Pärssinen, Matti; Kotila, M.; Cuevas, R.; Phansalkar, A; Manner, Jukka

Environmental impact assessment of online advertising

Published in:
Environmental Impact Assessment Review

DOI:
10.1016/j.eiar.2018.08.004

Published: 01/11/2018

Document Version
Publisher's PDF, also known as Version of record

Please cite the original version:
Pärssinen, M., Kotila, M., Cuevas, R., Phansalkar, A., & Manner, J. (2018). Environmental impact assessment of online advertising. *Environmental Impact Assessment Review*, *73*, 177-200 .
https://doi.org/10.1016/j.eiar.2018.08.004

Environmental Impact Assessment Review 73 (2018) 177–200

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Environmental impact assessment of online advertising☆

M. Pärssinen[a,*], M. Kotila[b], R. Cuevas[c], A. Phansalkar[d], J. Manner[e]

[a] *Aalto University, Department of Communications and Networks, Espoo 02150, Finland*
[b] *Botlab, United States*
[c] *Universidad Carlos III de Madrid, Avenida de la Universidad, 30, Leganés 28911, Spain*
[d] *Botlab, United States*
[e] *Aalto University, Department of Communications and Networks, Espoo 02150, Finland*

ARTICLE INFO

Keywords:
Internet energy consumption
CO_2 emission
Online advertising
Invalid traffic

ABSTRACT

There are no commonly agreed ways to assess the total energy consumption of the Internet. Estimating the Internet's energy footprint is challenging because of the interconnectedness associated with even seemingly simple aspects of energy consumption.

The first contribution of this paper is a common modular and layered framework, which allows researchers to assess both energy consumption and CO_2e emissions of any Internet service. The framework allows assessing the energy consumption depending on the research scope and specific system boundaries. Further, the proposed framework allows researchers without domain expertise to make such an assessment by using intermediate results as data sources, while analyzing the related uncertainties. The second contribution is an estimate of the energy consumption and CO_2e emissions of online advertising by utilizing our proposed framework. The third contribution is an assessment of the energy consumption of invalid traffic associated with online advertising. The second and third contributions are used to validate the first.

The online advertising ecosystem resides in the core of the Internet, and it is the sole source of funding for many online services. Therefore, it is an essential factor in the analysis of the Internet's energy footprint. As a result, in 2016, online advertising consumed 20–282 TWh of energy. In the same year, the total infrastructure consumption ranged from 791 to 1334 TWh. With extrapolated 2016 input factor values without uncertainties, online advertising consumed 106 TWh of energy and the infrastructure 1059 TWh. With the emission factor of 0.5656 kg CO_2e/kWh, we calculated the carbon emissions of online advertising, and found it produces 60 Mt CO_2e (between 12 and 159 Mt of CO_2e when considering uncertainty). The share of fraudulent online advertising traffic was 13.87 Mt of CO_2e emissions (between 2.65 and 36.78 Mt of CO_2e when considering uncertainty).

The global impact of online advertising is multidimensional. Online advertising affects the environment by consuming significant amounts of energy, leading to the production CO_2e emissions. Hundreds of billions of ad dollars are exchanged yearly, placing online advertising in a significant role economically. It has become an important and acknowledged component of the online-bound society, largely due to its integration with the Internet and the amount of revenue generated through it.

1. Introduction

In 2013, the total energy usage of the ICT technology industry was estimated to be 1500 TWh (Mills, 2013). The aforementioned total ICT energy usage multiplied by the German electricity mix emission factor of 0.5656 kg CO_2e/kWh (Kern et al., 2015), the CO_2e emissions were over 848 million tons. The Internet's share of the global electricity consumption was 10% in 2014 (Mills, 2013): As a reference, the entire global residential space heating in 2014 consumed the same amount (International Energy Agency, 2017a). The expectation is that the emissions will grow to 1.3 billion tons of CO_2e in 2020, attributing to 2.3% of the world's CO_2e emissions (IHS Technology, 2015). Online advertising is a major social and economic driver of the information society. First, up until today, online advertising is associated with funding online search services, map services, and social media, to billions of users. Second, the market volume of online advertising reached

☆ We have read and understood the policy on declaration of interests and declare we have no competing interests.

* Corresponding author at: Department of Communications and Networking, Aalto University, School of Electrical Engineering, PO Box PL 15500, FIN-00076 Aalto, Maarintie 8, 02150 Espoo, Finland.

E-mail address: matti.a.parssinen@aalto.fi (M. Pärssinen).

https://doi.org/10.1016/j.eiar.2018.08.004
Received 21 September 2017; Received in revised form 15 August 2018; Accepted 16 August 2018
Available online 19 September 2018
0195-9255/

$72.5B in the US alone in 2016 with an annual growth rate of 22% (PwC, 2017). Third, online advertising represents a source of jobs. For instance, recent studies have estimated that 0.9 M (0.4%) direct and 5.4 M (2.5%) indirect jobs were associated with online advertising in the EU-28 workforce in 2014 (IHS Technology, 2015). Fourth, online advertising represents a fundamental source of income of companies known for their technological innovations, such as Google or Facebook (Google, 2017; Facebook, 2017). Therefore, the sustainable growth of this industry is seen as important.

The continuous increase of digital services such as streaming video, web browsing or data exchange over time has attracted some attention towards the environmental impact of the Internet. Direct environmental impact of digital services results from the energy consumption of devices involved in delivering the service and from the resources consumed to manufacturing and disposing of the devices (Schien and Preist, 2014). The Internet is a collection of over 50,000 independent networks and a large install base of routers (Gupta et al., 2015; Schien and Preist, 2014). The Internet architecture is evolving and changing: tablets and smartphones create new ways to access the Internet on top of desktops and laptops, and clouds and data centers are changing the traditional way of assessing the environmental impact of the Internet (Bull and Kozak, 2014). The key stakeholders on the Internet include more than 300 Tier-2 Internet service providers (ISPs), and tens of Tier-1 ISPs and Internet exchange points (IXPs) providing locations where multiple networks exchange traffic and routes (Gupta et al., 2015).

Malmodin et al. 2007 study found that the ICT sector produced 1.3% of the worldwide CO_2 emissions and consumed 3.9% of global energy production. Given the growth of ICT since 2007, this is a growing percentage (Bull and Kozak, 2014). More than 80% of the population in developed countries are heavy Internet users (Ji and Hong, 2016). Estimates of energy intensity, kWh/GB, of the Internet, vary significantly; in literature, we found results ranging from 136 kWh/GB (Koomey et al., 2004) to 0.0064 kWh/GB (Baliga et al., 2011), a factor of more than 21,000. The definition of the Internet is not constant throughout literature. Depending on the study, the Internet as a system might include only networks, while other studies also include data centers and all related equipment. These differences can be considered the main reason for the large variance in published results (Coroama et al., 2015).

The impact of digitalization on the global economy is challenging to define. Despite the positive impacts of dematerialization, decarbonization, and demobilization, there is increasing concern about the complexity and uncertainty in the environmental impact assessment (EIA) of ICT (Salahuddin et al., 2016). Another cause of concern is whether services moving online are sustainable development, rather than a burden on the environment. Favorable and adverse environmental impacts can be found on all system levels depending on the depth of causal chains and the time span assumed (Hilty and Page, 2015). The ICT sector is complex, interdependent, contains uncertainties and it is scale-dependent (Bull and Kozak, 2014). As a dynamic industry, it disrupts many other industries. In addition, there is a possible rebound effect; even though the energy intensity of devices has improved, the scale of use has increased at a rate which results to the total increase of energy consumption (Bull and Kozak, 2014).

There is a need for a comprehensive framework for EIA of Internet services. The framework must be modular and support many layers of analysis to overcome the complexity of the Internet. The considerable variability in results in previous studies and level of uncertainties indicate a need for a common framework. Many of the previous studies focus on device level analysis (Andrae and Edler, 2015; Ishii et al., 2015; Lambert et al., 2012) rather than the services on top of them. There are excellent research papers on methodologies of EIA (Morgan, 2017; Jones and Morrison-Saunders, 2017; Bidstrup et al., 2016; Cardenas and Halman, 2016; Leung et al., 2015; Pope et al., 2013) and case studies illustrating some of the Internet's pain points (Aslan et al., 2017; Kern et al., 2015; Whitehead et al., 2015; Whitehead et al., 2014; Bull and Kozak, 2014; Schien and Preist, 2014). The key findings from previous literature can be formed into a general framework for assessing the impact of any Internet service, including online advertising.

This research aims to determine a common framework, utilizing best practices, for assessing the energy consumption and CO_2e emissions part of the EIA of the Internet or a sub-segment of it. The economic and social impacts of the Internet are not in the focus of our research. The second aim is to validate the results by utilizing the determined framework to conduct the EIA of online advertising. The third aim is to approximate the impact of fraudulent online advertising on energy consumption and CO_2e emissions. To the best of our knowledge, this has not been studied previously.

Our research contributes to the ongoing discussion of methodology in the EIA of Internet-related technologies and services. In addition, we contribute an assessment of online advertising energy consumption and CO_2e emissions, to reveal a major consumer of energy for decision makers and regulators. Even with uncertainties taken into account, the energy consumption and CO_2e emissions are substantial.

Section 2 defines the materials and methods that have been used. Section 3 introduces the results and uncertainties. Section 4 discusses the results, and finally, in Section 5, the conclusions are presented.

2. Materials and methods

In the following chapters, we present previous knowledge, our framework, and methods used for conducting the EIA of online advertising.

2.1. Previous knowledge on methods

In this subsection, we present a short introduction to the main assessment methods and provide the essential concepts required for any impact assessment. Furthermore, we present some research previously conducted on the Internet domain and introduce domain-specific aspects of conducting an impact assessment found in the articles. The aim is to provide solid reasoning and theoretical background for our framework development and avoid known mistakes.

2.1.1. Main assessment methods

There are three main assessments regarding the environment: 1) Life Cycle Assessment (LCA), 2) Impact Assessment (IA), and 3) Environmental Impact Assessment (EIA).

