjecture as to other important areas of research, considering the question of the environmental impacts of ICT more broadly. First, the findings regarding desktop PC and TV equipment being the highest contributor of energy consumption in the home are familiar, and while these are being addressed though policies such as ENERGY STAR and efficiency regulations, there are limits to the ability of such policies to drive behavior change. There is a rich literature regarding the mechanisms of behavior change with respect to energy consumption which was beyond the scope of the research in this dissertation (e.g. [231]). Integrating such research alongside the study of energy and emissions due ICT end-uses is a clear next step in order to aid in the design of effective demand-side management programs.

Second, though not discussed in this thesis, water usage is an emerging area of potentially high importance, both in upstream manufacturing facilities, and operationally in datacenters, especially for cooling. Progress in water usage assessment has been primarily industry-led, through some water footprint analysis by Intel [232], and through the development of the Water Usage Effectiveness (WUE) statistic for datacenters pioneered by The Green Grid, an industry consortium [233]. Likewise, impact dimensions other than GHG emissions and primary energy use are underdeveloped, both in the consideration of impacts of ICT, and in the LCA field in general. Many of these dimensions may be numerically problematic as discussed in Section 2.4, thus there is a need for improved LCA models and characterization schemes to quantify impacts; however, regardless of the strength of numerical impact models, the risks of toxic releases and exposures in product manufacturing and disposal will need to be managed through regulatory responses, for which LCA-quantified impacts are only one of many important dimensions. The use of nanomaterials and other new chemicals is an area of particular concern; the work of Beaudrie et al is relevant here [234].

Finally, the application of ICT in other sectors such as energy and transportation was identified as a potential emissions wedge by several studies [30, 235]. More accurate estimates of the emissions savings potentials could be obtained through the use of techno-economic models to predict the ripple effects of changes to these industries. However, the research priority should be on identifying mechanisms to achieve the highest possible emissions savings, which are likely domain-specific; for example, higher uptake of smart grids requires policy instruments specific to the energy sector, while higher penetration of electric vehicles requires policy instruments specific to the automotive sector. I see little commonality among these various applications of ICT which would suggest the possibility of ICT-centric instruments applicable to each.

6.5 Conclusion

The research in this dissertation improves our understanding of the energy and GHG emissions due to ICT devices and end-uses through three integrative studies, which explored the life cycle GHG emissions and primary energy demand of desktop PCs, the embodied GHG emissions of 11 electronics devices, and the GHG emissions due to five categories of end-use across four devices including emissions due to device, network, and datacenter. The studies make a significant contribution of primary data, through the provision of source data from the study of embodied emissions in Ch. 4, and of methodological improvements, via the statistical model of GHG emissions relating to product characteristics derived in

Ch. 4, and via the approach for incorporating behavioral data from market research in Ch. 5. In addition, the model in Ch. 5 includes a significant compilation of secondary data sources, including forecasts to 2017, which are transparently reported so as to make them easily adaptable by other researchers. The study findings, detailed above, improve the ability of ICT-using organizations and individuals to preferentially support lower-impact products and behaviors, and support policy-makers who wish to encourage such behavior.

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Appendix A

Supplementary material for Chapter 3

A.1 Summary data tables

This section contains data tables for each figure in the text.

	Percentage share by life cycle phase				
	Manufacture	Distribution	Operation	End-of-life	
Primary energy					Total [MJ]
Williams 2004	84.3	5.9	9.8	0	5924
Atlantic Consulting 1998	28.8	0.1	70.4	-0.7	5334
Braune and Held 2006 [EPIC-ICT]	19.2	0	78.8	-1.9	–
Hischier et al 2007 [ecoinvent]	28.9	0.3	70.7	0.1	15011
IVF 2007	13.9	2.3	83.6	-0.2	16165
Masanet et al 2005	57.6	0	42.3	0.1	10113
Kenma 2005 [MEEUP]	13.7	5.3	80.5	0.5	20876
Global warming potential					Total [kg CO_2e]
Atlantic Consulting 1998	32.7	0.1	66.3	-0.9	249
Braune and Held 2006 [EPIC-ICT]	30.2	0	67	-2.8	–
Hischier et al 2007 [ecoinvent]	33.7	0	65.6	0.7	775
Choi 2006	89	1	8	2	–
Duan 2009	29.4	0	63.7	-6.9	–
IVF 2007	18.1	3.7	78.1	-0.1	761
Tekawa 1998 (includes CRT)	18.1	0.7	80.9	0.3	717
Apple 2010b (Mac Pro)	42	3	54	1	1880
Apple 2010a (Mac Mini)	57	3	39	1	270
Masanet et al 2005	57.6	0	42.3	0.1	1111
Hikwama 2005	34.1	0	63.7	2.2	–

Table A.1: Data table for Figure 3.1: Total impacts by life cycle phase

	Williams 2004 [MJ]	Braune and Held 2006 [MJ]	IVF 2007 [MJ]	Hischier et al 2007 [MJ]	Duan 2009 [EcoIndicator pts.]	Tekawa 1998 [kg CO_2e]	Hikwama 2005 [kg CO_2e]
Mainboard: ICs	37.5	0	24.2	26.7	0	0	25.2
Mainboard: other	9.5	53	44.5	38.9	55.7	73.2	69.8
Power supply	0	13	0	11.7	11	4.9	0
Drives	9.9	8	0	10.9	19.9	3.7	0
Casing	7.3	13	16.2	5.8	8.5	8.5	1.8
Other	35.8	13	15.1	6.1	5	9.8	3.3

Table A.2: Data table for Figure 3.2: Manufacturing impacts by subassembly

	Williams (2004)	IVF (2007)	Hischier et al. (2007)	Hikwama (2005)
Component mass per desktop [kg]				
Total desktop	9	10.5	11.3	10
Casing	6.4	7	6.1	5.5
Mainboard	2	1	1.4	1
Drives	0.6	–	1.5	2
Power supply	–	–	1.7	1.1
GWP per component [kg CO_2e/kg]				
Total desktop	–	13.2	22.7	–
Casing	–	3.2	2.4	–
Mainboard	–	63.8	71.6	–
Drives	–	–	18.7	–
Power supply	–	–	17.6	–
Primary energy per component [MJ/kg]				
Total desktop	587	183	390	–
Casing	61	44	42	–
Mainboard	252	883	1226	–
Drives	935	–	320	–
Power supply	–	–	302	–

Table A.3: Data table for Figure 3.3: Mass and impact factors by subassembly

Graph index	Study	UEC [kWh/yr]	Data quality	Home or office	Data type
1	Roth et al. (2002) (high-power PC)	717	Medium	Office	Secondary
2	Braune and Held(2006) [EPIC-ICT] (gamer PC)	587	Low	Home	Primary
3	US EPA(2010) [Energy Star, baseline]	408	Medium	Both	Secondary
4	US EPA(2005) [Energy Star, baseline]	354	Medium	Office	Secondary
5	Braune and Held (2006) [EPIC-ICT]	331	Low	Office	Primary
6	Kemna (2005) [MEEUP]	322	High	Home	Mixture
7	Moorefield et al. (2008)	305	High	Office	Primary
8	Roth et al. (2002)	298	Medium	Office	Secondary
9	US EPA (2005) [Energy Star, baseline]	285	Medium	Home	Secondary
10	Kemna (2005) [MEEUP]	281	High	Office	Mixture
11	Braune and Held (2006) [EPIC-ICT]	279	Low	Office	Primary
12	US EPA(2010) [Energy Star, certified]	275	Medium	Both	Secondary
13	US EPA(2005) [Energy Star, certified]	271	Medium	Office	Secondary
14	Porter et al. (2006)	256	High	Home	Primary
15	Hischier et al. (2007) [EcoInvent]	238	Low	Office	Mixture
16	Roth and McKenney(2007)	236	Medium	Home	Secondary
17	Duan et al. (2009)	223	Medium	Both	Secondary
18	US EPA(2005) [Energy Star, certified]	214	Medium	Home	Secondary
19	Kawamoto et al. (2001)	213	Low	Office	Primary
20	Hischier et al. (2007) [EcoInvent]	204	Low	Home	Mixture
21	MTP(2006)	196	High	Home	Primary
22	IVF(2007)	194	High	Office	Mixture
23	IVF(2007)	141	High	Home	Mixture
24	Schlomann et al. (2005)	122	Medium	Office	Mixture
25	Atlantic Consulting(1998)	110	Low	Office	Secondary
26	Nordman and Meier(2004)	93	Low	Home	Mixture
27	Schlomann et al. (2005)	78.1	Medium	Home	Mixture
28	Choi et al. (2006)	76.1	Medium	Office	Secondary
29	Hikwama(2005)	75.1	Low	Home	Secondary
30	Williams(2004)	53.7	Low	Office	Secondary
31	Choi et al. (2006)	49.1	Medium	Home	Secondary
32	Kawamoto et al. (2001)	49	Low	Home	Primary

Table A.4: Data table for Figure 3.4: Desktop unit energy

Graph index	Study	Lifespan (years)	Includes re-use?	Data quality	Data type
1	JEITA(2006) (Home)	8.4	Includes reuse	Medium	Primary
2	Babbitt et al. (2009) (1990 purchases)	7.86	First life only	High	Primary
3	Tekawa et al. (1997) (Office)	7	Not specified	Low	Secondary
4	IVF(2007)	6.6	Includes reuse	Medium	Primary
5	Oguchi et al. (2006)	6.6	Includes reuse	Medium	Primary
6	Duan et al. (2009)	6	Includes reuse	Low	Secondary
7	Kemna(2005)	6	Includes reuse	Medium	Primary
8	Babbitt et al. (2009) (1995 purchases)	5.88	First life only	High	Primary
9	JEITA(2006) (Office)	5.8	Includes reuse	Medium	Primary
10	Babbitt et al. (2009) (2000 purchases)	5.49	First life only	High	Primary
11	Tekawa et al. (1997) (Home)	5	Not specified	Low	Secondary
12	Hikwama(2005)	5	First life only	Low	Secondary
13	ESRI(2007)	4.3	Not specified	Medium	Primary
14	Braune and Held(2006) [EPIC-ICT]	4	Not specified	Medium	Secondary
15	Hischier et al. (2007) [EcoInvent]	4	First life only	Medium	Secondary
16	Choi et al. (2006)	4	Includes reuse	Medium	Secondary
17	Masanet et al. (2005)	4	Not specified	Low	Secondary
18	Williams(2004)	3	First life only	High	Secondary
19	Atlantic Consulting(1998)	3	First life only	Low	Secondary
20	Smulders(2001)	3	First life only	High	Primary
21	Williams and Hatanaka(2005)	2.99	First life only	High	Primary

Table A.5: Data table for Figure 3.5: Desktop lifespan

	Primary energy [MJ/kWh]	Global warming potential [kg CO_2e/kWh]
LCA studies		
Williams 2004	3.6	–
Atlantic Consulting 1998	11.5	0.51
Hischier et al 2007	12	0.58
IVF 2007	10.8	0.47
Kemna 2005	10.5	0.46
Masanet et al 2005	–	0.4
Average (excl. Williams)	11.2	0.47
Countries (ecoinvent data)		
Switzerland	10.6	0.13
USA	13.9	0.83
Europe-UCTE	12.8	0.59
Germany	12.6	0.72
France	13.6	0.11
UK	12.4	0.68
Norway	5.2	0.05
China	14.1	1.45
Japan	13.1	0.6

Table A.6: Data table for Figure 3.6: Electricity impact factors

A.2 Mapping to subassembly categories

The list below briefly discusses interpretation of LCA studies when expressing their results in terms of subassemblies in Section 3.4.1.

- Tekawa et al [160]: Component-level information is available in terms of total share of manufacturing impacts only; the mapping to this study's categories is straightforward.
- Williams [13]: The study includes a substantial amount of "other" impacts due its focus on upstream manufacturing steps. In grouping these results into component categories, "integrated circuits" included Williams' estimates for semiconductors, silicon wafers, electronic chemicals, and semiconductor manufacturing equipment. The "mainboard:other" category consisted of "printed circuit boards", "passive components", and a subset of "bulk materials–control unit". The "drives" category consisted of "disk drives and other parts" and a subset of "bulk materials–control unit". The casing consisted of a subset of "bulk materials–control unit". The bulk materials are divided according to Williams' descriptions in the paper's supporting information. Where materials are shared, such as aluminum, which is split between hard drives and circuit boards, the total impacts are divided equally among the identified categories. This study's categorization of these results is imperfect; in particular, mainboard impacts are significantly lower than other studies. It is possible some of the impacts apportioned to semiconductors should be applied to the mainboard instead.
- Hikwama [165]: Components in the inventory are grouped by sub-assembly with a straightforward mapping to the component categories in this study.
- Braune and Held [168]: A breakdown of manufacturing impacts by subassembly type with a straightforward mapping to categories used in this study, but in relative terms only; absolute numbers were not provided.
- Hischier et al [95]: The data are organized into sub-processes which map very closely to the component categories used in this study.
- IVF [169]: The product inventory is not characterized hierarchically, making it impossible to assign impacts to sub-assemblies like disk drives and power supplies. To map these impacts to

component categories in this study, it was assumed that sheet steel and ABS plastic belong to the housing; all surface mount devices, printed wiring boards, solder, and "big capacitors and coils" belong to the mainboard; and all remaining materials (except integrated circuits, which can be mapped directly) are grouped as "other".

- Duan et al [159]: A breakdown of manufacturing impacts by component type is provided in relative terms only, with a straightforward mapping to this study's categories.

A.3 Integrated circuit content

LCA studies represent integrated circuit content in three different units: area of silicon wafer input; area of finished die output, and mass of packaged chip. The text converts all identified inventories into finished die area; this section details the calculations behind this conversion. Note the energy and other impacts in the chip package (and the packaging process) are assumed to be negligible compared to those of the silicon die.

Input silicon wafer is converted to finished die through processing, but some area is wasted due to defective wafers and defective dies. Boyd et al. [172], summarizing industry data for a 45nm process, reports a typical yield of 88% for wafers (finished wafers/started wafers), and a yield of 443 good chips per wafer with average size of 111 mm^2; total functional area is thus 49,000 mm^2 per wafer. As this process uses 300 mm wafers with a total area of about 70,000 mm^2, and 12% of wafers are discarded, this means one unit of wafer input produces about 0.6 units of finished die. Comparable estimates of 0.55 [95] and 0.63 [12] are found in the literature. Thus, Williams [13] estimate of 110 cm^2 wafer input per desktop is equivalent to about 66 cm^2 of finished die per desktop.

Several studies measure IC content by mass of packaged ICs, and include an estimate of the silicon die mass as a percentage of the packaged IC mass, ranging from 0.9% to 5%. The area of a silicon die per unit mass can be determined by dividing the the standard thickness of a silicon wafer, 0.078 cm [236], by the mass density of silicon, 2.32 g/cm^3, which gives the area of a finished die to be about 5 cm^2/g.

Supporting information for the ecoinvent database [95] reports silicon die area per unit mass to be 2.7 cm^2/g for logic chips (2% Si die by mass) and 1.2 cm^2/g for memory chips (0.9% Si die by mass); these differ from the expected 5 cm^2/g which should apply to all silicon die of thickness 0.078 cm.

Consequently, when the ecoinvent database attempts to supply a quantity of silicon die using a mass ratio, it uses an erroneously low estimate for die area. The source of the discrepancy here is an apparent confusion between finished die area and package area in the calculations. See Section B.4 in Appendix B for further discussion.

Only one study, Yao et al. [20], provides measurements directly in terms of finished die; these were obtained using laboratory x-ray measurements of a mainboard with packaged chips. This study is largely a response to Williams [13] and attempts to correct Williams' estimates by calculating primary energy consumption using the same methods, but with a different estimate for semiconductor content. They appear to make two errors, however; first, they apply Williams' estimate of energy per area of input wafer to their measurements of area per finished die, neglecting to account for the 0.6 conversion factor discussed above; second, they report Williams' estimate of semiconductor energy requirements to be 909 MJ per desktop, but neglect to add the additional terms specified by Williams for silicon wafers, electronic chemicals, and semiconductor manufacturing equipment, which bring the total to 1992 MJ. Both of these errors make Yao's reported estimate of 99 MJ per desktop or 8.25 MJ per cm^2 of finished die lower than they should otherwise be.

Appendix B

Supplementary material for Chapter 4

B.1 Summary data tables

This section contains data tables summarizing all results for each graph in the text.

Category	Unit	Desktop (ei)	Desktop - tower	Desktop - small	Thin client	LCD monitor, 17" (ei)	LCD monitor, 21.5"	Laptop, with dock, 12" (ei)	Laptop, 16"	Netbook, 10"	iPad	iPod touch	Kindle	Rack server	Switch
Power supply	Mass [g]	1463	1461	476	182	114	173	537	433	297	89	89	89	2911	193
Casing	Mass [g]	6207	6171	1258	860	862	2157	1413	904	265	151	49	59	8767	1404
Circuit boards	Mass [g]	1558	1028	407	227	94	38	345	281	127	30	6	33	2199	460
IC's (packages)	Mass [g]	119	40	35	8	19	2	86	21	17	2	1	2	88	47
IC's (die)	Area [mm^2]	2195	500	218	126	355	22	1577	483	463	170	52	66	1683	366
IC's (die)	Mass [mg]	3970	905	394	228	642	39	2851	873	837	307	94	120	3043	663
Battery	Mass [g]	0	0	0	0	0	0	273	244	178	129	16	51	0	0
Display	Mass [g]	0	0	0	0	4006	2350	328	553	204	342	35	34	0	0
Other	Mass [g]	1796	1959	796	0	0	350	367	334	250	34	3	45	1506	16
Total	Mass [g]	11144	10660	2972	1277	5096	5070	3349	2770	1337	777	198	312	15471	2119

IC: integrated circuit. Circuit boards category excludes IC's.

Table B.1: Summary data table, product composition by mass

Category	Desktop (ei)	Desktop - tower	Desktop - small	Thin client	LCD monitor, 17” (ei)	LCD monitor, 21.5”	Laptop, with dock, 12” (ei)	Laptop, 16”	Netbook, 10”	iPad	iPod touch	Kindle	Rack server	Switch
Power supply	38.2	40.5	17.2	5.1	10.9	10.1	2.9	9	7.8	2.3	2.3	2.3	89.3	10.8
Casing	13.1	15.3	2.9	3.7	6.8	10.2	64.4	6.8	2	1.3	0.4	0.5	18.5	3.8
Circuit boards	76.9	38.6	23.7	12.6	9.6	2.2	32	16.2	8.6	1.7	0.4	2.4	128.8	25.3
IC’s (packages)	80.4	15	11.2	5.6	14.2	1.2	58.9	15.5	12.1	1.3	0.6	1.2	50.8	34.3
IC’s (die)	79	21.5	9.4	5.4	17	1	67.8	20.8	19.9	7.3	2.2	3.6	72.4	15.8
Battery	0	0	0	0	0	0	1.4	1.3	0.9	0.7	0.1	0.3	0	0
Display	0	0	0	0	236.3	138.6	19.3	31.9	6.7	9.9	0.8	2	0	0
Other	29.9	28.9	7.2	0	0	1.9	7.4	4.9	2.9	0.1	0	0.3	18.2	0.2
Transport	2.8	2.7	0.8	0.3	1.3	1.3	0.8	0.7	0.3	0.2	0	0.1	3.9	0.5
Assembly	1.2	1.2	1.2	0.9	1.2	1.2	1.2	0.9	0.9	0.6	0.6	0.6	1.2	1.2
Total	321.6	163.7	73.5	33.6	297.3	167.8	256.2	107.8	62.2	25.5	7.5	13.3	383.1	91.8

IC: integrated circuit. Circuit boards category excludes IC’s.

Table B.2: Summary data table, embodied GHG emissions, in kg CO_2e

Category	Desktop (ei)	Desktop - tower	Desktop - small	Thin client	LCD monitor, 17” (ei)	LCD monitor, 21.5”	Laptop, with dock, 12” (ei)	Laptop, 16”	Netbook, 10”	iPad	iPod touch	Kindle	Rack server	Switch
Power supply	723	754	314	96	201	190	54	173	151	42	42	42	1653	203
Casing	215	273	49	70	121	203	330	134	39	22	7	8	302	58
Circuit boards	1621	757	439	233	180	41	606	323	161	32	7	45	2407	480
IC’s (packages)	1778	301	229	126	269	24	1259	306	245	25	11	22	1008	650
IC’s (die)	1223	318	138	80	256	16	1003	307	294	108	33	53	961	233
Battery	0	0	0	0	0	0	28	25	18	13	2	5	0	0
Display	0	0	0	0	3518	2064	288	475	101	148	11	30	0	0
Other	536	516	132	0	0	41	133	88	54	3	0	6	342	4
Transport	45	43	12	5	20	20	13	11	5	3	1	1	62	9
Assembly	25	25	25	19	25	25	25	19	19	13	13	13	25	25
Total	6165	2987	1338	630	4590	2624	3738	1861	1088	410	127	225	6761	1661

IC: integrated circuit. Circuit boards category excludes IC’s.

Table B.3: Summary data table, cumulative energy demand, in MJ

Product (this study)	Mass [g]	GHG [kg CO_2e]	Primary energy [MJ]
Desktop (ei)	11144	321.6	6165.2
Desktop – tower	10660	163.7	2986.8
Desktop – small	2972	73.5	1338.3
Thin client	1277	33.6	630.1
LCD monitor, 17” (ei)	5096	297.3	4589.5
LCD monitor, 21.5”	5070	167.8	2624.1
Laptop, with dock, 12” (ei)	3350	256.2	3738.2
Laptop, 16”	2770	107.8	1861.1
Netbook, 10”	1337	62.2	1087.8
iPad	777	25.5	409.6
iPod touch	198	7.5	127.1
Kindle	312	13.3	225.1
Rack server	15471	383.1	6761.1
Switch	2119	91.8	1660.8

Table B.4: Summary data table, mass, embodied GHG, and embodied primary energy demand, this study

Apple Product	Mass [g]	GHG [kg CO_2e]
27-inch LED Cinema Display	10900	516.6
Thunderbolt Display	10922	301.6
Apple TV	270	25.2
21.5-inch iMac	9304	349.2
27-inch iMac	13800	455.7
iPad 2	590	63
iPhone 3GS	135	24.75
iPhone 4	135	25.65
iPod classic	139	11.5
iPod nano	21.1	7.02
iPod shuffle	12.5	2.88
iPod touch	101	15.37
11-inch MacBook Air	1080	162
13-inch MacBook Air	1350	198.4
MacBook	2132	142.6
13-inch MacBook Pro	2041	203
15-inch MacBook Pro	2539	289.8
17-inch MacBook Pro	2994	334.8
Mac mini with Lion Server	1400	146.9
Mac mini	1300	153.9
Mac pro	18100	789.6
Xserve	13540	416

Table B.5: Summary data table, mass and embodied GHG, Apple dataset

B.2 Adjustments and comparison to ecoinvent

This study used the data and assumptions from the ecoinvent database, with a few adjustments and modifications. Three products from the ecoinvent database [191], a desktop ('desktop computer, without screen, at plant'), laptop ('laptop computer, at plant'), and LCD monitor ('LCD flat screen, 17 inches, at plant'), were re-implemented in our modeling framework. This study's results can be compared against the original results from the ecoinvent database both to illustrate the effects of the adjustments, and to confirm that this study's framework reproduces the ecoinvent modeling assumptions. A summary of the original results and our adjusted results is in Table B.6 below, followed by a summary of the major adjustments made in this study.