LCA is a systematic and transparent method for assessing environmental impacts associated with the creation, use and disposal of products and systems, from the cradle to the grave (Bull and Kozak, 2014; Ji and Hong, 2016, Whitehead et al., 2015, ETSI Standard, 2015). LCA is at a high level of abstraction (Ji and Hong, 2016). LCA has developed over the last decades, and there are international standards and guidelines written on it. LCA is related to a functional unit. However, different methodological choices can be made based on the aim and the scope of the assessment (Arushanyan et al., 2014). In practice, all LCAs include simplifications. The impacts of the simplifications to the output are not always well-known and explicitly addressed in the studies (Moberg et al., 2014). The six main challenges of LCA are: defining the functional unit, boundary selection, allocation, spatial variation, local environments, and data availability (Bull and Kozak, 2014). There is a need for streamlined tools, which are built on comprehensive and detailed frameworks that can be used by non-experts (Whitehead et al., 2015).

IA is defined as a technical tool for analyzing the consequences of a planned action (Leung et al., 2015; Bond et al., 2018; Bidstrup et al., 2016). IA reflects the positivist theory, or rationalism, implying better data leads to better decisions (Bond et al., 2018). Characteristics of a solid IA include: 1) aiming for the best outcome possible with given resources and constraints, 2) providing given outcome and constraints with the smallest resources, 3) adopting the best procedures, 4) ensures legal conformance, 5) includes fair judgements, and 6) can be translated into practice.

EIA is a catalyst for change (Jones and Morrison-Saunders, 2017) and a globally established multidisciplinary tool to promote sustainability (Pope et al., 2013; Loomis and Dziedzic, 2018). EIA predicts various impacts of a project on its surroundings. Impacts include biophysical, social and health environments. An effective EIA follows the following guidelines: complies with best practices, documents have been well prepared, proper methods for impact assessment have been chosen, influences decision-making and balances economic and ecologic aspects (Loomis and Dziedzic, 2018). EIA has several strengths: it is widely acknowledged, comprehensive procedural guidance on it exists, it has an international body of practitioners, it offers different perspectives and theoretical bases, and affects decision-making (Pope et al., 2013). The weaknesses include capacity issues in many countries, weak practices in alternative consideration, an expanding range of practices, low baseline data quality, assumptions, degree of uncertainty and low public participation. Unfortunately, EIA is not integrated into the design process of a project proactively; rather it is preventive in nature (Pope et al., 2013).

2.1.2. Assessment standards

There are at least two widely acknowledged standards for conducting a LCA in the ICT domain: the ICT sector guidance built on the greenhouse gas (GHG) protocol product life cycle accounting and reporting standard (ICT Sector Guidance, 2017) and the European Telecommunications Standards Institute (ETSI) ES 203 199 standard for environmental engineering; methodology for environmental LCA (ETSI Standard, 2015).

The GHG Protocol ICT sector guidance provides methods for calculating GHG emissions for ICT products with a focus on ICT services. The primary domains included are telecommunication network services, desktop managed services, cloud and data center services, hardware, software and transport substitution (ICT Sector Guidance, 2017). According to the GHG protocol, LCA is more suitable for products than to intrinsically complex ICT services. The GHG protocol is still in the development phase. GHG protocol suggests practitioners should apply their expertise to determine the suitable technique or option to use, depending on the type of assessment and the data available. In addition, the protocol suggests matching the data collection effort for any specific process or item to the expected significance of the related emissions (ICT Sector Guidance, 2017).

The GHG protocol gives allocation guidelines for ICT services. In general, data traffic, number of ports used, and number of subscribers are appropriate allocation drivers. However, for the customer domain use stage, multi-functional goods allocation can be done by measuring or estimating the power consumption of the device and estimating the usage profile. Alternatively, usage-based allocation of end-user devices to services can be estimated with a number of subscribers or amount of peak bandwidth or mean traffic. The energy consumption of service will have some functional dependence on the mean traffic. The allocation can take on a variety of different calculation methods to account for the service traffic dependence on the equipment power (ICT Sector Guidance, 2017).

ETSI standard 203 199 for environmental engineering provides requirements and methodologies for ICT LCA. At the time the present document was published in 2015, ETSI acknowledged that meeting all requirements is challenging and may not be possible. ETSI introduces three layers of relevant ICT domains built on top of each other: services, networks, and goods. ICT services inherit methods from networks and goods. According to the ETSI standard, boundaries should not overlap to avoid double counting when an ICT service is assessed. ICT networks should be grouped into fixed and wireless networks. In addition, an ICT network should consist of customer premises (terminals, terminating goods and protectors), access network goods, and a core network. The annual network use should be defined concerning the traffic scenario and the different node types required to perform the intended function. According to ETSI, the basic functionality of a mobile communication system is the possibility to communicate with speech and data "anywhere, anytime" (ETSI Standard, 2015).

According to the ETSI standard, multi-functional devices accessing more than one ICT network, the share of data traffic shall be used to allocate devices to an access network. The impact of each ICT device used should be allocated to the service based on either estimated or measured use time or amount of data traffic (ICT Sector Guidance, 2017). When considering a data center where the ICT service is operated, the impact to the energy usage should be allocated based on the number of subscriptions or the amount of data (ETSI Standard, 2015).

2.1.3. Structure of an impact assessment

The fundamental concepts of the impact assessment include the best practices, boundary selection, allocation, and uncertainty analysis. The best practices are formed by governments, professional associations, industries, funding agencies, and researchers. The best practices have been criticized for slowing creativity and innovations, losing contextual information, for the loss of adaptive learning, the bias of fitting the problem into given best practice, being a mechanistic process and decreasing critical thinking among practitioners (Morgan, 2017). Boundary selection defines which devices, processes and activities are included in the assessment. A system boundary should be implicit (Bull and Kozak, 2014). Ideally, a system boundary is established after reviewing existing data and verifying specific flows are not significant to merit inclusion (Bull and Kozak, 2014). With any complex assessment, like with assessing the energy consumption of the Internet, plurality is essential to gather the relevant sciences together to form an assessment containing aspects of social, moral, economic and ecologic points of views (Bond et al., 2018).

Allocation is a method for dividing the environmental burdens of a multi-functional process. Allocation can be done by sub-dividing burdens into sub-processes, based on physical relationships, or based on non-physical relationships. As an alternative, the product system can be expanded to avoid allocation altogether (Bull and Kozak, 2014). In this study, we have combined the best practices, allocation into sub-processes, and allocation based on the non-physical relationship of traffic allocation.

Uncertainties to any assessment can arise from the following reasons: 1) poorly measured data, 2) data gaps, 3) unrepresentative proxy data, 4) model uncertainty, 5) unobservable data, 6) outdated data and 7) methodological choices (Bull and Kozak, 2014). Impact assessments usually lack spatial variation and local environment data, and the effects are assumed to be global and homogenous, thus creating uncertainties (Bull and Kozak, 2014). For the Internet, globalism is natural as it has no national boundaries. However, when considering CO_2e emissions created by the Internet, the local grid mix is a significant factor.

2.1.4. Assessments in the Internet domain

Most of the Internet IAs defines a functional unit around a product. Only a few studies have been modeled around a service (Bull and Kozak, 2014). There are four methodological approaches to assess Internet energy consumption: 1) top-down, 2) bottom-up, 3) model based, and 4) the unified method. The top-down methodology based analyses require two distinct factors: 1) the energy consumption of the whole system or a part of the system, and 2) the total traffic associated with the system in question (Coroama and Hilty, 2014; Coroama et al., 2015; Ishii et al., 2015; Aslan et al., 2017). The top-down methodology can produce a relatively large estimation error (Ishii et al., 2015; Schien and Preist, 2014; Aslan et al., 2017; Coroama and Hilty, 2014) as it relates the total energy consumption of network devices to the total data volume. By addressing the entire population, the top-down methodology provides more robust results but lacks the capability to form future scenarios, as there is no relationship between network parameters and network energy consumption (Schien and Preist, 2014). The bottom-up methodology is based on direct observations of one or more case studies generalized into total results (Coroama et al., 2015; Coroama and Hilty, 2014; Bond et al., 2018; Aslan et al., 2017). The methodology estimates energy intensity per network device class and aggregates results to all network devices of the end-to-end connection (Schien and Preist, 2014; Ishii et al., 2015). The central assumptions are average energy consumption and data throughput per device class, and the number of such devices in the end-to-end connection (Schien and Preist, 2014; Ishii et al., 2015; Aslan et al., 2017). The model-based methodology models parts of the Internet based on network design principles. Manufacturers' device energy consumption data is inserted into the model leading to total energy consumption, which is related to corresponding data (Coroama and Hilty, 2014). Models rarely take relevant characteristics of an actual network, such as redundancy, cooling, power transmission, or over-provisioning, into account (Ishii et al., 2015). The unified methodology combines the top-down and bottom-up methods. In this methodology, the ratios are calculated top-down and results estimated from bottom-up for each sub-process, such as end-user devices, access networks or data centers in a reference year (Ishii et al., 2015). The unified method evaluates energy consumption characteristics and provides forecasts based on technology trends (Ishii et al., 2015). Several researchers have used the unified methodology (Aslan et al., 2017).

Advancements in the ICT sector emphasize the ability to generalize from already conducted case studies. The combination of technological development and a massive number of different ICT products makes extrapolations and scaling from available data an interesting option (Arushanyan et al., 2014). Based on Arushanyan et al. 2014 review study; in the ICT domain, the manufacturing and use phases have the most significant environmental impact. The same study suggests that in mobile phones the raw material acquisition stage is the most dominant stage regarding environmental impact. Furthermore, in servers, the use stage is the main contributor to the carbon footprint, and in data centers, even in green data centers, the main impact comes from the use stage (Arushanyan et al., 2014).

The average allocation rule is widely adopted. Equipment energy consumption is allocated evenly among the total traffic volume over a fixed time (Coroama and Hilty, 2014). In addition, simplified models of the Internet have been used to overcome the complexity and scale. Such models are sensitive to input variable assumptions and system boundary cut-off criteria. A combination of methods can be used to verify estimates. A guideline for Internet service impact assessment includes: access networks are treated separately, renewal of the equipment taken into account, transmission network is inside the system boundary, recent references, well-justified extrapolation (Aslan et al., 2017), and a share of energy consumption allocated to the digital service (Schien and Preist, 2014).