Parts were categorized as follows: circuit boards includes mainboards, RAM, video cards, and any other circuit boards, as well as all integrated circuits, connectors, capacitors, processor heat sinks, and other board-mounted components; casing includes all metal and plastic frames and screws from the device exterior; display is the screen unit only; power supply includes power cables as well as internal power supplies and smaller external supplies including chargers; battery includes only large cells, such as lithium-ion laptop batteries; and other includes any remaining components such as interior power cables, internal frames, disk and optical drives, case fans, and any remaining parts.

	Desktop		Laptop		LCD monitor	
	Original	Adjusted	Original	Adjusted	Original	Adjusted
Assembly	1.4	1.2	0.9	1.2	52.7	1.2
Battery			1.6	1.4		
Casing	15.6	13.1	61	64.4	6.9	6.8
Circuit boards	180.1	236.4	104	158.7	34.3	40.8
Display			19.3	19.3	236.3	236.3
End of life	5.5		3.9			
Other	32.7	29.9	9.1	7.4		
Packaging	2.8		2.9		3.1	
Power supply	28.4	38.2	3.8	2.9		10.9
Transport	2.7	2.8	0.8	0.7		1.3
Total	269.3	321.6	207.4	256	333.3	297.3

Table B.6: Global warming potential results for original ecoinvent study and this study's adjustments, in kg CO_2e

B.2.1 System boundary

This study excludes the use and end-of-life phases in order to focus on impacts during device production. Device packaging is excluded due to lack of data for packing for some of the products being studied; ideally packaging would be included in the study boundary for all products, but the magnitude of impacts due to packaging are typically small, so its exclusion should not significantly affect the results. Final assembly and transport are included using the standard ecoinvent assumptions. Note that the LCD screen in ecoinvent did not include transport, and included an extra assembly step which I believe is spurious (see discussion below); I have adjusted this study so it is consistent with the others.

B.2.2 Silicon die and integrated circuits

Silicon die content is calculated using an empirically derived relationship, discussed in Section B.4. The silicon die content per packaged chip is estimated to be about 18 mm^2 of die per gram of packaged chip, which is significantly larger than the ecoinvent model, which estimates 5.5 mm^2 per gram for logic chips ("integrated circuit, IC, logic type, at plant") and 10.1 mm^2 die per gram for memory chips ("integrated circuit, IC, memory type, at plant"). The lower estimates in ecoinvent are due to apparently erroneous assumptions in the ecoinvent database, discussed in previous work [1, 133] and in Section B.4. The desktop, laptop, and LCD monitor models have been adjusted to use the silicon die models in this study, which has significantly increased the impacts due to integrated circuits. In addition, updated life cycle assessment results for silicon die have been applied [172], though this has a relatively small influence on the results.

B.2.3 LCD assembly

The ecoinvent process "LCD flat screen, 17 inches, at plant" includes an assembly process called "assembly, LCD screen" which includes significant chemical usage. However, the top-level process for the LCD monitor also includes an LCD module ("LCD module, at plant") which itself contains a very similar assembly process ("assembly, LCD module"). The two processes, "assembly, LCD screen" and "assembly, LCD module", are in fact nearly identical in their contents, except the inventory contents in the latter are 3.91 times larger in all cases, and there are a small number of items present in the latter process but not in the former. The ecoinvent documentation is not fully clear on the purpose and function of the "assembly, LCD screen" process.

There is no reason to suppose that additional chemical-intensive processes are required in order to assemble the completed components of an LCD monitor (casing, LCD module, cables, etc.); the finished product can be disassembled into such components using a hand screwdriver. Therefore, either the chemical-intensive "assembly, LCD screen" process is spurious, or the "LCD module, at plant" process is intended to represent only part of the central display apparatus. I believe the former is more likely, for two reasons. First, this would be more consistent with the conventions of ecoinvent in which top-level processes include finished components; notably, the laptop computer process includes this LCD module, but not the "assembly, LCD screen" process. Second, the study upon which this data was originally drawn defines an "LCD module" as including "the LCD panel (i.e., front and back glass panels, liquid crystals and polarizers, column and row drivers), the backlight unit, and the main LCD controller PWB" [237]. This represents all of the major components in an LCD monitor [237] which implies that the LCD module is indeed the entire central display apparatus.

In order to maintain a consistent approach I have assumed that the "LCD module, at plant" process represents a finished display component, and that products which include this component do not require an additional chemical-intensive assembly step. Therefore, I have adjusted the "LCD flat screen, 17 inches, at plant" process to remove the "assembly, LCD screen" component. This process accounted for 53.0 kg CO_2e of the LCD flat screen's global warming potential.

B.2.4 LCD power supply

There is no power supply modeled in the ecoinvent LCD monitor process. However, the main circuit board process is defined as a mixture of a surface-mount populated printed wiring board and a through-hole populated printed wiring board. The surface-mount board modeled in ecoinvent contains components which suggest it is used for logic applications, while the through-hole board contains power electronics which suggest it is used in power supplies. In order to maintain consistency with other products, I have split these two components in my adjusted study and assumed that the through-hole circuit board process models the monitor's power supply.

B.2.5 Other variation

The above adjustments account for nearly all of the differences between this study's results and the original ecoinvent studies. The remainder is caused by this study's modeling framework which has condensed the ecoinvent database into a subset of about 100 important processes. In some cases there is a reduction of detail in which I have chosen to use proxy materials; for example, I model only one type of radial cylindrical inductor, whereas ecoinvent has separate processes for small and large inductors. The reduction of detail simplifies this project with minimal loss of accuracy.

B.3 Uncertainty factors

The ecoinvent database uses a semi-quantitative scale based on pedigree matrices to assign uncertainty distributions[191]. In general, if a product includes n kg of a substance, then n is assumed to be the mean of a random variable N with standard deviation s, where s depends on the quality of data which produced the estimate of n kg, and the value of s is a function of expert judgments and is determined using a pedigree matrix.

Operationally, the ecoinvent documentation describes several uncertainty factors, U_i, which quantitatievly score modeling uncertainty in terms of reliability, completeness, temporal correlation, geographical correlation, further technological correlation, and sample size. When assessing the uncertainty of a database model which is intended to model a physical component, the analyst refers to a pre-defined matrix and scores the model in each of the above categories, such that higher-quality or less uncertain models receive lower scores. Each score is mapped to a numerical uncertainty factor using a predefined scoring system. A quantity called the geometric standard deviation is defined, σ_g^2, which is obtained through a numeric combination of uncertainty factors U_i. The geometric standard deviation is calculated as $\sigma_g^2 = \exp(U)$ where $U = \sqrt{\sum_i (\ln^2 U_i)}$. This standard deviation is applied along with the mean quantity to define a probability distribution for each quantity, which is generally assumed to be lognormal in the ecoinvent database. With such distributions applied throughout the model, it is possible to derive output standard deviations through Monte Carlo analysis.

This method has obvious limitations as it is based on expert judgments rather than empirical measurements and not does capture structural uncertainties in the model such as truncation error; this uncertainty analysis should therefore be understood as an attempt to bound that uncertainty which is internal to the ecoinvent modeling framework. Structural uncertainties that challenge the framework itself are not considered.

I have assigned standard deviations to all line items in each product's bill of materials according to my judgment of how well the ecoinvent processes, especially those modeling electronics components, map to the components in the products under study. In the interests of simplicity, most quantities are assessed the same score, with the exception of silicon die and LCD screens. The scoring according to the pedigree matrix format in the ecoinvent database is shown below in Table B.7. The scores are my assessment; the uncertainty factors are a function of the scores, determined by a mapping defined in the ecoinvent documentation [191].

Category	Score	Uncertainty factors U_i
Reliability	3: Non-verified data partly based on qualified estimates	1.1
Completeness	4: Representative data from only one site relevant for the market considered OR some sites but from shorter periods	1.1
Temporal correlation	3: Less than 10 years of difference to our reference year (2000)	1.1
Geographical correlation	2: Average data from larger area in which the area under study is included	1.01
Further technological correlation	3: Data on related processes or materials but same technology, OR Data from processes and materials under study but from different technology	1.2
Sample size	5: unknown	1.2

Table B.7: Pedigree matrix scoring for uncertainty characterization: assessment of ecoinvent component models

Using the above method and uncertainty factors in order to express the correlation of ecoinvent electronics component data as applied to the products in this study, a geometric standard deviation $\sigma_g^2 = 1.36$ is obtained. This factor is applied as the default for all inventory items in this study. For silicon die and LCD screens which have additional uncertainty, the reliability and technological correlation scores are downgraded from 3 to 4, which changes the uncertainty factors from 1.10 and 1.20 to 1.20 and 1.50, respectively, and results in a new geometric standard deviation $\sigma_g^2 = 1.65$. Transport processes are assigned a score of $\sigma_g^2 = 2.1$ in order to maintain consistency with other electronics processes in ecoinvent.

These standard deviations are sufficient to impose probability distributions on all components in each product LCA model, with which Monte Carlo analysis was performed to produce the output standard deviations described in the text. Numerical results of that analysis are shown in Table B.8.

B.4 Silicon die content in integrated circuits

Silicon die are a key component contributing to emissions, but the precise quantity of silicon die in a device can be difficult to estimate, even through teardown analysis, because the silicon die are usually encased in packages. Die can be identified through x-rays, removal of package through mechanical

	Mean	Standard deviation	
	[kg CO_2e]	[kg CO_2e]	[% of mean]
Rack server	378.6	40.9	0.11
Desktop (ei)	307.9	31.6	0.1
LCD monitor, 17” (ei)	295	45.4	0.15
Laptop, with dock, 12” (ei)	249.3	44.8	0.18
LCD monitor, 21.5”	167.4	31.8	0.19
Desktop - tower	158	15.2	0.1
Laptop, 16”	107.2	10.6	0.1
Switch	91.4	8.8	0.1
Desktop - small	72.7	7.6	0.1
Netbook, 10”	60.6	7	0.12
Thin client	34.9	3.4	0.1
iPad	25.7	3.9	0.15
Kindle	13.2	1.7	0.13
iPod touch	7.5	0.9	0.12

Table B.8: Monte Carlo analysis results

grinding (which is time-consuming, intricate work), or by approximation given the characteristics of the package. The ecoinvent database models follow the third approach based on a small set of empirical measurements. In this study, a wider sample of packaged ICs were x-rayed in order to measure their silicon die content; this dataset, presented below, was used to develop higher-quality approximations of silicon die based on package characteristics which were applied in the study.

Figure B.1 below shows the results of X-ray measurements of packaged ICs which were used to derive conversion ratios for estimating silicon die content. Twenty-two ICs were successfully X-rayed and their silicon die area measured. The dataset is split to illustrate that most surface-mount (SMT) ICs are very small and show high diversity in package types; the linear trend is mostly driven by large ball-grid array (BGA) ICs with large die. Errors are thus likely when estimating die content of small ICs, but the absolute magnitude of these errors will also be small in proportion to the size of these ICs. Diversity in packaging technique leads to non-linear variation which is more pronounced in measurements of mass; it is thus preferable to use the top-down area of the package to estimate die content.