2.2. Key definitions

2.2.1. The Internet

One of the main challenges in conducting an EIA for the Internet is setting the system boundary. Fig. 1 presents the main building blocks of the Internet ecosystem. The users use the applications through access networks. There are two different access types: mobile- and fixed access. Fixed access includes the Wi-Fi networks. Both access networks are connected to the operator packet switched core (PS-Core) network. The operator core is connected to the Internet, routing traffic to the corresponding data center (DC), where the actual servers providing applications and services reside. Some of the content is processed in the operator core as CDN service. In this study, CDN is estimated to reduce the traffic advancing to the Internet core. Each of the aforementioned technology domains can be described to contain different configurations of equipment, emphasizing the importance of where the boundary of each subsystem is set. Ultimately these building blocks constitute the actual system boundary topology that is being assessed. Note, there is a difference between the Internet ecosystem, later referred to as the Internet, and the Internet connectivity layer, later referred to as the Internet core.

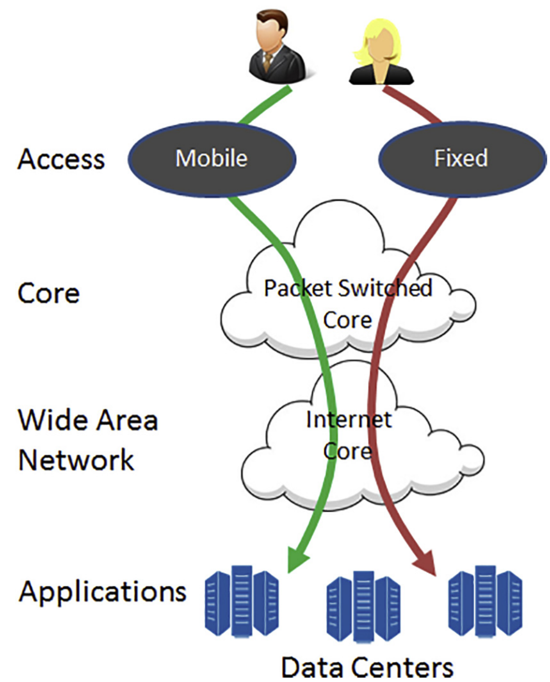


Fig. 1. The main building blocks of the Internet ecosystem.

2.2.2. IP protocol suite and traffic classes

The IP protocol suite is a layered protocol stack where all protocols on a higher level can communicate with lower level protocols through a standard interface. There are two versions of the Internet protocol (IP), the version 4 and the version 6. On top of the IP protocol are the two main transport protocols, namely the transmission control protocol (TCP) and the user datagram protocol (UDP). On top of these are the Internet application protocols such as the hypertext transfer protocol (HTTP), the file transfer protocol (FTP), secure socket layer (SSL) protocol, and many others. The simplified IP suite protocols are presented in Fig. 2 (a). We have highlighted the relevant protocols for this research with gray.

Fig. 2 (b) presents the idea of traffic classes. The IP protocol suite delivers actual services. These services can be separated into different traffic classes representing some common characteristics of individual services. Cisco Systems defines four major traffic classes: 1) *video*, 2) *file sharing*, 3) *web, email, and data*, and 4) *online gaming* (Cisco Systems, 2017a).

2.2.3. Online advertising and advertising fraud

In the US the online advertising revenue has risen from \$26B in 2010 to \$42.8B in 2013, up to \$73B in 2016 (Meeker, 2017; De Haan et al., 2016). According to Gartner, global mobile advertising revenue grew by 92% from \$10B in 2012 to \$19.3B in 2013 and was expected to rise by 100% per year until 2016 (Chen et al., 2016). Operators continue to upgrade their infrastructure to keep up with this pace and to support extra overhead (Chen et al., 2016).

Many websites rely on online advertising as a source of revenue, and a typical web page has multiple ads on it. Online ads use rich graphics, animation, and video, which consume more processing and energy than the rest of the content. HTML5 supported rich media ads are displayed directly on end-user devices. An ad occupies a small portion of the user's display but involves CPU intensive computing processes. The ad format is driving the CPU use and energy consumption; in 2010 a Flash-technology ad used from 50 to 100% of CPU capacity totaling to a 15 W

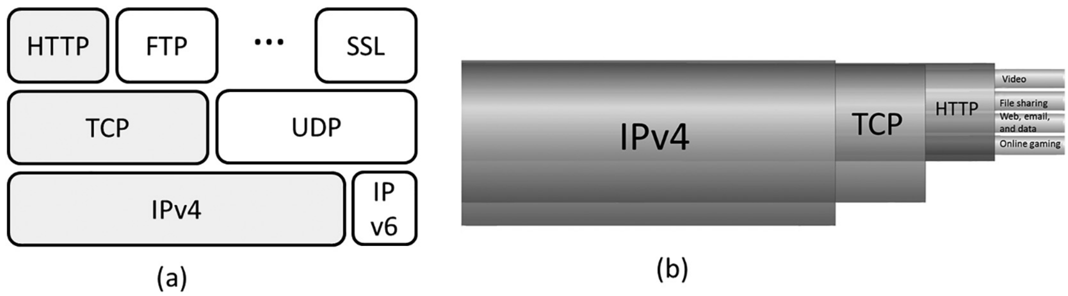


Fig. 2. The simplified IP protocol suite and the traffic classes.

CPU power consumption (Simons and Pras, 2010). The increasing number of ads is counterproductive to the environment (Simons and Pras, 2010).

Online advertising promises real-time measurements, targeting, and optimization at scale. Every intention of every user is collected (Dalessandro et al., 2015). Millions of ads are delivered to capitalize few purchases. A study, done in 2015, of 58 campaigns shows over 50% of the campaigns see less than one purchase per million ad impressions, and this is considered as an excellent result in the advertising industry. A model of 50 positive cases would have to have 50 million ad impressions as a proof (Dalessandro et al., 2015). An advertiser, wanting to conduct a comparison between targeting firms requires tens of millions of ad impressions to prove the performance of each firm (Chen et al., 2016). Everything is on a massive scale.

According to a 2012 study, 10–25% of click frauds were undetectable (Chen et al., 2016). There are three different ways for a click-fraud to occur: 1) use of click bots, 2) tricking users into clicking ads, and 3) paying human clickers. Over 40% of mobile ad clicks are either accidental or fraudulent (Chen et al., 2016). According to a 2017 study (Botlab, 2017), based on a substantial dataset, the percentage of fraudulent online ad-impression with high credibility is 23% of the total online advertising traffic.

2.2.4. *Online Advertising as a contributing factor*

A typical scenario is where an end-user device requests a webpage; the webpage makes requests to dozens of data centers, some of which keep the connection open with the end-user throughout their visit to the page. The connection can be kept open even when the user is idling, resulting in an always-on mobile radio. As long as the user is not moving to the next page, or closing the browser window, the mobile radio remains in the high-power state.

In addition to online ads, the ad industry utilizes trackers, which are small pieces of code residing on websites (Solarwinds, 2018). They are used to track a user's browsing behavior and deliver online ads based on this tracked behavior data (Englehardt and Narayanan, 2016; Solarwinds, 2018)]. According to a Solarwinds company 2018 study, the average load time for the top 50 websites was 9.46 s with trackers and 2.69 s without. This additional load time is energy consuming. The same study found 298 individual trackers, out of which 225 (75%) were associated with online ads to the website. On average, news sites have 41 different trackers and 42% of sites loaded with 30 to 49 trackers, highest having 85 (Solarwinds, 2018). The News category of sites has the highest number of trackers (Englehardt and Narayanan, 2016). Each tracker increases websites download time and total payload.

A study conducted at Princeton University in 2016, consisting of an analysis of 1 million websites, found massive amounts of hidden trackers embedded in websites (Englehardt and Narayanan, 2016). The reasoning for the use of such trackers is that third parties can obtain valuable information about the visitors to a given site. The study found over 81,000 individual third parties present in at least two websites. Third parties responsible for trackers engage in a practice referred to as cookie-syncing. Cookie-syncing is a technique where multiple tracking tags are included in a single container; when the end-user loads the container, connections are established to the data-centers associated with all the tags inside the container (Englehardt and Narayanan, 2016). As a conclusion, online advertising increases energy consumption end-to-end with four factors: 1) the amount of downloaded data increases, 2) the varying inter-transfer interval reserves network, data center, and end-user device resources, 3) the time required to access the payload content or application increases, and 4) the amount of active connections increases.

The New York Times measured in 2015 the mix of online ads and editorial content on top 50 news websites and discovered that over half of all downloaded data originates from online ads. For example, loading Boston.com with ads and trackers had a download time of 30.8 s compared to the 8.1 s of the just the editorial content without ads and trackers. In this case, online ads and trackers created 15.4 MB of data compared to the 4 MB of the editorial content. More than half of all the data come from ads and trackers (Aisch et al., 2015).

2.2.5. *Allocation principle for end-user devices*

In general, the way the user is assumed to use the product is decisive regarding its environmental impact and a source of uncertainty (Arushanyan et al., 2014). In addition, operators have noticed the importance of understanding the behavior of their users and started gathering data from their customers. However, understanding how, when, and where services are consumed is one of the most challenging issues in operator data analysis (Silva et al., 2018). The collecting of significant amounts of behavior data is challenging, since operating systems may restrict access to information, users may have privacy concerns, and data gathering may drain the device's battery (Silva et al., 2018). As a concept, usage is referred to, e.g. the number of hours of use per year, the share of non-use time the equipment is idle or completely turned off, number of years in use, and product reuse and/or recycling (Arushanyan et al., 2014). Usage behavior differs between individuals, cultures, countries, age groups, as well as over time. Therefore, it is often uncertain for a specific case. Mobile user behavior data presents a variety of aspects such as spatial, temporal, application-specific, network traffic, and contextual information. Smartphone user behavior changes over time, space, and on their activities, making pattern mining even more challenging. Some studies try to address these challenges by identifying user profiles based on the applications installed (Silva et al., 2018).