These results were used to create ratios that allow estimation of silicon die by packaged IC area and by IC mass. The mass of a die was calculated using the volume density of silicon, 2.33 g per cm^3, and the standard thickness of a 300 mm wafer, 775 μm [238]. Using a simple linear fit provides a best-fit mass ratio of about 18 mm^2 of silicon die per gram of packaged IC ($R^2 = 0.58$), and a best-fit area ratio of about 0.078 mm^2 of silicon die per mm^2 of packaged IC footprint area ($R^2 = 0.70$). By comparison,

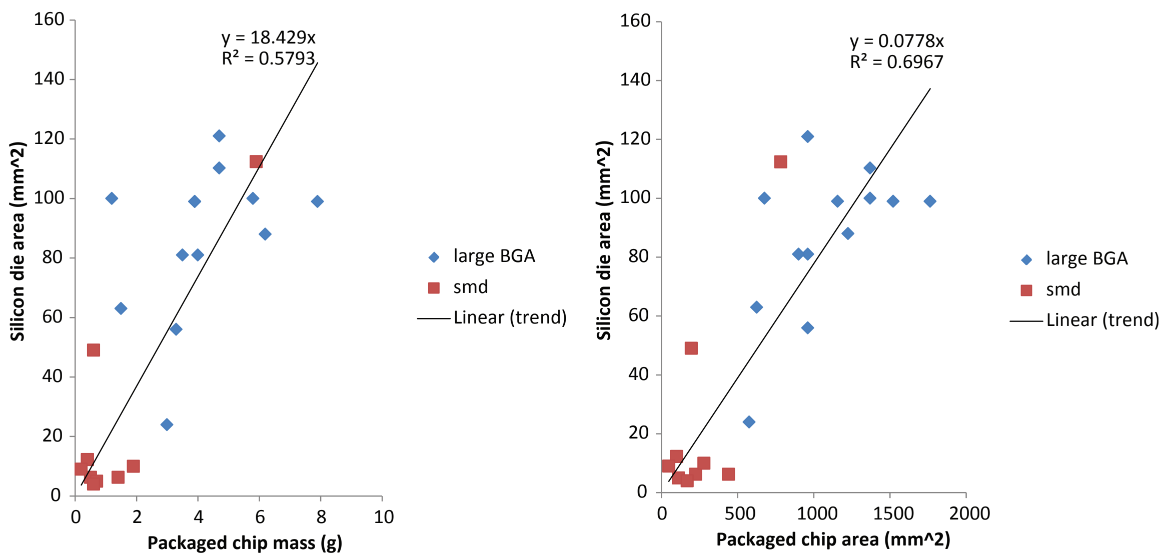

Figure B.1: Silicon die area measurements via X-ray, with regression lines

the ecoinvent database assumes 5.5 mm^2 silicon die per gram of packaged IC for logic chips and 10.1 mm^2 silicon die per gram of packaged IC for memory chip.

B.4.1 Discrepancy in ecoinvent models

The ecoinvent calculation uses a mass ratio to determine die size. Given an example packaged IC with dimensions of 27 mm * 27 mm * 2.36 mm, a mass of 2.62 g, and an assumption that the silicon die mass is 2% of the packaged IC mass, the ecoinvent calculation of silicon die area per kilogram of packaged IC is as follows, from [95]:

$$\text{Die area per kg packaged IC} = (0.027 * 0.027) * 0.02/0.00262 \tag{B.1}$$

$$= 0.0056\,[\mathrm{m}^2/\mathrm{kg}] \tag{B.2}$$

The equation has the following factors:

- Left side of equation: Die area / packaged IC mass
- Right side of equation: Packaged IC area * (die mass / packaged IC mass) / (packaged chip mass)

The units of each factor are as follows:

- Left side of equation: m^2 die/ kg packaged IC

- Right side of equation: (kg die/kg packaged IC) / kg packaged IC

Unfortunately, the units on the right side of the equation do not resolve to those on the left side; this is the source of the discrepancy. The difficulty could be resolved by replacing the mass ratio with a ratio expressing die area divided by packaged chip area:

- Left side of equation: m^2 die / kg packaged IC
- Right side of equation: m^2 chip * (m^2 die/m^2 packaged IC) / kg packaged chip

The data above gives an area ratio of 0.078 mm^2 die per mm^2 packaged IC. Using the example chip with area 27 mm * 27 mm and mass of 2.62 g would imply a die area of (0.027*0.027) * 0.078 / 0.00262 = 0.021 m^2 per kg of packaged IC, which is a factor of 3.9 higher than the ecoinvent calculated result of 0.0056 m^2 per kg packaged IC. Alternatively, the intended result, m^2 die / kg packaged IC, can be determined empirically as I have done by examining the die area and packaged IC masses of several packaged ICs. The area ratio measured, 18 mm^2 die per gram of packaged IC, or 0.018 m^2 die per kg of packaged IC, is a factor of 3.2 higher than ecoinvent's assumption of 0.0056 m^2 die per kg of packaged IC. These results indicate that the ecoinvent dataset significantly underestimates the silicon die content of packaged IC's due to a calculation error. Thus, the area and mass ratios developed in this section are applied throughout the study instead of the ecoinvent models to approximate silicon die content in packaged ICs.

B.4.2 Stacked IC's

Some IC packages contain multiple die in order to save space and improve connectivity between modules. The practice is especially common in mobile devices which require high performance but are heavily space-constrained; a common use is to combine multiple memory die, alone or with a processor, either by stacking silicon die directly on top of one another within one package, a technique known as "stacked die", or by stacking packaged chips, a technique known as "package-on-package" [239]. The assessment technique of x-raying packages was not able to clearly detect stacked die or package-on-package configurations, so I refer to industrial literature to identify these chips and make appropriate corrections to our bills-of-materials.

Third party analysis of the iPad showed that its A4 processor contains one CPU die and two memory die [240]. Cross-sectional photographs from that analysis show that the RAM dies are 85% of the size of the processor die in one dimension. Assuming the same is true in the other dimension, the RAM die area is 72% of the processor die, which means that the approximately 50 mm^2 CPU die is accompanied by two RAM die with area about 36 mm^2 each. The NAND solid-state storage chip did not include stacked die in the iPad model we analyzed, though higher-capacity iPad models would have [241]. The 4th generation iPod touch uses the same A4 processor with memory die as the iPad [242]. The 3rd generation model we analyzed has a Samsung ARM processor with the same amount of RAM [243] and thus also likely uses a stacked configuration; the package is smaller, but we assume the same ratio of stacked memory die to processor die as in the iPad. The 3rd generation Kindle uses a low-cost ARM processor which does not appear to include stacked die or chips [244]. The use of stacked packaging technologies is unlikely in this product due to its low cost and lower performance requirements.

Stacked-die packages are common in flash memory used in memory cards and in cell-phone processors [239]. Because of the added cost and complexity of using stacked die packaging, they are most likely to appear in small devices which are heavily area-constrained, and unlikely to appear in laptop and desktop computers and other larger equipment. I found no third-party teardowns of the other products in our study to compare against, but did search for information on each major IC (CPU and RAM) and found no evidence to suggest that any stacked-die or package-on-package technologies were in use. As such, no further adjustments were made to account for stacking technologies.

Technical and economic constraints point to future widespread usage of many types of stacking technologies, especially in mobile devices [239]. These trends will make identifying the die area used in a product considerably more difficult. Mass of packaged chips would no longer be viable as a functional unit; life cycle assessments must accurately account for die area. X-raying would no longer be a viable technique for tabulating this area, unless very high-resolution cross-sectional x-rays were available; grinding packages away to reveal the die inside will probably be the only reliable technique for accurately measuring silicon die content of an integrated circuit. Ideally, manufacturer specifications could be made available and incorporated into life cycle assessments in order to make such painstaking measurements unnecessary.

B.5 Linear regression model selection

Three linear models are discussed in the text. Table B.9 are the fit results for the best fifteen models which were attempted during the model selection process. The cross-validated sum of squares (cvss) and raw and adjusted R^2 are shown for each of two datasets; dataset one represents this study, and dataset two is Apple's dataset. The cvss scores are normalized to the mass-only model. The combined score is equal to the sum of the squares of the two cvss scores. Italicized rows represent the three models which are presented in the text.

Model predictors	$cvss_1$	$cvss_2$	score	R_1^2	R_1^2-adj.	R_2^2	R_2^2-adj.
Ma, int=0	*1*	*1*	*2*	*0.85*	*0.84*	*0.89*	*0.88*
Bo, Ps, Di, Ba, int=0	0.38	1.39	2.09	0.97	0.96	0.96	0.96
Bo, Di, Ba, int=0	*0.42*	*1.4*	*2.12*	*0.97*	*0.96*	*0.94*	*0.93*
Bo, Di, Ba	0.45	1.4	2.17	0.92	0.9	0.87	0.84
Ca	1.32	1.25	3.3	0.55	0.51	0.75	0.74
Bo, Ps, Di, Ba, Ca, Ot	0.62	1.81	3.66	0.94	0.88	0.95	0.93
Bo, Ps	1.36	1.91	5.5	0.55	0.47	0.68	0.64
Ca, int=0	1.63	1.94	6.42	0.73	0.71	0.8	0.79
Bo	1.24	2.36	7.11	0.55	0.51	0.59	0.57
Bo, Vo	1.98	1.91	7.56	0.57	0.5	0.7	0.67
Bo, Ps, Di, Ba, Ca, Ot, int=0	*0.45*	*2.77*	*7.85*	*0.97*	*0.95*	*0.97*	*0.96*
Bo, Ps, Di	0.51	2.76	7.88	0.86	0.82	0.82	0.78
Ca, Vo, int=0	2.3	1.94	9.04	0.74	0.69	0.82	0.8
Bo, Ps, Di, Ba, Vo, int=0	0.56	3.01	9.37	0.97	0.95	0.96	0.95
Bo, Ps, Di, Ba, Vo	1.69	2.77	10.49	0.93	0.89	0.93	0.91

Ma: product mass; Bo: circuit board mass; Ps: power supply mass; Di: display mass
Ba: battery mass; Ca: casing mass; Ot: other mass; Vo: product volume; int: y-intercept term
Models discussed in the text are in italics

Table B.9: Model selection results for the top fifteen models.

The circuit board + display + battery model, which had the third-best score, was selected because its score is very close to that of the model with the second-best score, and it requires one fewer predictor. The circuit board + power supply + display + battery + casing + other model was selected as an illustrative case because it had very low residual error (visible through its high R^2) but performed poorly when cross-validated on Apple's dataset. This suggests that the apparent additional precision supplied by adding more terms to that model is due to overfitting. Regression outputs for the three selected models are shown below in Tables B.10 and B.11.

	Mass	GHG	Model estimates [kg CO_2e]		
	[g]	[kg CO_2e]	pcb+disp+batt	Mass only	All internal
Desktop (ei)	11144	321.6	285.4	302.5	310.3
Desktop – tower	10660	163.7	188.3	289.3	181
Desktop – small	2972	73.5	74.5	80.7	64.9
Thin client	1277	33.6	41.5	34.7	50.3
LCD monitor 17-inch (ei)	5095	297.3	296.2	138.3	294.7
LCD monitor 21.5-inch	5070	167.8	160.5	137.6	162.9
Laptop with dock 12-inch (ei)	3349	256.2	167.6	90.9	171.4
Laptop 16-inch	2770	107.8	161.8	75.2	162.2
Netbook 10-inch	1337	62.2	90.7	36.3	83.9
iPad	777	25.5	67.1	21.1	69.3
iPod touch	198	7.5	8.2	5.4	2.8
Kindle	312	13.3	23.8	8.5	21.5
Rack server	15471	383.1	402.7	419.9	383.5
Switch	2119	91.8	84.2	57.5	111.7

Table B.10: Linear regression model outputs, this study's dataset

	Mass	GHG	Model estimates [kg CO_2e]		
	[g]	[kg CO_2e]	pcb+disp+batt	Mass only	All internal
27-inch LED Cinema Display	10900	517	351.3	430.4	375.9
Thunderbolt Display	10922	302	359.4	431.2	386.5
Apple TV	270	25	16.2	10.7	0.3
21.5-inch iMac	9304	349	363.7	367.4	317
27-inch iMac	13800	456	551.8	544.9	525.8
iPad 2	590	63	74.2	23.3	68.9
iPhone 3GS	135	25	18.1	5.3	17.2
iPhone 4	135	26	17.2	5.3	16.8
iPod classic	139	12	8.1	5.5	8.7
iPod nano	21	7	1.9	0.8	1.1
iPod shuffle	13	3	0.9	0.5	0
iPod touch	101	15	10.6	4	7.1
11-inch MacBook Air	1080	162	128.3	42.6	112
13-inch MacBook Air	1350	198	163.8	53.3	140.6
MacBook	2132	143	204.8	84.2	193.7
13-inch MacBook Pro	2041	203	222.1	80.6	237.6
15-inch MacBook Pro	2539	290	264.3	100.2	272.1
17-inch MacBook Pro	2994	335	334	118.2	344.7
Mac mini with Lion Server	1400	147	132.5	55.3	112.1
Mac mini	1300	154	132.5	51.3	102
Mac pro	18100	790	588.7	714.7	782.5
Xserve	13540	416	588.7	534.6	428.1

Table B.11: Linear regression model outputs, Apple's dataset

Appendix C

Supplementary material for Chapter 5

C.1 Summary data tables

This section provides numeric data tables corresponding to the graphs in the text, for ease of reference.