Smartphone apps are frequently used for planning the day, communicating with colleagues, ordering goods or entertainment and socializing. A 2018 study on a large data-set from smartphones of 5342 users in Brazil suggests that the applications with the highest access rates are WhatsApp, Facebook, and browsers. WhatsApp accounted for 60% and Facebook for 18% of the access records. The share of the total usage time of WhatsApp was 60.19%, Facebook 16.72%, and Browsers 8.28%. The same study indicates there is activity around the clock. The most active hours range from 4:00 to 22:00 (Silva et al., 2018). A 2015 study with a data set from 24 smartphone users suggests the top five most used apps were SMS, Phone, Mail, Facebook, and Safari. Facebook and Safari were used for longer durations than the others. In the same study, the overall average duration of a usage session was measured to be 172.8 s, with a minimum duration of several seconds to a maximum of 11 h. The results demonstrate strong variability in usage time for all 24 users (Jesdabodi and Maalej, 2015). A 2010 study on smartphone user behavior, with a data set from 255 users, concludes a substantial diversity in usage behavior, e.g. interactions can last from 30 to 500 min a day and consists of 10–200 app sessions per day, while each session can last from several minutes to an hour. In addition, the study shows that demographic information can be an unreliable predictor of user behavior, and usage diversity exists even when the underlying device is identical. Along with all dimensions of the study, users differ by one or more orders of magnitude. Bursty user interactions at short time scales combined with diurnal patterns at longer time scales have led to an energy consumption process with very high variance and seemingly unpredictable. The authors emphasized strong diversity in usage behavior (Falaki et al., 2010). As for the generalization of results, the authors admit the results may not represent even the entire Brazilian population in all regions (Silva et al., 2018). We predict that in 2016, the variation is even stronger compared to the 2010 study result.

For mobile devices, the most energy consuming hardware components are screen and graphics processing unit, CPU, network, hard drive, and memory (Pang et al., 2016). The applications and software run on the mobile device influence the consumed energy. Energy consumption naturally affects battery life and limits device use. Batteries in mobile devices do not accurately report the actual energy use, and users are seldom aware of energy consumption on their mobile device.

Products have to seamlessly enable support for multiple radio interfaces for providing “always-on” Internet connectivity and higher data rates via either 2G, 3G, 4G or WLAN. Due to requirements of high data rates, the complexity of radio interfaces doubles every 2.5 years (Wang, 2016). Energy consumption of a mobile device is related to the workload characteristics and transfer size. For example, a few hundred bytes transferred on an extended period can consume more energy than transferring a megabyte in one shot (Balasubramanian et al., 2009).

To go into more details, in 3G, nearly 60% of the energy is consumed in high power states after completion of a transfer. This is called tail-energy consumption (Balasubramanian et al., 2009). Energy consumption due to the network activity in the cellular device is dependent on two different factors. First is the transmission distance related to transmitting power level. The second is the radio resource control (RRC) protocol, which is responsible for activity based channel allocation and adjustment of energy consumption of the radio (Balasubramanian et al., 2009). When the radio is not active, it is in an idle state. When the radio is active, higher energy states, like dedicated channel (DCH) or forward access channel (FACH), are used. DCH ensures high throughput and low latency but consumes more energy. FACH is used for little traffic and is a shared channel between many devices, and therefore consumes less energy. The idle state consumes 1% of the energy of the DCH state (Balasubramanian et al., 2009). The current online advertising approach puts continuous pressure on the DCH and creates bursty traffic with the result of long connection times without user activity.

When a device is transforming from an active state to an idle state, there is an inactivity-timer, which is set by the mobile operator. It can vary between different geographical locations. Typically the inactivity-timer in 3G is around 12 s. The energy consumed during the inactivity-timer is called tail-energy, and it represents more than 60% of the total energy consumption of transmission. In comparison, the connection ramp up consumes 14% of total energy. The average energy consumption varies significantly in 3G with varying inter-transfer interval. In WLAN, energy consumption is highest in maintaining an active connection. 3G consumes significantly more energy to download data blocks of all sizes compared to GSM or WLAN (Balasubramanian et al., 2009).

The tail-energy effect means, although there are many idle times between data transmissions, each idle time is still smaller than the inactivity-timer value, and these data transmissions reset the timers again and again. Consequently, the radio interface is always on and the radio resource cannot be released, which consumes end-user device energy significantly and decreases the network capacity (Zhao et al., 2015). For example, heartbeat messages are often used by mobile applications and service backends to maintain connections between each other and update their status. Intuitively, the more frequently the heartbeats are sent, the better synchronization of services is. However, frequent heartbeats are one of the causes of the limited battery life, since the data transmission and excessive signaling keeps radio interfaces always active (Wang, 2016; Haverinen et al., 2007). Intuitively, the more frequent and higher the traffic to and from a mobile device, the higher is the energy consumption and therefore more frequent charging is needed for a device.

As an impact of the tail-energy effect, a smartphone web browser wastes much energy when downloading a website (Zhao et al., 2015). Related with website visits, we conclude on the basis of the characteristics of the current online advertising stack model, as outlined in the Section *Online Advertising as a contributing factor*, that there are two probable and problematic outcomes: 1) device maintains the high energy state as traffic is transmitted continuously, before the operator inactivity-timer is exceeded, or 2) the device alternates between high power state and idle state due to the ad trackers' continuous need for transmitting small payloads with the end-user device. In this light, we recommend using the traffic shares as an allocation basis, instead of hours users spent with the device.

As the 2014 study suggests, the environmental impact of the smartphone use stage was mainly due to the electricity used for charging the phone (Moberg et al., 2014). In a 2016 report, the share of mobile voice traffic from total mobile traffic was roughly 3%. Therefore 97% of all traffic initiated from user activity is directed to data networks and can be associated with services (Obile, 2016). We used these as a baseline assumption for our allocation of user devices. The user behavior is included in the assumption of charging the phone, laptop or tablet, and the relevant share of activity towards the assessed Internet service is a result of standard IP protocol share analysis. Traffic analysis based on the IP protocol suite and traffic classes are a more reliable source of data compared to averaging out the aggressively varying behavior of over four billion end-user devices with hundreds of applications. Nevertheless, we have added the user device usage as parameters into our Python simulation whenever someone would prefer to use it.

2.3. Method for assessing energy consumption of online advertising

Based on the previous knowledge of methods presented in Section 2.1 we created a stepwise framework for assessing the environmental impact of the Internet service locally or globally. The framework consists of eight phases, each phase containing a collection of best practices. All of the phases are utilized in some of the previous studies, but to the best of our knowledge, have not been presented as a generic framework before. We gather many fragmented best practices into a general Internet service environmental impact assessment framework. The phases are presented on a more detailed level in the following sections together with a case study on EIA of online advertising. The framework is presented in Fig. 3.

Our framework consists of eight phases. We have created a system boundary, assessed energy consumption and shares of traffic with top-down or bottom-up methodologies, extrapolated the peer-reviewed base values to the year 2016, and analyzed the results. We have compared direct energy consumption only, excluded energy supply chains containing the supply of primary power, power plants, and grids bringing them to devices. An average grid mix has been used when estimating the CO_2e footprint. In our study, we have included the mobile Internet, as it is in an increasingly important role and its energy consumption has been significant (Coroama and Hilty, 2014). In

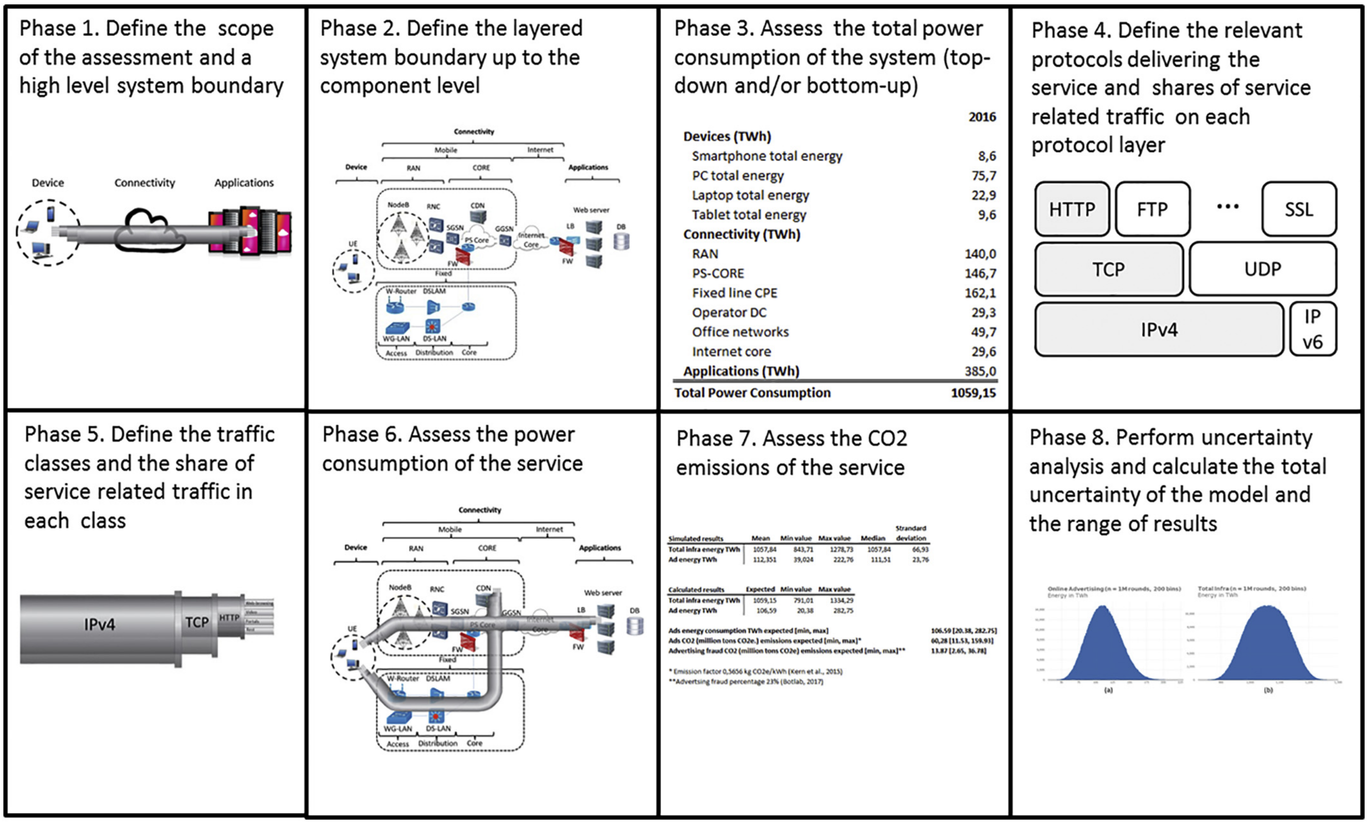


Fig. 3. A framework for the EIA of the Internet service.

addition, we have taken content delivery networks (CDN) into account, as they process services closer to the end users, thus have reduced the need for higher capacity in the Internet core. Comparisons to previous studies should be done with care, as the system boundaries vary between results (Coroama and Hilty, 2014).

The assessment is divided into four discrete analysis layers. The first layer is the energy consumption of the system boundary infrastructure. The second layer is the shares of access network traffic and the shares IP protocols delivering the service. The protocols were selected, as there is current, reliable, and measured data available. The third layer is the traffic classes representing end-user activity. The fourth layer is the share of individual services in each class. Each Internet service belongs to at least one of the classes.

In this study, we utilize the bottom-up method with product based information whenever feasible and reliable data is available. In other cases, the top-down method is used. The data was collected from leading documents in the industry and from scientific articles from the years 2008 to 2017. The proxy data especially is a source of uncertainty for this study. We aim to justify our framework and pinpoint to the significant contributor to global energy consumption, online advertising.

Our framework is aligned with the GHG protocol guidelines and the ETSI standard. Our contribution to the protocol is the method of relying on standard ways to carve out relevant traffic by utilizing the IP protocol stack with trusted available data. Traffic analysis is missing from both of these standards as a key component of the use stage. In addition, instead of changing the allocation method between different technology domains, we maintain the data traffic as an allocation driver end-to-end. This selection has the benefit of taking the whole data path of each session into account and is not in conflict with either of the standards. The user behavior is already accounted for in the average energy consumption of the end device, i.e. smartphones are charged daily. Based on our expertise, online advertising is not a typical service a user subscribes to, i.e. when mobile data is used online advertising activates without any user activity or possibility to control it. In addition, online advertising and trackers are active even without any user interaction with the end device. We have provided a practical and transparent Python tool which can be utilized in future assessments with varying aim and scope.

2.4. Phase 1: scope and high-level system boundary

Our case study is conducted on a global scope. The time boundary set to the year 2016 and the topical boundary is set to being able to access Internet service at any time. Internet usage involves four fundamental high-level sub-systems: 1) the devices the users use to establish a connection, 2) the connectivity connecting the users with the applications, 3) the applications, and 4) the traffic flowing across other sub-systems. The high-level system boundary used in our assessment of online advertising energy consumption and CO_2e emissions is presented in Fig. 4.

The device sub-system consists of four primary categories: 1) smartphones, 2) PCs, 3) laptops, and 4) tablets. To simplify the framework, the average energy consumption of end-devices is assumed to be entirely used to access Internet-based or related services. The connectivity sub-system consists of six primary technology categories: 1) a radio access network (RAN), 2) a PS-Core, 3) fixed line customer premises equipment (CPE), 4) an operator DC, 5) office networks and 6) the Internet core. We included CDNs into the system boundary. CDNs are part of operator PS-Core networks. The energy consumption of CDNs is included in the application sub-system, as essentially CDNs are local proxies for content. The applications sub-system consists of DCs and servers needed to provide services to the end users. The traffic sub-system consists of all the traffic relevant to delivering services across the infrastructure to the end users. The IP protocol suite and traffic classes are utilized to investigate the share of online advertising from the total traffic.

According to Coroama and Hilty, it is useful and transparent to estimate end-device, Internet connectivity, and application energy

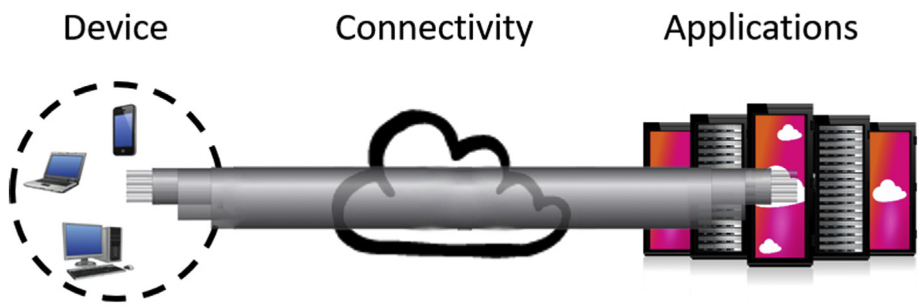


Fig. 4. The high-level system boundary.

consumptions separately and to add partial results up when necessary (Coroama and Hilty, 2014). The assessment should also systematically differentiate between access technologies. DCs should be treated separately as valid primary data is scarce (Schien and Preist, 2014). We follow the suggested principles.

2.5. Phase 2: system boundary

Internet communication includes masses of devices and technologies. The technical complexity of the Internet is increasing, thus creating the need for establishing the simplified multilayer topology of the Internet communications. We evaluated system boundary topologies, but no predefined topology suited the needs of our research. A 2015 study analyzed network energy consumption, but the system boundary excluded DCs and end-user devices (Ishii et al., 2015). A 2014 study excluded CDNs, had an oversimplified mobile network topology and focused on the transmission network as a system boundary (Yang et al., 2015). Nevertheless, it supports our system boundary topology by defining the three main components of a mobile network as mobile devices, a RAN, and a PS-Core. None of the system boundaries found, to the best of our knowledge, included traffic classes. Traffic distributions between different access networks and CDNs, Internet protocols and traffic classes form a baseline for our reasoning. Our system boundary topology supports energy consumption assessment in layers. The analysis layers were: total infrastructure, shares of traffic, shares of protocols, shares of traffic classes and services in those classes. Fig. 5 presents the system boundary of our study.

The highest level of topology abstraction includes the following subsystems: devices, connectivity, applications, and traffic. Devices or user equipment (UE) include smartphones, PCs, laptops, and tablets. Connectivity further divides into three main parts. The first part is mobile connectivity, including both the RAN and the PS-Core. RAN is further divided into NodeBs, which are base stations in a modern RAN, and controllers (RNCs). RNCs connect to the PS-Core via serving GPRS support nodes (SGSN) and to the Internet core through gateway GPRS support nodes (GGSN). The second part is the fixed network, including the fixed access network devices, wireless CPE, wireless routers and digital subscriber line access multiplexers (DSLAMs). The DSLAM is connected to the PS-Core. In addition, the fixed network includes office local area networks (LANs).

The CDN network servers are located in the PS-Core as proxies for services like websites and video content. Once the content is located in the CDN, there is no need to access the Internet core. CDN operates for both fixed and mobile networks. The third part is the Internet core, consisting of core routers responsible for routing traffic between networks. The ingress connections from the Internet core to the actual

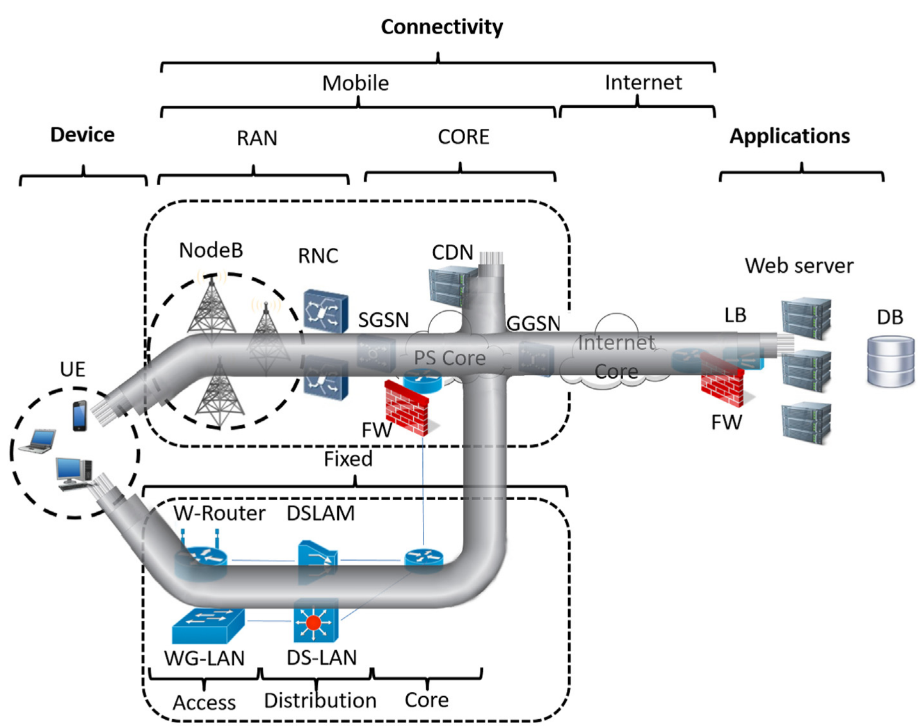


Fig. 5. A simplified system boundary topology of the Internet communication.

Table 1
Technology domains and used methods.

Technology domain	Method used for evaluation
Devices	
Smartphone total energy	Bottom-up
PC total energy	Bottom-up
Laptop total energy	Bottom-up
Tablet total energy	Bottom-up
Connectivity	
RAN	Top-down
PS-CORE	Top-down
Fixed line CPE	Top-down
Operator DC	Top-down
Office networks	Top-down
Internet core	Top-down
Applications	Top-down

applications residing in DCs go through a firewall (FW) and usually load balancing has been included. The application servers are connected to databases and form the services.

It should be noted that when a device searches for a web page with its browser, unless the content is found in CDN proxies, the complete end-to-end connectivity, and relevant applications are active. In Table 1 we present the main technological domains and methods used. Note that we did not include CDN as a technology domain separately; proxy servers process service data like servers in the centralized DCs but are located closer to the end users.