	Total emissions [Mt CO2e]			
	2012		2017	
	Mean	stdev	Mean	stdev
By end-use				
Online video	23.9	2.0	36.7	5.3
Other online	31.4	2.2	35.1	4.5
Offline	14.1	1.2	5.7	0.7
IP video on demand	26.7	2.1	34.1	5.0
Broadcast TV	74.8	7.9	65.4	13.5
Total	170.9	8.8	177.0	16.0
By location				
Broadcast TV network	4.7	0.5	4.8	1.0
Datacenter	27.4	3.2	33.6	7.1
Fixed network	10.4	0.9	13.3	2.3
Mobile network	6.2	0.8	5.1	1.1
Devices	122.3	9.3	120.3	16.9
Total	170.9	9.9	177.0	18.6

Table C.1: Total US consumer emissions by end-use and location, with Monte Carlo results

End-use	Platform	Location of emissions	2012 Energy per platform [kWh / yr]	2012 GHG emb. per platform [kg CO_2e / yr]	2012 GHG total per platform [kg CO_2e / yr]	2012 GHG US consumer total [MT CO_2e / yr]	2017 Energy per platform [kWh / yr]	2017 GHG emb. per platform [kg CO_2e / yr]	2017 GHG total per platform [kg CO_2e / yr]	2017 GHG US consumer total [MT CO_2e / yr]
Broadcast TV	TV platform	Broadcast TV network	21.4	0.0	12.9	4.6	21.4	0.0	12.9	4.8
		Devices	285.6	26.9	198.2	71.0	247.8	22.8	171.5	63.7
		Total [TV, broadcast TV]	307.0	26.9	211.1	75.6	269.2	22.8	184.3	68.5
IP VoD	TV platform	Datacenter	55.6	1.6	34.9	12.5	60.3	1.7	37.9	14.1
		Fixed network	20.8	1.0	13.5	4.8	24.1	1.4	15.8	5.9
		Devices	37.4	3.5	26.0	9.3	55.4	5.1	38.4	14.2
		Total [TV, IP VoD]	113.9	6.1	74.4	26.7	139.8	8.2	92.1	34.2
Online video	PC platform	Datacenter	57.1	1.6	35.9	8.3	53.0	1.5	33.3	7.2
		Fixed network	21.2	1.0	13.7	3.2	20.8	1.2	13.7	3.0
		Mobile network	6.3	1.9	5.6	1.3	2.6	0.7	2.3	0.5
		Devices	29.9	5.3	23.2	5.4	39.8	6.9	30.8	6.7
		Total [PC, online video]	114.5	9.8	78.5	18.2	116.2	10.3	80.0	17.3
	Smartphone	Datacenter	3.3	0.1	2.1	0.2	11.6	0.3	7.3	1.5
		Fixed network	0.8	0.0	0.5	0.1	3.2	0.2	2.1	0.4
		Mobile network	13.2	3.9	11.8	1.4	9.7	2.7	8.5	1.8
		Devices	0.1	0.6	0.6	0.1	0.4	1.6	1.8	0.4
		Total [Smartphone, online video]	17.4	4.6	15.0	1.8	24.9	4.8	19.7	4.1
	Tablet	Datacenter	12.0	0.3	7.6	0.5	51.2	1.4	32.2	3.9
		Fixed network	4.3	0.2	2.8	0.2	19.2	1.1	12.6	1.5
		Mobile network	7.2	2.1	6.4	0.4	8.5	2.3	7.4	0.9
		Devices	2.0	10.2	11.4	0.7	6.1	28.1	31.7	3.8
		Total [Tablet, online video]	25.5	12.9	28.2	1.7	84.9	32.9	83.9	10.1
	TV platform	Datacenter	4.6	0.1	2.9	1.0	9.0	0.3	5.7	2.1
		Fixed network	1.7	0.1	1.1	0.4	3.6	0.2	2.4	0.9
		Devices	3.4	0.3	2.4	0.8	9.8	0.9	6.8	2.5
		Total [TV, online video]	9.7	0.5	6.4	2.3	22.4	1.4	14.8	5.5
Other online	PC platform	Datacenter	27.1	0.8	17.0	4.0	17.9	0.5	11.3	2.4
		Fixed network	10.0	0.5	6.4	1.5	6.9	0.4	4.6	1.0
		Mobile network	6.2	1.8	5.5	1.3	1.6	0.4	1.4	0.3
		Devices	101.0	17.8	78.4	18.2	115.9	20.1	89.6	19.4
		Total [PC, other online]	144.2	20.9	107.4	25.0	142.4	21.4	106.9	23.2
	Smartphone	Datacenter	2.1	0.1	1.3	0.2	4.9	0.1	3.1	0.6
		Fixed network	0.4	0.0	0.2	0.0	1.1	0.1	0.7	0.1
		Mobile network	13.0	3.9	11.7	1.4	5.9	1.6	5.1	1.1
		Devices	1.7	7.8	8.8	1.1	2.3	10.1	11.5	2.4
		Total [Smartphone, other online]	17.2	11.8	22.1	2.7	14.1	12.0	20.4	4.2

End-use	Platform	Location of emissions	2012 Energy per platform [kWh / yr]	2012 GHG emb. per platform [kg CO_2e / yr]	2012 GHG total per platform [kg CO_2e / yr]	2012 GHG US consumer total [MT CO_2e / yr]	2017 Energy per platform [kWh / yr]	2017 GHG emb. per platform [kg CO_2e / yr]	2017 GHG total per platform [kg CO_2e / yr]	2017 GHG US consumer total [MT CO_2e / yr]
	Tablet	Datacenter	6.0	0.2	3.7	0.2	17.9	0.5	11.3	1.4
		Fixed network	2.0	0.1	1.3	0.1	6.4	0.4	4.2	0.5
		Mobile network	7.1	2.1	6.3	0.4	5.1	1.4	4.5	0.5
		Devices	5.2	25.8	28.9	1.7	4.7	21.5	24.3	2.9
		Total [Tablet, other online]	20.2	28.2	40.3	2.4	34.1	23.7	44.2	5.3
	TV platform	Datacenter	2.2	0.1	1.4	0.5	3.0	0.1	1.9	0.7
		Fixed network	0.8	0.0	0.5	0.2	1.2	0.1	0.8	0.3
		Devices	3.4	0.3	2.4	0.8	3.3	0.3	2.3	0.8
		Total [TV, other online]	6.4	0.4	4.2	1.5	7.5	0.5	4.9	1.8
Offline	PC platform	Devices	56.1	9.9	43.6	10.1	17.3	3.0	13.4	2.9
	Smartphone	Devices	1.2	5.6	6.3	0.8	0.3	1.3	1.5	0.3
	Tablet	Devices	4.8	24.0	26.9	1.6	1.2	5.5	6.2	0.7
	TV platform	Devices	6.8	0.6	4.7	1.7	6.5	0.6	4.5	1.7
	Total [Broadcast TV, all platforms]					75.6				68.5
	Total [IP Video on demand, all platforms]					26.7				34.2
	Total [Online video, all platforms]					24.0				37.0
	Total [Other online, all platforms]					31.6				34.5
	Total [Offline, all platforms]					14.2				5.6
	Total [All end-uses, all platforms]					172.1				179.8

Table C.2: Energy and GHG emissions by end-use and platform

		2012				2017			
Platform	Location of emissions	Energy per platform [kWh / yr]	GHG emb. per platform [kg CO_2e / yr]	GHG total per platform [kg CO_2e / yr]	GHG US consumer total [MT CO_2e / yr]	Energy per platform [kWh / yr]	GHG emb. per platform [kg CO_2e / yr]	GHG total per platform [kg CO_2e / yr]	GHG US consumer total [MT CO_2e / yr]
Desktop PC	Datacenter	84.2	2.4	52.9	5.4	70.9	2.0	44.6	4.0
Desktop PC	Fixed network	31.5	1.5	20.4	2.1	28.3	1.6	18.6	1.7
Desktop PC	Devices	308.0	47.0	231.8	23.8	298.0	43.0	221.8	20.1
Total		423.8	50.9	305.1	31.3	397.3	46.6	285.0	25.8
Laptop (Wi-Fi)	Datacenter	84.2	2.4	52.9	6.2	70.9	2.0	44.6	4.4
Laptop (Wi-Fi)	Fixed network	31.5	1.5	20.4	2.4	28.3	1.6	18.6	1.8
Laptop (Wi-Fi)	Devices	87.0	22.0	74.2	8.7	84.0	20.0	70.4	7.0
Total		202.8	25.9	147.5	17.3	183.3	23.6	133.6	13.2
Laptop (Mobile)	Datacenter	84.2	2.4	52.9	0.7	70.9	2.0	44.6	0.9
Laptop (Mobile)	Fixed network	24.5	1.2	15.9	0.2	21.8	1.3	14.3	0.3
Laptop (Mobile)	Mobile network	223.5	66.1	200.3	2.6	43.3	12.0	37.9	0.8
Laptop (Mobile)	Devices	87.0	22.0	74.2	1.0	84.0	20.0	70.4	1.5
Total		419.2	91.7	343.2	4.4	220.0	35.2	167.2	3.5
Smartphone	Datacenter	5.4	0.2	3.4	0.4	16.5	0.5	10.4	2.1
Smartphone	Fixed network	1.2	0.1	0.8	0.1	4.2	0.2	2.8	0.6
Smartphone	Mobile network	26.2	7.8	23.5	2.9	15.6	4.3	13.7	2.8
Smartphone	Devices	3.0	14.0	15.8	1.9	3.0	13.0	14.8	3.1
Total		35.8	22.0	43.4	5.3	39.3	18.0	41.6	8.6
Tablet (Wi-Fi)	Datacenter	18.0	0.5	11.3	0.5	69.1	1.9	43.4	3.4
Tablet (Wi-Fi)	Fixed network	6.7	0.3	4.4	0.2	27.6	1.6	18.2	1.4
Tablet (Wi-Fi)	Devices	12.0	60.0	67.2	2.9	12.0	55.0	62.2	4.9
Total		36.7	60.8	82.9	3.5	108.8	58.5	123.8	9.8
Tablet (Mobile)	Datacenter	18.0	0.5	11.3	0.2	69.1	1.9	43.4	1.8
Tablet (Mobile)	Fixed network	5.2	0.2	3.4	0.1	21.5	1.2	14.2	0.6
Tablet (Mobile)	Mobile network	49.1	14.5	44.0	0.8	40.0	11.0	35.0	1.4
Tablet (Mobile)	Devices	12.0	60.0	67.2	1.2	12.0	55.0	62.2	2.5
Total		84.2	75.3	125.8	2.2	142.6	69.2	154.8	6.3
TV platform	Broadcast TV network	21.4	0.0	12.9	4.6	21.4	0.0	12.9	4.8
TV platform	Datacenter	62.4	1.8	39.2	14.0	72.3	2.0	45.4	16.9
TV platform	Fixed network	23.4	1.1	15.1	5.4	28.9	1.7	19.0	7.1
TV platform	Devices	340.0	32.0	236.0	84.5	326.0	30.0	225.6	83.8
Total		447.2	34.9	303.2	108.6	448.6	33.7	302.9	112.5
Total [all platforms]					172.6				179.8

Table C.3: Energy and GHG emissions by platform

C.2 Model input parameters

C.2.1 Device parameters

Operational energy use

Operational energy use is based on a Consumer Electronics Association survey based on US consumers in 2010 [5]; for tablets and smartphones which had limited coverage in that study, laboratory measurements are applied giving a pessimistic estimate [217]. The CEA study is an update of a previous 2007 study by Roth et al [4]; trends evident across these two studies are applied in order to estimate device annual energy use in 2012 and 2017. All forecasts to 2017 are based only on the trends from these studies and discussion in [5]; details are below.

	Device unit electricity (kWh/year)				
	2006	2010	2012 (est)	2017 (est)	CAGR 2010-2017
Desktop PC	237	220	212	193	-1.8%
Laptop PC	72	63	61	56	-1.6%
LCD monitor	85	97	100	109	1.7%
Game console	36	135	149	190	5.0%
Set top box	131	136	136	136	0
TV set	249	183	173	152	-3%
DVD / Blu-ray player	36	28	25	18	-6%
AV receiver	–	65	65	65	0
Tablet	–	–	12	12	0
Smartphone	–	–	3	3	0

Table C.4: Device operational energy assumptions, with 2006 baseline from [4] and 2010 baseline from [5]

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Desktop PC UEC declined by 1.8%/yr from 2006 to 2010 largely due to higher availability of power management features and decreases in active power draw; these trends are assumed to continue.

Set-top box power grew slightly in the case of cable STBs and declined slightly for satellite STBs; average power is assumed to be stable through 2017, though this may decline if better power management features are designed.

LCD monitor energy grew by 3.3%/yr from 2006 to 2010 largely due to growth in average screen size; this growth is expected to continue slightly, but at half the rate to account for improved power efficiency.

DVD player energy decreased by 6%/yr due to improved power management features, important as these are very low-utilization devices; this trend is assumed to continue, in part due to power management and in part due to reduced usage in favour of streaming video.

Laptop energy decreased by 3.3%/yr from 2006 to 2010 due to improved power management features; as laptop energy is already quite low, it is assumed to continue declining at half this rate through 2017.

Game console energy grew by 40%/yr from 2006 to 2010 due to large changes in device form and function, as these devices found a niche as media access platforms for connected TVs; active power per console spiked in 2006 with the introduction of a new generation of consoles and then quickly declined as more efficient versions were introduced. An NRDC blog post estimates the new XBox One and PS4 consume 253 and 184 kWh/year, respectively [245] – significantly higher than the CEA's average of 135 kWh/yr in 2010, though these numbers are expected to decline as subsequent models become more efficient. Overall, a modest 5%/yr gain in annual energy is assumed from 2010 to 2017.

AV receivers were not modeled in the 2007 study; their energy consumption is assumed to remain stable through 2017.

TV energy declined by 7.5%/yr from 2006 to 2010, but only by 2.7%/yr from 2009 to 2010. Competing trends are at play; growth in new TV screen size creates upward pressure on power consumption, but this is more than offset by large gains in LCD energy efficiency. LCDs and plasma TVs which entered the market from 2006 to 2009 had much higher active power consumption than LCDs manufactured in 2010. Accordingly, the 2.7%/yr decline in energy consumption is assumed to increase through 2017 as more efficient LCDs achieve greater market share.

Smartphone and tablet energy is not covered in these two studies; energy consumption is assumed to remain stable through 2017 as these devices are already heavily power-optimized.

Embodied emissions

Device embodied GHG emissions per product $G_{D,emb.}$ and device lifespan L_D, which together determine annual device embodied GHG emissions, are based on a comprehensive review of prior LCA literature developed by researchers at LBNL [42]. For forecasts to 2017, the US industrial average decline of

1.75% per year is applied, per Energy Star, so that embodied emissions per device decline by 9.2% from 2012 to 2017.

Installed base

Installed base is used in the model to calibrate device traffic rates and to scale device impacts to obtain the average person's impacts due to ICT end-uses. Baseline estimates for device installed base are obtained from Consumer Electronics Association survey data for US consumers in 2010 [5]. For TV sets, set-top boxes, and game consoles, household penetration rates are assumed to be constant through 2017; installed base estimates for 2012 and 2017 are generated by scaling 2010 data according to US population growth. Because PC, tablet, and smartphone ownership rates are in flux, more detailed forecasts were obtained for these devices.

Tablet installed base is based on a forecast from Forrester [111] which estimated 60MM tablets in-use in a consumer context in the US in 2012; extrapolating trends from 2016 to 2017 gives an estimate of 120MM tablets in 2017. This estimate is exclusive of tablets used for work purposes. Smartphone installed base is based on a forecast from eMarketer [112] which estimated there were 120M smartphone users in the US in 2012, growing to 207MM in 2017; we assume a one-to-one mapping between smartphone users and smartphone devices in use. Installed base forecasts for desktop and laptop PCs were constructed from shipment forecasts from IDC [218], assuming 20% annual retirement for desktops and 25% for laptops, respectively corresponding to 5 and 4 year lifespans. IDC forecasts a 22% decline in annual desktop shipments and a 10% decline in laptop shipments from 2012 to 2017, which translates to a 12% decline in desktop installed base and an 8% decline in laptop installed base over that time span.

LCD monitor installed base is assumed to follow desktop and laptop installed base given reported ratios of 0.96 monitors per desktop and 0.26 monitors per laptop [5].

C.2.2 Network and datacenter intensities

Energy and embodied GHG intensities are obtained by dividing total energy and total embodied emissions by total data traffic. All traffic estimates are obtained from the Cisco VNI [102], for a US consumer context unless otherwise specified. Cisco estimates US consumer traffic to be 135.8 EB/yr in 2012, of which 134 EB/yr travels by fixed network and 1.8 EB/yr on mobile networks; in 2017, consumer traffic is 386.5 EB/yr, with 369 EB/yr fixed and 17.5 EB/yr mobile. Consumer traffic represents 86% of total

US IP traffic in 2012 and 87% of total IP traffic in 2017. Including both consumer and business, US IP traffic represents 31% of global traffic in 2012 (23% of mobile and 31% of fixed), and 31% of global traffic in 2017 (18% of mobile and 32% of fixed).

Fixed and mobile networks are each modeled as a combination of fixed or mobile access network plus a part of a core network. To obtain fixed and mobile GHG intensities, core network GHG intensity and access network GHG intensity are obtained separately and then summed.

Core IP network intensity

Core IP network estimates are based on work from Malmodin et al, who conducted a life cycle assessment of shared data transport/transmission and IP edge/metro/core networks in Sweden [246]; that study estimated 126 GWh electricity and 22 $\mathrm{kt\,CO_2e}$ for Swedish core IP networks in 2010 carrying 1.5 EB of data, which yields an energy intensity of 0.08 kWh/GB and an embodied GHG intensity of 0.014 $\mathrm{kg\,CO_2e/GB}$. This estimate is applied directly assuming that US core IP networks are comparable to Swedish networks. Swedish core IP network energy grew 4.6% annually from 2006 to 2010 [246]; this rate of growth is assumed to continue through 2017. As global data traffic doubled from 2010 to 2012 [102], core IP network energy intensity would thus decline to 0.04 kWh/GB in 2012 and 0.01 kWh/GB in 2017; likewise, assuming similar trends for embodied emissions, embodied GHG intensity declines to 0.6 $\mathrm{g\,CO_2e/GB}$ in 2012 and 0.3 $\mathrm{g\,CO_2e/GB}$ in 2017.

One other data source is Schien et al [247] which estimated between 0.010 and 0.023 kWh/GB for core networks using a bottom-up model, though a later study by the same authors [41] includes Malmodin's result of 0.08 kWh/GB as an upper bound. The CEET wireless cloud study assumed $43\mu\mathrm{J/bit}$ [43], based on a bottom-up model from Baliga et al [248], which corresponds to about $0.1\mathrm{kWh/GB}$.

Mobile access network intensity

Mobile access network intensity is based on a 2011 forecast that estimates radio access networks globally use of 72 TWh/yr energy in 2012 and 91 TWh/yr in 2017, with corresponding embodied emissions of 22 $\mathrm{Mt\,CO_2e/yr}$ in 2012 and 26 $\mathrm{Mt\,CO_2e/yr}$ in 2017 [249]; these results were interpolated from the study's original forecast for 2007, 2014, and 2020. The forecast is inclusive of all deployed networks globally including 2G, 3G, and subsequent generations, and accounts for likely continuous improvements in energy efficient technology. An independent study from the GSM Association estimates that global mobile networks consumed about 87 TWh of electricity in 2010 (the original study reports 78 TWh electricity and 43 TWh primary energy from diesel generators, of which 9 TWh is output as electricity) [250]. This estimate is about 40% higher than the forecast we have applied, but includes a share of core IP network energy on top of global radio access network energy; the rough agreement gives some confidence in their accuracy.

Based on global mobile data forecasts of 10.7 EB/year in 2012 and 132 EB/year in 2017 from the Cisco VNI[102], mobile access networks have a global energy intensity of 6.7 kWh/GB in 2012 and 0.7 kWh/GB in 2017, and a global embodied GHG intensity of 2.1 kg CO_2e/GB in 2012 and 0.2 kg CO_2e/GB in 2017. Cisco reports that US mobile traffic is about 23% of global mobile traffic in 2012 and will account for 18% in 2017. The GSM study reports that USA and Canada are collectively responsible for 14.2% of global mobile network energy in 2010 [250]; if the US is assumed to account for 13% of global mobile network energy and embodied emissions in 2010 (subtracting out Canada's energy), and this result is assumed to be stable to 2012, then US mobile networks produce 23% of global mobile traffic using 13% of global mobile access network energy, implying that US mobile access networks are 40% less energy intense than the global average. Assuming that this is true for embodied emissions as well, and that this ratio holds into 2017, this yields US mobile network access energy intensity of 3.7 kWh/GB in 2012 and 0.4 kWh/GB in 2017, and embodied GHG intensity of 1.1 kg CO_2e/GB in 2012 and 0.1 kg CO_2e/GB in 2017.

Mobile network overall intensity

When summing mobile access network intensity and core IP network intensity, the latter is negligible; combined mobile network intensity is equivalent to mobile access network intensity, i.e. energy intensity is 3.7 kWh/GB in 2012 and 0.4 kWh/GB in 2017, while embodied GHG intensity is 1.1 kg CO_2e/GB in 2012 and 0.1 kg CO_2e/GB in 2017.

By comparison, Malmodin estimates 3G mobile broadband networks have an energy intensity of 2.9 kWh/GB, while 2G and PSTN have energy intensities of 37 kWh/GB and 18 kWh/GB, respectively, considering a Swedish context in 2010 [251]. The majority of traffic in such a system would be carried by the more modern 3G network, but energy consumed by older networks will push up the average energy intensity. The estimates we have applied, derived from [249], appear to be consistent with

Malmodin's.