A system boundary, in extreme cases, included all ICT equipment connected to the Internet as a part of the Internet. According to Coroama and Hilty, the inclusion of everything creates variability when evaluating a specific task with a specific device (Coroama and Hilty, 2014). For our scope, none of the services can be used without devices connected to the Internet. For example, social media is not worth anything without the billions of participants in the network, and similar reasoning applies to almost any web services. For our purposes, a single user is not relevant, but masses of devices and users are. According to the same study, if we wanted to determine the energy consumption of watching a single video from the Internet, the system boundary should include one user device for the duration of the video, Internet transmitting the data, and a server providing that data (Coroama and Hilty, 2014). We argue many parts are missing or unclearly expressed in the system boundary. Even though averages are used, the idea of being informed requires more than just the exact time and place of consumption; the share of idle time must also be allocated. For DCs, the average represents the actual energy consumption well (Wahlroos et al., 2017).

There are uncertainties related to our system boundary. The proposed system boundary gives an opportunity to repeat the analysis and increase the detail level whenever more specific device inventory and device-specific energy consumption information is available. The same idea applies to all layers of analysis. The system boundary topology is not oversimplified or too detailed for our purposes when intermediate results from previously conducted studies are extrapolated to the year 2016.

2.6. Phase 3: total energy consumption estimation of the infrastructure

The section aims to present the methods we used to calculate the 2016 total energy consumption of our system boundary.

2.6.1. End user devices

An Internet user is defined as a person with access to the Internet from a home residence through mobile equipment or a computer (Vlachos, 2016). In 2012, 34.3% of the global population were Internet users (Whitehead et al., 2014). In 2017, the number of Internet users has risen to 3.4–3.9 billion users, and it continues to grow at a nearly flat annual rate of 10% (Vlachos, 2016; Internet World Stats, 2017).

In a 2017 study, the install base for smartphones was 400 million devices in 2010, and 2.8 billion devices in 2016 (Meeker, 2017). The number of annually produced smartphones is expected to grow from around 350 million in 2010 to around 3 billion devices in 2030. With linear growth, the annual growth rate is 37.9%. In this study, we will use the Statista values for a number of smartphones globally (Statista, 2018a). The amount of smartphones in 2016 is 2562 million devices. The data from Statista is publicly available. The 2016 Statista value is 8.5% lower than the Meeker 2017 report suggests (Meeker, 2017). Therefore, we will use the 10% as a level of uncertainty in our study.

The most popular smartphones in 2016 had a battery capacity ranging from 1810 mAh (iPhone 6) to 3000 mAh (HTC 10). The amount of electricity needed to charge a phone battery was 6.9 Wh for iPhone 6, and 11.4 Wh for HTC 10 (Canstar Blue, 2016). If we assume once a day charging for a full year, the energy consumption of smartphones will be in the range of 2.519 kWh to 4.161 kWh per year. We will use the average annual energy consumption of 3.34 kWh, and extrapolate the past and future years with energy usage improvement of 3%. Our estimation of uncertainty was in the range of 30%.

In 2010, the growth of the PC install base was estimated to be 10% annually (Koomey et al., 2011). In a more recent 2015 study, the quantity of desktops is expected to decline in the future (Yang et al., 2015; Pickavet et al., 2008). Desktop computers are rarely turned off when they are not in use (Minovski et al., 2016). On the other hand, transitioning to laptops and tablets has a positive impact on average energy consumption (Pickavet et al., 2008). The install base of desktops in 2012 was 326 million devices, and the amount has not increased by 2016, instead, the development has been flat at 325 million devices (Statista, 2018b). The number of laptops is expected to increase from 200 million devices in 2010 to 548 million devices in 2016, reaching up to 780 million devices in 2020 (Andrae and Edler, 2015). We will use the 10% as a level of uncertainty for the number of PCs, laptops, and tablets in our study.

A 2014 study investigated the energy consumption of desktops and laptops (Van Heddeghem et al., 2014). In 2007, an office desktop on average consumed 149 kWh (137 kWh in 2012), and a household desktop on average consumed 231 kWh of energy (213 kWh in 2012). A desktop computer requires a monitor, and a LCD monitor on average consumed 70 kWh of energy in 2007 (the same in 2012). Taking the average consumption of a desktop and a LCD monitor, we ended up with 2007 average energy consumption of 260 kWh (245 kWh in 2012). Extrapolating the 2007 and 2012 energy consumption values, we ended up with an average of 233 kWh for 2016, and an annual decrease of approximately 1%. Our estimation of uncertainty was in the range of 30%. Another study estimated that desktops in idle mode consumed 45 W (394 kWh/year) in 2010 (Kern et al., 2015). The expected annual energy consumption improvement is 3% from 2011 to 2030 (Andrae and Edler, 2015).

In 2007, an office laptop on average consumed 46 kWh (39 kWh in 2012), and a household laptop on average consumed 70 kWh of energy (59 kWh in 2012). The average of energy consumed by a laptop in 2007 was 58 kWh (49 kWh in 2012). Extrapolating the 2007 and 2012 energy consumption values, we ended up with an average of 41.8 kWh, and an annual decrease of approximately 4% (Van Heddeghem et al., 2014). Our estimation of uncertainty was in the range of 30%.

The install base of the three largest tablet platforms, Android, iOS and Microsoft Metro, has increased from 15.9 million devices in 2010 to 741 million devices in 2016 (TekCarta., 2018). The install base of desktops was 326 million devices in 2012, and it was at the same level in 2016, at 325 million devices (Statista, 2018b). Combining the presented 2016 device numbers, we reach 1614 million desktops, laptops, and tablets. This is close to the 2016 Ericsson report, where laptops and tablets have leveled to 1.7 billion devices (Obile, 2016).

A 2016 test investigated the energy consumption of iPad Air2 (www.zdnet.com, 2016). In the test, the iPad was charged overnight and the energy consumption measured. The energy consumption was 35.3 Wh during an overnight charge. Over a 365 day period, the energy consumption amounts to 12.9 kWh. For 2016, we will use a value of 12.9 kWh for energy consumption and extrapolate the past and future years with energy usage improvement of 3%. Our estimation of uncertainty was in the range of 30%.

2.6.2. Mobile access network

Mobile networks provide connectivity via base stations to the core network routers. Core routers direct traffic between multi-tiered networks towards the destination (Schien and Preist, 2014). Mobile access networks consist of 2G, 3G, 4G and 5G (Andrae and Edler, 2015). Gozalvez estimated 85% coverage for 3G by 2017 and 50% 4G coverage of global population (Gozalvez, 2012). In a mobile network, only 10% of the energy consumed is customer end-point related. The most energy-hungry parts of a mobile network are the RAN and DC (Fettweis and Zimmermann, 2008; Koutitas and Demestichas, 2010). The factors affecting energy consumption in mobile networks are cooling, capacity, coding, and workload scheduling.

In a 2015 study, 2–5G RANs are estimated to consume 200 TWh of energy in 2010 and decrease to 100 TWh by 2020, assuming a 22% energy efficiency improvement annually (Andrae and Edler, 2015). For 2016 RAN, energy consumption is estimated to be 140 TWh. We will use the estimations above as our base values because operating different generation RANs at the same time is taken into account. Running different generation RANs simultaneously represents a realistic situation in the network operator business. For earlier years, we estimate lower energy efficiency improvement, as macro cells were dominating the configuration. Thus the capacity need was lower (Badic et al., 2009).

Results from other researchers indicate the total global energy consumption of telecom operator networks in 2007 was estimated to be 160 TWh, and in 2012 260 TWh/year, with an annual growth rate of 10.2% (Lambert et al., 2012). An older 2008 study estimated energy consumption growth rate to be 16–20% annually (Fettweis and Zimmermann, 2008; Badic et al., 2009). According to a 2011 study, (Han et al., 2011) RAN consumes 57%, PS-Core 35% and DC 7% of the energy consumed by a typical mobile network. We will use the division above when evaluating the energy consumption of PS-Core and operator DC. A 2012 study approximated the energy consumption of global RANs to be 105 TWh, and another 2013 study for the same system estimated 125 TWh (Korotky, 2013; Andrae and Edler, 2015). Based on these previous studies, we will use an uncertainty level of 20% in our estimation.

Sources of uncertainty are: 1) energy efficiency improvement percentages, 2) inherent uncertainties of our references, 3) the system boundary of the previous studies, 4) the pace at which operators take new generation RANs into use, and 5) the removal of the legacy systems. Some of the incumbent operators are operating 2–5G RAN simultaneously, which is highly inefficient from the energy consumption perspective.

2.6.3. Fixed access network

Access networks dominate the energy consumption of ICT with increasing access rates (Coroama and Hilty, 2014; Koutitas and Demestichas, 2010). Fixed access networks consist of fixed access wired and fixed access wireless networks (Andrae and Edler, 2015). Networking equipment wastes energy because the energy proportionality is low (Heller et al., 2010). Improvement of data rates in optical networks improves the overall transport network energy efficiency. At the same time, the total fixed access traffic is expected to increase from 320 EB in 2010 to 1900 EB in 2020, and to rise to 13,000 EB in 2030 (Andrae and Edler, 2015).

According to a 2015 study, the fixed access infrastructure will continue to expand, and its energy consumption improvement is estimated to be 10% per year. In the same study, 2012 energy consumption was estimated to be 196 TWh for fixed access wired and 51 TWh for fixed access wireless networks (Andrae and Edler, 2015). We will use the 2012 estimation as a base value, and extrapolate the past and future years' energy consumption with a 10% annual improvement percentage. Energy consumption in 2016 was estimated to be 162 TWh. The 2012 base value was selected because both the wireless and wireline networks are included. In addition, the study is relatively recent and peer-reviewed.

Caroma et al., argue that energy consumption of access networks should be allocated by time used and not data, as the amount of electricity used does not vary with data (Aslan et al., 2017). For this paper, we will not use the time used as an allocation key, as being online requires connectivity even if services are not used all the time.