The CEET wireless cloud study [43] applied an estimate that 4G LTE wireless technology uses between 328 uJ/bit and 615 uJ/bit in 2010 [252], improving 26% per year [219]; this would correspond to 0.40 to 0.75 kWh/GB in 2012 and 0.088 to 0.17 kWh/GB in 2017. Our estimate for overall mobile network energy intensity for 2017 is significantly higher than the forecasted energy intensity of 4G LTE alone, but the study our forecast is based upon also includes the energy of older 3G networks which would carry some of the traffic.

Schien et al [41] applied a distribution of estimates for mobile networks ranging from 0.030 kWh/GB (min), 0.12 kWh/GB (mode), and 0.73 kWh/GB (max), modeling 3G networks in the UK in 2012, all of which are several times lower than our estimates, though the first two are based on a bottom-up model. The latter figure, 0.73 kWh/GB, was obtained by dividing total base station power by total traffic. They used a Vodafone estimate of 2.1 kW per base station, and having obtained an energy intensity of 328 J/Mb (0.73 kWh/GB), thus assumed average base station traffic of 6.5 Mb/s. Our forecast is built upon a study [249] that assumes a global average of 1.3 kW per base station and an average traffic rate of 1.5 Mb/s per base station in 2014, yielding an energy intensity of 870 J/Mb (1.9 kWh/GB); when that study's results are interpolated back to 2012 the intensity grows larger. The total global mobile traffic estimate used in [249], 45 EB/yr in 2014, is slightly larger than Cisco's estimate of 31 EB/yr in 2014 we which have applied. The discrepancy between our forecast and the result used by Schien et al appears to be related to the assumption of average mobile data traffic; average traffic per base station in [249] may be lower due to the inclusion of older technologies like 2G, while Schien et al focused on 3G only.

Fixed access network intensity

Fixed access network energy is based on a study from Lanzisera et al which estimates that customer access and residential customer premise equipment collectively consumed 10.5 TWh/yr in the US in 2012, having grown 11% per year since 2007 [208]. The study was based on an estimate of US installed stock alongside laboratory power measurements; its authors estimate total results to be within about 20% of the nominal estimate, based on a basic sensitivity analysis. In the absence of any available forecast, we have assumed the same trends continue, such that fixed access networks will consume 18 TWh/yr in the US in 2017. The majority of fixed access network energy is due to customer premise equipment, i.e. modems and routers; according to Consumer Electronics Association data, broadband network devices account for 6.3 TWh/yr in US residences in 2010 [5], which is roughly comparable to though slightly lower than the results from Lanzisera [208]. With US fixed consumer traffic being 134 EB/yr in 2012 and 369 EB/yr, fixed access network energy intensity is therefore estimated to be 0.08 kWh/GB in 2012, and 0.05 kWh/GB in 2017.

This estimate is much lower than Malmodin's assumption of 0.3 kWh/GB for modems and routers, plus 0.08 kWh/Gb for access lines [251] in 2010. To some degree this can be explained by reduced energy intensity caused by a doubling of data traffic from 2010 to 2012, as Malmodin's study assumed a data year of 2010. In addition, their estimate for the the energy consumption of network devices – 118 kWh/yr per household, accounting for 1.5 devices per household – differs from CEA data for US consumers in 2010 which estimated 1.2 devices per household, with unit energy consumption around 50 kWh/yr per device [5]. This implies about half of the energy consumption as Malmodin's study, but with double the traffic, accounting for the roughly 4X difference in energy intensity estimates.

There are no direct studies of embodied emissions of fixed access equipment in the US, but a study of global networks estimated that embodied GHGs for customer premise equipment, the main component in fixed access networks, was estimated to be 2.3 $\mathrm{Mt\,CO_2e/yr}$ in 2007 for equipment using 35 TWh/yr of electricity [25], which yields a ratio of 65 $\mathrm{kt\,CO_2e/TWh}$. This is again much smaller than emissions due to use electricity, which would be roughly 600 $\mathrm{kt\,CO_2e/TWh}$ assuming a US average grid. This ratio of embodied emissions to use energy was applied to the previous estimates, producing first-order estimates of 0.7 $\mathrm{Mt\,CO_2e/yr}$ in 2012 and 1.2 $\mathrm{Mt\,CO_2e/yr}$ in 2017.

Fixed network overall intensity

By summing fixed access network and core network intensity, overall fixed network intensity is estimated to be 0.12 $\mathrm{kWh/GB}$ in 2012 and 0.06 $\mathrm{kWh/GB}$ in 2017, while embodied GHG intensity is 0.006 $\mathrm{kg\,CO_2e/GB}$ in 2012 and 0.003 $\mathrm{kg\,CO_2e/GB}$ in 2017.

This may be compared to a pessimistic bottom-up study of a fixed link videoconference which estimates an upper bound of 0.2 kWh/Gb for average data transfers in 2009 [221]; with improved efficiency since then, this would likely be below our estimate for 2012; however, that study applied a bottom-up methodology which does tend to produce lower estimates than top-down approaches. Other estimates of fixed network intensity reviewed in [72] are from older data years. For comparison to additional studies, see the discussion on core network intensity and fixed access network intensity above.

Datacenter intensity

Datacenter energy is taken from a recent industry survey by DatacenterDynamics, which estimated a total of 87 TWh in the US in 2012, inclusive of all cooling and infrastructure energy [253]. This estimate is comparable to Koomey's estimate of 76 TWh in 2010 [23] and was generated independently. Datacenter Dynamics forecasts North American datacenter energy will reach 116 TWh/yr in 2016, growing 6% annually; from this we estimate US datacenter energy to be 116 TWh/yr in 2017. The forecast annual growth rate of 6% matches the growth rate observed by Koomey from 2005 to 2010, a period of time which included an economic downturn.

Total US IP traffic in 2012 is 158 EB/year according to Cisco [102], which implies an aggregate US datacenter energy intensity of 0.55 kWh/GB of IP traffic. However, while about 86% of IP traffic is generated due to consumer end-uses according to Cisco, a significant portion of servers are servicing business workloads. A study of US business end-uses estimated that about 80% of server closet, server room, and localized datacenter energy is consumed serving business applications [42]; those datacenters were collectively responsible for about 60% of total datacenter energy in 2008. For the remaining mid-tier and enterprise-class datacenters, we assume 80% of their energy consumed is due to consumer end-uses, on the basis that 80% of inbound traffic to these data centers is due to consumer end-uses according to Cisco [108]. Therefore, we assume about 50% of datacenter energy is consumed in serving consumer workloads, i.e. 43 TWh/yr in 2012, and 58 TWh/yr in 2017. This corresponds to datacenter energy intensity of 0.32 kWh/GB in 2012 and 0.15 kWh/GB in 2017, or 328 J/Mb in 2012 and 866 J/Mb in 2017.

Unfortunately, this approach has a major discrepancy when compared with other studies; Schien et al report bottom-up energy intensity of 0.89 J/Mb for Akamai CDN servers [41]; Chandaria et al assumed 0.4 J/Mb for CDN servers streaming video content from BBC [45]. The CEET wireless cloud study [43] estimated 20 J/Mb for servers, based on data from Facebook and Google. On the other hand, a top-down model from Malmodin estimated 1 kWh/GB for data centers in 2010 using a similar methodology to our study [251].

Google estimates that an active user performs 25 searches and watches 60 minutes of Youtube content per day and calculates a corresponding daily footprint of 8 g CO_2e/day [224]. Google reports their carbon intensity to be 357 g CO_2e/kWh – better than the US grid average – implying that this activity required 0.022 kWh of energy. Assuming this activity corresponds to roughly 0.3 GB of data traffic, this corresponds to an energy intensity of 0.075 kWh/GB, or 33 J/Mb – larger than the bottom-up estimates above. Google also indicates that their datacenters are much more efficient than the industry average. Applying Google's energy to total US consumer traffic levels of 136 EB/year in 2012 would yield a total energy consumption of 10.2 TWh – less than 25% of total estimated datacenter energy consumption due to consumer workloads.

If Google's data centers are indeed among the most efficient, the industry-wide average datacenter intensity should be above 0.075 kWh/GB. However, our 2012 estimate of 0.32 kWh/Gb is four times larger and could conceivably be too large, especially since our estimation of the total amount of datacenter energy dedicated to consumer workloads – 50% of the total – is based on rough assumptions. Nevertheless, if datacenter energy intensity was lowered to be closer to Google's reported intensity, this would leave a large portion of total datacenter energy unallocated. Better data is needed in order to identify the portion of datacenter energy dedicated to consumer workloads; ideally a disaggregated model could be developed to account for different levels of energy intensity which correspond to different network services. In the mean time, our study proceeds under the above original assumptions with datacenter energy intensity of 0.32 $\mathrm{kWh/GB}$ in 2012 and 0.15 $\mathrm{kWh/GB}$ in 2017, with a sensitivity analysis to test the effects of applying Google's intensity as the industry average.

Embodied GHG emissions are estimated based on a 2008 inventory of the total number and type of servers in US datacenters [24] and the approximate embodied emissions of each [42]; this yielded a ratio of about 30 $\mathrm{kT\,CO_2e/TWh}$ of use-phase electricity in 2008, which we assume scales linearly as use electricity grows. This estimate is first-order, but since use emissions would generate about 600 $\mathrm{kT\,CO_2e/TWh}$, embodied GHG emissions likely contributes less than 10% to overall datacenter emissions and do not warrant deeper investigation. Datacenter embodied GHG intensities are estimated to be $0.009\mathrm{kg\,CO_2e/GB}$ in 2012 and $0.004\mathrm{kg\,CO_2e/GB}$ in 2017.

C.2.3 End-use parameters

Data traffic per end use

Typical device traffic per month estimates are derived from the Cisco VNI and related reports[102, 103, 254]. The study provides estimates of monthly traffic per device among mobile-connected devices;

share of traffic offloaded to fixed networks from mobile devices; installed base of mobile devices; and overall network traffic due to TVs, PCs, tablets, and smartphones. Using our own estimates of PC and TV installed base, we derive average monthly traffic estimates for each of the four devices, the results of which are in the main text. In order to confirm that the Cisco model has been interpreted correctly and that our installed base estimates are consistent with the internal assumptions in the Cisco model, overall traffic due to each type of device was calculated and is shown in Table C.5; at the bottom, total US consumer traffic due to all devices in our model is compared to total US consumer traffic as reported by Cisco. The numbers agree within 2% for 2012, suggesting that our assumptions are reasonable; a slight gap in traffic in 2017 is likely due to additional devices not modeled here but included in the Cisco model, such as smart glasses and machine-to-machine modules.

	Installed base (millions)		Fixed traffic (EB/yr)		Mobile traffic (EB/yr)	
	2012	2017	2012	2017	2012	2017
TVs	358	371	70	178		
PCs, mobile-connected	13	21	3	8	0.8	2.3
PCs, fixed/wifi only	219	189	58	89		
Tablets, mobile-connected	17	41	1	15	0.2	4.1
Tablets, fixed/wifi only	43	79	2	36		
Smartphones	121	207	1	15	0.8	8.2
All devices total (EB/year, this study)			135	341	1.8	14.6
US consumer total (EB/year, via Cisco)			134	369	1.8	17.5

Table C.5: Total traffic from all devices, comparing this study assumptions with original Cisco model

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The Cisco VNI stratifies network traffic by major end-use. Considering internet traffic which is exclusive of IP video-on-demand, fixed network traffic is 68% online video in 2012 and 75% in 2017, while mobile network traffic is 50% online video in 2012 and 62% in 2017. Considering overall IP traffic which includes internet and IP video-on-demand, IP video-on-demand represents 45% of IP traffic in 2012 and 42% of IP traffic in 2017, all of which travels on fixed networks.

The distribution of network traffic by end-use is not known at a device level, e.g. it is unknown what percentage of a desktop PC's fixed internet traffic is attributable to video, with the exception of IP video-on-demand to televisions which is explicitly reported; of the average monthly TV traffic per device, 14.5 GB/month in 2012 and 33.4 GB/month in 2017 is due to IP video on demand. For all other devices and networks, the share of online video traffic is assumed to match the percentages listed above, i.e. fixed traffic is 68% video in 2012 and 75% online video for all devices; mobile traffic is 50% online video in 2012 and 62% online video in 2017 for all devices that use mobile networks.

Derivation of time spent with online video

Time spent on each end-use on each device is estimated using the above traffic figures alongside various market research reports which track consumer behavior. This category is difficult to accurately estimate because of large amounts of variation across different market research reports, likely due to differences in scope and boundary or modeling assumptions, along with poor coverage in academic literature. The approach taken here is to estimate average online video data rates, in GB per hour, so that time spent with online video on each device can be calculated directly from the previously derived traffic model; data rate estimates are tuned slightly so that calculated time spent with online video is consistent with available market research data, where possible. Data rate assumptions and resulting estimated time spent per person in the US are shown in Table C.6. The data rates may be compared with published data rates of Netflix online streaming: 0.3 GB/hr at low quality, 0.7GB/hr at medium quality, 1.0 GB/hr at high quality at standard definition, and 2.8 GB/hr at high quality at high definition [255].

	Video traffic (GB/month per device)		Device penetration (% of population)		Video traffic rate (GB/hr)		Online video time spent (hrs/month/person)	
	2012	2017	2012	2017	2012	2017	2012	2017
PC	14.8	29.6	0.74	0.67	1	1.5	11.0	13.2
Tablet	3.1	29.1	0.19	0.37	0.3	0.8	2.0	13.4
Smartphone	0.7	7.3	0.39	0.64	0.3	0.8	0.9	5.8
TV (internet)	1.8	6.4	1.15	1.15	0.8	1.2	2.6	6.2
TV (IPVoD)	14.5	33.4	1.15	1.15	0.8	1.2	20.8	31.9
						Total (internet and IPVoD)	37.3	70.4
						Total (internet video only)	16.5	38.6

Table C.6: Derivation of time spent with online video

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The model's estimate of 16.5 hours of online video per month per person in 2012 (excluding IP video on demand) is consistent with eMarketer's estimate of 16.1 hrs/month per person on PC, tablet, and smartphone only [209] (of which about 2 hrs/month per person occurs on tablets and 2 hrs/month per person on smartphones), and similar to an Alcatel-Lucent study which relied a model similar to Cisco's and estimates 16.2 hrs/month per person [100]. Other estimates for 2012 are 13.6 hrs/month from comScore [101] and only 4.2 hrs/month per person from Nielsen [98]. It is difficult to reconcile the low Nielsen estimate with the levels of online video traffic estimated by Cisco, as that would imply unrealistically high average data rates; this interesting discrepancy is unresolved.

Alcatel-Lucent predicts that online video will grow to 102 hrs/month by 2017 accompanied by a severe 80% decline in traditional TV consumption [100], but we are hesitant to adapt such a drastic forecast here, especially given Nielsen's recent reports which suggest that time spent watching traditional TV has been relatively stable into 2013 [98]; likewise this forecast is incompatible with Cisco's data forecast without an unrealistically large increase in video data rates. Forecasts in the Alcatel-Lucent study show data rates for online video services growing roughly 50% from 2012 to 2020. We have assumed comparable levels of growth in data rates, which, given the data forecast from Cisco, leads to a doubling in total time spent with online video per person from 2012 to 2017, with most of the growth occurring on tablets and TV sets. Traditional TV is estimated to be 138 hrs/month per person in 2012 based on Nielsen data, and is assumed to decline by 10% to 124 hrs/month in 2017.

Time spent with other end-uses

Each device is actively used for a certain number of hours per month, with that time split amongst online video, online non-video, offline, and traditional television. Some data sources track the amount of time spent online, either on specific devices or per person overall; others track the amount of time spent on specific devices. Due to differences in methodology across studies it is difficult to compare results; our model is developed with the goal of being consistent with the majority of data sources, as well as with the online video time spent estimates previously derived. Several studies track how time spent online is distributed across devices, which makes a good benchmark for validation; these are listed in Table C.7 below, along with our assumptions for 2012 and 2017. Each of the three studies compared against agrees that the majority of time spent online happens on PCs; the distribution across tablet and mobile devices varies according to assumptions of tablet penetration, which grew significantly from 2012 to 2013.

The estimates were based on a few key assumptions, as follows. Tablets devices are each used for

	eMarketer (2013)[209]	GfK (2012) [256]	comScore (2013) [101]	This study assumptions	
				2012	2017
PC	49%	73%	52%	67%	42%
Tablet	39%	6%	13%	10%	19%
Mobile	12%	17%	35%	21%	37%
TV		4%		2%	2%
			Total hours/month	71	127

Table C.7: Modal share of time spent online per person

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about 60 hours/month, per eMarketer [209]. The average US consumer in 2012 spent 20 hours/month on smartphone non-voice activities according to eMarketer; voice activities account for 20% of smartphone time according to GSMA Intelligence [257]; and about 40% of US consumers owned a smartphone in 2012 according to our estimates; therefore the average smartphone device was used for about 65 hours/month in 2012. The average US person spent 75 hours/month online on PCs in 2012 according to eMarketer[209]; 64% of PC online time occurs in the home, according to Temkin Group [258]; and there are 0.74 PCs in use per person in the US; therefore the average PC is used for 64 hours/month for online uses only. Among French users in 2008, offline PC time comprised 38% of the total [259]; this has likely declined; we assume 30% of PC time is offline in 2012, so that the average PC is used for a total of 92 hours/month. Tablets and smartphones are each assumed to be used for online end-uses 60% of the time in 2012, with the remaining time spent on gaming, phone calls and messaging, and other uses. For all devices, total hours spent online is assumed to grow by 20% from 2012 to 2017; time spent offline is assumed to decline to be 10% of total device time. The resulting total amount of time spent online, 71 hours/month, is in the midrange of other estimates: Ofcom estimates UK adults spent 35 hours/month online in 2012 [260]; eMartketer estimates typical online usage of 75 hrs/month on PCs (apparently including time spent at work); and Temkin Group estimates 116 hrs/month per person on PCs at home [258].

Time spent online (excluding video) and offline represents a small percentage of total time spent on TVs. Nielsen reports 2.9 hours/month per person spent using DVD/Blu Ray devices, and 2.2 hours/-month per person using game consoles [98]; we assuming half of game console time is spent online, with the remainder offline.

C.3 Uncertainty model

There are many forms of uncertainty which affect the model. All model parameters are estimates of empirical quantities, usually estimating a US consumer average, and have varying degrees of precision. Very few of the model parameters used in our study include any treatment of uncertainty or expression of confidence in their source studies. Nevertheless, a semi-quantitative treatment uncertainty is undertaken by assigning 95% confidence intervals for each parameter according to our best judgment, supported by evidence where available.

An additional large source of uncertainty is structural; any number of the modeling assumptions could be challenged, and a change in parameters could greatly affect the outputs. For example, if our assumption for average datacenter energy intensity was reduced to be closer to that reported by Google, then datacenter energy tabulated for each end-use would drop accordingly – perhaps being cut in half. There is little utility in assigning confidence intervals that span the entire range of possible modeling assumptions. Rather, the impact of changes in modeling assumptions would be more appropriately assessed through scenario analysis, as was performed in the text for the case of datacenter energy intensity. Each modeling assumption is reasonable according to our best judgment and is thoroughly justified, and the model has been specified in such a way as to make it easily adaptable should other researchers wish to explore the impacts of changes in modeling assumptions. Therefore, the uncertainty analysis assumes that the underlying modeling assumptions are fixed, and attempts to calculate reasonable confidence bounds on the outputs under these assumptions.

Output model uncertainty is estimated through Monte Carlo analysis, by assuming normally distributed inputs, such that the assigned confidence intervals represent a range of ± 1.96 standard deviations from the mean.

C.3.1 Parameter uncertainty estimation

Device energy and emissions

Uncertainty bounds for device energy consumption are based on field measurements from a Minnesota plug load study [228]. Full field data is not available, but the study reports sub-categories of devices based on their physical characteristics or usage profiles from which we can roughly estimate population characteristics, assuming Minnesota residents are representative of US consumers. Of desktop PCs, 42 were sampled with a mean energy consumption of 282 kWh/yr, and standard deviation of 202 kWh/yr. This yield a standard error of 32 kWh/yr, implying that the larger population mean lies within ±22% of the sample mean with 95% confidence. Likewise, the same study measured a sample of 110 TV sets. These TV sets had a mean energy consumption of 166 kWh/yr per device, with standard deviation of 176 kWh/yr, and a standard error of 17.9 kWh/yr implying that the population mean lies within ±19% of the sample mean with 95% confidence. These two products are probably the most variable among consumer electronics devices due to their wide range in physical forms and in usage patterns; thus bounds of ±20% could be conservatively applied to all other devices. Energy estimates for 2017 are somewhat speculative, and are thus assigned wider bounds of ±30%.

No such sample exists for embodied emissions, but a study of uncertainty in process-sum LCA of ICT equipment, using a server as a case study, estimated bounds of about ±15% for embodied emissions [133]. There exist structural uncertainties in the estimation of embodied emissions, especially relating to modeling assumptions; for example, process-sum LCA is vulnerable to cut-off error and may under-report emissions by 50% or more, when compared to hybrid or economic input-output LCA [2]. Such structural uncertainties are beyond the scope of the uncertainty assessment of this study. This study assumes bounds of ±20% for device embodied emissions in 2012 and ±30% in 2017.

Device installed base is assumed to have bounds of ±5% in 2012 and ±10% in 2017 in most cases, as it is informed by high-quality data sources. The exception is smartphones and tablets, both of which are undergoing rapid changes in penetration due to their relative novelty. For these two devices, installed base is assumed to have bounds of ±10% in 2012 and ±20% in 2017.

Network and datacenter intensities

Network and datacenter intensities each rely on a ratio of energy or embodied emissions divided by total traffic. The traffic data is from Cisco and is probably accurate to within ±10% in 2012, given historical accuracy reported by the authors [102]; 2017 traffic is more uncertain. Datacenter and mobile network overall energy were both corroborated by two independent studies and are assumed to be relatively accurate. Fixed network overall energy is dominated by customer premises equipment which is obtained from high-quality consumer electronics data [5]. Overall, it seems reasonable to assume that intensities are accurate within ±20% in 2012 and ±40% in 2017, assuming the modeling assumptions are appropriate. Embodied GHG intensities have poorer quality data sources and are thus assigned wider bounds of ±30% in 2012 and ±50%.

Network and datacenter intensities are the most vulnerable to structural uncertainties in the modeling assumptions; especially datacenter uncertainty due to disagreement among other published studies. For this reason, a scenario analysis of datacenter intensity was performed in the text.

End-use traffic and time

Traffic per end-use is obtained directly from the Cisco model, which reports traffic at a disaggregated level; these are assumed to be accurate within ±10% in 2012 and ±20% in 2017, based on Cisco's reported 10% historical accuracy as discussed above. Again, as these parameters (e.g. typical monthly video traffic per tablet) represent estimates of the population mean, these confidence intervals describe bounds on the mean, and do not capture variability within the population.

User time spent for each device was obtained from a synthesis of market research reports; estimates were tuned to be as consistent as possible with each data source. Additional calibration for time spent with online video was performed using the traffic model. Accordingly, these estimates are believed to be fairly accurate; confidence intervals are assumed to be ±15% in 2012 and ±30% in 2017.