In 2013, Alcatel-Lucent estimated average power consumption of fixed access networks to be 31.9 GW (279 TWh) (Andrae and Edler, 2015). This estimation is 20.5% higher compared to our estimation of 222 TWh in 2013. Therefore, we will use an uncertainty of 20% in our uncertainty analysis. We have recognized the yearly energy consumption improvement percentages and the use of referenced intermediate results as uncertainties.

2.6.4. Operator PS-cores and DCs

Operator DCs operate servers needed to run operator key functionalities such as network management, charging systems, and other business support systems. The operator DCs are not part of the service core DCs running the actual applications for end users. An operator PS-core network connects RANs to the Internet core. A 2011 study suggests that a PS-Core consumes 35% and an operator DC 7% of the total energy consumption of an operator (Han et al., 2011). We calculated the PS-Core and operator DC base values from the same 2015 study, which was used in defining the energy consumption of RANs (Andrae and Edler, 2015). In 2016, PS-Core consumed 146.7 TWh and operator DC 29.3 TWh of energy. For the annual energy consumption growth rate, we will use 12% (Pickavet et al., 2008).

In a 2008 Ericsson study, an estimation of 60 TWh of energy was consumed in RAN backhaul networks (Fettweis and Zimmermann, 2008). Our estimation of energy consumption of PS-core in 2008 was 55 TWh. There is an uncertainty of 10%. In the same year, the Environmental Protection Agency (EPA) estimated a 14% annual growth rate for networking equipment (Taylor and Koomey, 2008). There is an uncertainty of 15% in the growth rate. Combining these uncertainties we use the 25% total uncertainty when calculating PS-Core and operator DC energy consumption.

We have recognized the energy consumption growth percentages and the assumption of energy consumption shares between a RAN, operator DCs and a PS-Core as uncertainties. The justification for using the same energy consumption growth percentages for a PS-Core and operator DCs is founded on the evidence of reduced energy intensity in networking devices and on virtualization of servers and growth of data in both.

2.6.5. Office networks

An inventory based study done in 2006 estimated office networks to consume 7.2 TWh of energy (Taylor and Koomey, 2008). According to another 2008 inventory based study (Pickavet et al., 2008), networking equipment globally consumes approximately 25 GW (219 TWh). We will use a more recent 2012 study, suggesting office network energy consumption of 27.8 TWh in 2007 and 42.4 TWh in 2012 (Lambert et al., 2012). The estimation included office switches, routers, enterprise WLANs and security devices. The extrapolated 2016 energy consumption of office networks is 49.7 TWh. We estimate the same 25% uncertainty rate as with PS-Core.

The growing data transmission rate and more energy-hungry device generations lead to increased energy consumption. We have recognized the old references for base values and many years of extrapolation as uncertainties.

2.6.6. The Internet core

According to a 2008 study, the energy intensity of Internet data transfers decreases by 30% yearly (Coroama and Hilty, 2014). System boundaries have a significant impact on energy consumption estimations (Aslan et al., 2017). Internet energy consumption, excluding access networks and end devices, was 85 TWh in 2006 (Taylor and Koomey, 2008). Lantizera et al., in a 2012 study included network equipment in their top-down analysis and estimated 50.8 TWh to be the global energy consumption of the Internet core, and 67.3 TWh for all network equipment (Ishii et al., 2015). We will use the peer-reviewed reference value of 85 TWh from 2006 as our base value for the Internet core, as it has a system boundary excluding access networks and end devices. In addition, with a 10% annual energy efficiency improvement, it is very close to Lantizera's 2012 result. The 2016 energy consumption of the Internet core was 29.64 TWh. We note the 2014 study, with an estimated annual energy consumption of the Internet core at 7.8 TWh (Schien and Preist, 2014), which is almost less than a tenth of the energy consumption of Koomey et al., results. For this reason, we estimate a high uncertainty rate of 40%.

The energy consumption of the Internet core has decreased due to the use of CDNs and the popularity of direct peering arrangements between operators and IXPs. We have recognized the significant variance between reference base values and many years of extrapolation with a fixed growth rate as uncertainties.

2.6.7. Data centers

A DC is defined as space housing ICT assets, such as racks, servers, switches, and storage, with controlled environmental conditions such as temperature, humidity, and dust (Ebrahimi et al., 2014; Whitehead et al., 2014). DCs induce a power overhead such as cooling and lighting (Coroama and Hilty, 2014). DCs have the fastest growing carbon footprint and energy consumption across the whole ICT sector (Fettweis and Zimmermann, 2008; Whitehead et al., 2014; Ebrahimi et al., 2014; Andrae and Edler, 2015; Salahuddin et al., 2016; More and Ingle, 2017). DCs vary in size, from single rack closets to massive server farms (Whitehead et al., 2014; Valliyammai et al., 2014). In a 2017 study, the total workload energy consumption inside a DC is divided between servers at 70%, access switches at 15%, distribution switches at 10%, and core switches at 5%. Servers are further divided into 43% CPU, 4% discs and 12% memory. Similarly, switches are divided into chassis at 36%, line cards at 53%, and port transceiver at 11% (More and Ingle, 2017; Koomey, 2007). Energy proportionality of servers is still low. The majority of servers operate at a utilization rate below 0.20, consuming 60–100% of the maximum power available (Ebrahimi et al., 2014). Even at 10% CPU utilization, power consumption was more than 50% of the maximum (Valliyammai et al., 2014).

In a 2011 study, a projection of a slow-down in DC energy consumption growth rate was introduced. The reduction was due to energy efficiency improvements, the recession, and virtualization. As a result, worldwide DC energy consumption grew from 70.8 TWh in 2000 to 152.5 TWh in 2005, and 301.1 TWh in 2010 (Koomey, 2008; Koomey, 2011). With similar assumptions, energy consumption in 2015 was estimated to be 371.1 TWh (Whitehead et al., 2014). In this study, we used the aforementioned base values, as they have the same system boundary across the period, and extrapolated the 2016 DC energy consumption of 385.04 TWh.

In a 2008 study, a yearly average of 29 GW (254 TWh) and a growth rate of 12% were estimated for DC power consumption (Pickavet et al., 2008). Another 2008 study estimated energy consumption of 180 TWh (Fettweis and Zimmermann, 2008). Alcatel-Lucent approximated that in 2015 DCs used 325 TWh annually (Alcatel-Lucent, 2015; Andrae and Edler, 2015). There is a shift in energy usage from consumer devices onto networks and DCs (Andrae and Edler, 2015). According to a 2016 article in The Independent, applications, with required hardware running, in DCs consume 416.2 TWh of electricity on a global scale (The Independent, 2016). From these results, we conclude an uncertainty rate of 25% for DC energy consumption in 2016.

Table 2
ICT energy consumption 2016 breakdown with the system boundary.

	2016
Devices (TWh)	
Smartphone total energy	8.6
PC total energy	75.7
Laptop total energy	22.9
Tablet total energy	9.6
Connectivity (TWh)	
RAN	140.0
PS-CORE	146.7
Fixed line CPE	162.1
Operator DC	29.3
Office networks	49.7
Internet core	29.6
Applications (TWh)	385.0
Total Energy Consumption (TWh)	**1059.1**

We have recognized the old reference for base value and many years of extrapolation between base values as uncertainties. There are some key trends that support the increase in DC energy consumption: 1) the energy used per unit for all product types is higher as a function of time (Koomey, 2007; Koomey et al., 2011), 2) performance is more important than energy efficiency (Jagroep et al., 2017), and 3) application energy efficiency and energy consumption is not well known (Pickavet et al., 2008).

2.6.8. Summary of the energy consumption

The energy consumption of our infrastructure system boundary is presented in Appendix A Table A.1. For further analysis, we will use the subset of Table A.1, 2016 values, as presented in Table 2.

2.7. Phase 4: Internet protocol distribution

The methods for estimating future traffic can be classified into forecasts and projections. Forecasts are predictions with initial conditions and varying future values. Projections are expectations based on extrapolation or semi-empirical relationships with a lower number of variables and transparency. Widely adopted best practices for projecting trends in IP traffic include regression analysis, neural networks, extrapolations and curve fittings (Vlachos, 2016). These projections must be based on Internet traffic generated by all connecting devices (Vlachos, 2016). Relevant IP traffic measurement points include Internet eXchange Points (IXPs), ISPs and major backbones. Common traffic metrics include incoming and outgoing traffic from IXPs and peak flows from traces (Vlachos, 2016).

An Internet traffic classification method is a process of identifying shares of network protocols, applications on top of them, and investigating the corresponding traffic per traffic class (Wang et al., 2014). There are two main specifications for classification: 1) identify application protocols, and 2) classify network traffic into a range of common groups of applications such as file transfer, web browsing, and email (Wang et al., 2014). There are 14 main applications identified in the Wang et al., substantial data sets: HTTP, HTTPS, BitTorrent, SSH, Razor, POP3, FTP, IMAP, DNS, SMTP, MSN, SMB, XMPP and SSL (Wang et al., 2014). We first investigate the total IP traffic on a global level and subdivide it into two different access technologies and a CDN. Second, we use the IP protocol suite to identify the share of traffic related to HTTP(S) traffic, which is the relevant part of the traffic for our further analysis purposes. Third, we divide the HTTP traffic into four traffic classes. Fourth, we estimate the share of online advertising in each traffic class and extrapolate the 2016 energy consumption of online advertising.

Globally IP traffic is increasing, but the growth rate has been slowing down towards 2014 (Vlachos, 2016). Cisco Systems is a leading body delivering estimations of global traffic (Lee and Lee, 2013; Vlachos, 2016). The total IP traffic included fixed network traffic, mobile data traffic and managed IP traffic (Cisco Systems, 2017a). We have included fixed network traffic and mobile data traffic in our assessment. We have scoped out managed IP traffic generated by traditional commercial TV service providers. This traffic remains within the footprint of a single service provider; therefore, it is not considered relevant IP traffic for our assessment. Thus it is included in the total IP traffic.

CDNs have become a dominant method for delivering video-streaming content (Cisco). A large proportion of Internet video traffic will cross CDNs, but it is not additional traffic. Therefore it is not included in the total IP traffic. The share of IP traffic passing CDN is utilized for assessing the share of traffic passing to the Internet core network.

According to a Cisco 2017 study (Cisco Systems, 2017b), the total global IP traffic is 1200 EB in 2016. In 2016, fixed line dominated the IP traffic, but wireless is growing at a fast pace. The total traffic was distributed between the fixed network (68.63% of the total traffic), managed IP traffic (23.85% of total traffic) and mobile network IP traffic (7.5% of the total traffic) (Cisco Systems, 2017a).

In 2016, CDN traffic represented 39.9% of the total IP traffic, and it has increased to a level of 38.340 EB/month with a compound annual growth rate of 44% (Cisco Systems, 2017a). According to a 2013 study, CDN traffic amounts to more than 50% of all web traffic, and it is expected to increase as *video* traffic increases (Frank et al., 2013). In addition, mainstream applications are increasingly exchanged through application-specific peering to further avoid transit costs (Gupta et al., 2015). Online advertising is often delivered through CDNs (Pujol et al., 2014). We estimate the uncertainty of 10% to all traffic amounts as the references are quite recent and from widely cited sources.

In 2013, IPv4 constituted 99.4% of traffic (Czyz et al., 2014). In 2014, IPv6 accounted for 1% (Pujol et al., 2014) - we estimate a slow increase to 1.5% in 2016 and an uncertainty of 20%. In 2013, TCP's share of traffic, according to a dataset from two exchange IXPs, two transit ISPs, one content ISP, and a CDN server provider, on average was 85.27% (range 73.87% to 97.22%) and UDP's 14.73%. We expect a slight yearly increase of 1.5% in TCP traffic until hitting 89.77% in 2016, as HTTP based applications are increasing in number. HTTP(S) dominates the application mix in all parts of the network measured using any methodology. We estimate the uncertainty of 0.5% for IPv4 and 5% for TCP.

The HTTP protocol is a standard interface for videos, social networking, e-commerce, and software delivery. These applications are often supported by advertisements, which are also delivered via HTTP (Pujol et al., 2014). In 2013, the share of HTTP(S) was more than 69.2% (Czyz et al., 2014). The share of HTTPS is increasing. We expect a pessimistic increase to a 74.2% HTTP(S) share in 2016. All the rest are small shares of traffic (Czyz et al., 2014). In the 2014 data sets (Pujol et al., 2014), the share of HTTP(S) out of the TCP traffic ranged from 64.58% to 95% with an average of 81.38%. Therefore, we estimate the uncertainty of 10%.

As the size of the networks and the amount of devices increases and their performance improves, it has become a challenge for ISPs to collect and analyze massive sets of raw data, flow records, activity logs, and SNMP metrics (Yang et al., 2015). Predicting facts before they happen is challenging. Therefore projections always have uncertainties (Korotky, 2013; Vlachos, 2016). Some of the key uncertainties are: 1) traffic remaining within a service provider, 2) peering traffic, 3) diversity of traffic monitoring, 4) capturing techniques (Vlachos, 2016), and 5) models (Korotky, 2013). With proper prediction models, the uncertainty can be as low as 5–10% (Vlachos, 2016). According to Cisco, the uncertainty level decreased from 20% in 2006 to 3% in 2011, the average uncertainty being 11.56% (Vlachos, 2016). Between 2012 and 2014, the average uncertainty was 4.12% (Vlachos, 2016). Cisco's 2008 prediction for fixed IP traffic in 2012 was 31.339 EB/month, while the measured value was 31.338 EB/month, leading to a low value of uncertainty (Vlachos, 2016). A summary of the shares of Internet traffic and the IP protocol suite is presented in Appendix A Table A.2 and A.4.

2.8. Phase 5: the share of service related traffic in traffic classes

Several studies have been conducted to define the share of different applications from total IP traffic. In a 2014 study, the top applications of 2010 for fixed networks have the following shares of application traffic: streaming over HTTP at 25%, file hosting at 2–10%, and social networking at 5% (García-Dorado et al., 2012). For mobile Internet in 2015, the top applications were social networks at 55.65%, search engines at 14.27% and e-commerce at 7.53% (Yang et al., 2015).

We will utilize the Cisco Visual Networking Index (VNI) results (Cisco Systems, 2014–2017a) to present shares of traffic classes from total IP traffic. Cisco has conducted the VNI results from several years, and it has been used in most of the traffic-related studies as a reference.

Cisco defines four traffic classes: 1) *video*, 2) *file sharing*, 3) *web, email, and data*, and 4) *online gaming* (Cisco Systems, 2017a). The *video* traffic class consists of an online video that is downloaded or streamed for viewing on a device. Video streaming has been growing at a significant rate due to popularity and the availability of high-quality video streams (García-Dorado et al., 2012). Major contributors in fixed line video traffic are: 1) Netflix at 35%, 2) YouTube at 17%, 3) Amazon video at 4%, and the rest at 44% (Meeker, 2017). *File sharing* includes traffic from P2P applications and another web-based file sharing. The web browsing, email, instant messaging, and data traffic -class includes web, email, instant messaging, and other data traffic (excludes *file sharing*). *Online gaming* includes casual online gaming, networked console gaming, and multiplayer virtual-world gaming.

According to a Cisco 2017 report (Cisco Systems, 2017a) in 2016, video traffic represented 61.48% of the total worldwide mobile IP traffic. The second most significant contributor to mobile traffic was the *web, email, and data* traffic class with a share of 38.01%. The *file sharing* (0.49%) and *online gaming* (0.02%) traffic classes played a minor role. In the fixed network, the *video* traffic class represented a share of 72.84% of the total consumer IP traffic. The *file sharing* had 12.53%, and the *web, email, and data* traffic class had 12.90% share of the traffic. *Online gaming* represents a share of 1.74% of the total IP traffic in fixed networks. All of the shares above are from consumer users. Consumer traffic represents an 81.46% share of the total IP traffic (Cisco Systems, 2017a). The results are presented in Appendix A Tables A.3 and A.5.

We utilized these intermediate results and calculated the energy consumption of all traffic classes. We utilized the traffic shares and divided the shared technology domains accordingly. As an example of a 100% mobile traffic related technology domain, we used the following Eq. (1) for calculating the RAN energy consumption share of the *web, email, and data* traffic class:

$$\mathrm{E}_{\text{web,email,and data,RAN}} = \mathrm{E}_{\text{RAN}} * \%\text{IPv4} * \%\text{TCP} * \%\text{HTTP} * \%\textit{Mobile traffic}_{\text{web,email,and data}} \tag{1}$$

The Internet core is an example of a component sharing traffic from fixed and mobile networks. We used the following Eq. (2) for calculating the Internet core energy consumption share of the *web, email, and data* traffic class:

$$\begin{aligned}\mathrm{E}_{\text{web,email,and data,Internet core}} = {} & (\mathrm{E}_{\text{Internet core}} * \%\text{Fixed} - \text{line traffic} * \%\text{IPv4} * \%\text{TCP} * \%\text{HTTP} * \%\textit{Fixed traffic}_{\text{web,email,and data}}) \\ & + (\mathrm{E}_{\text{Internet core}} * \%\text{Mobile traffic} * \%\text{IPv4} * \%\text{TCP} * \%\text{HTTP} * \%\textit{Mobile traffic}_{\text{web,email,and data}}) \\ & - ((\mathrm{E}_{\text{Internet core}} * \%\text{CDN} * \%\text{Fixed line traffic} * \%\text{IPv4} * \%\text{TCP} * \%\text{HTTP} * \%\textit{Fixed traffic}_{\text{web,email,and data}}) \\ & + (\mathrm{E}_{\text{Internet core}} * \%\text{CDN} * \%\text{Mobile traffic} * \%\text{IPv4} * \%\text{TCP} * \%\text{HTTP} * \%\textit{Mobile traffic}_{\text{web,email,and data}}))\end{aligned} \tag{2}$$

Table 3
The energy consumption of each HTTP traffic class in 2016.

	Video	File sharing	Web, email, and data	Online gaming	Total	Note
Devices (TWh)						
Smartphone	3.45	0.03	2.13	0.001	5.61	100% mobile traffic relater
PC	36.19	6.22	6.41	0.86	49.68	100% fixed line traffic related
Laptop	10.95	1.88	1.94	0.26	15.03	100% fixed line traffic related
Tablet	4.57	0.79	0.81	0.11	6.28	100% fixed line traffic related
Connectivity (TWh)						
RAN	56.47	0.45	34.92	0.02	91.85	100% mobile traffic relater
PS-CORE	52.54	8.31	11.26	1.15	73.25	68.63% fixed line +7.5% mobile traffic related
Fixed line CPE	77.44	13.32	13.72	1.85	106.33	100% fixed line traffic related
Operator DC	10.51	1.66	2.25	0.23	14.65	68.63% fixed line +7.5% mobile traffic related
Office networks	23.74	4.08	4.20	0.57	32.59	100% fixed line traffic related
Internet core	6.38	1.01	1.37	0.14	8.89	68.63% fixed line +7.5% mobile - 39.92% CDN * (68.63% fixed line +7.5% mobile)
Applications (TWh)	137.93	21.81	30.38	3.01	193.14	68.63% fixed line +7.5% mobile
Total	380.53	53.31	100.85	7.33	597.31	

A summary of the calculations is presented in Table 3 below:

As expected, *video* traffic consumes the most energy with nearly 380 TWh per year out of all HTTP based traffic. The impact of CDNs is mostly in reducing both the service latency and the need to invest in expensive Internet core and transit capacity, for example, underwater transatlantic capacity. CDNs do not take away the need for server processing. HTTP protocol-based services consume nearly 600 TWh of energy per year.

2.9. Phase 6: energy consumption of online advertising

To analyze the share of energy consumed by online advertising with our framework, we need to investigate the proportion of the total traffic related to online advertising. We estimate the share of online advertising in each HTTP based traffic class. No direct shares of online advertising were found in any references. We estimate the shares of online advertising by first introducing the online advertising and its characteristics. Secondly, we present the concept of effectiveness in ad impressions. Thirdly, we investigate mobile and video ad characteristics.

The main difference between online and offline advertising is the cost of targeting (Goldfarb, 2014). In a 2011 study, it has been observed that 12% of all HTTP requests consist of ad-related traffic and the percentages tend to rise with market growth (Ihm and Pai, 2011). Any ad space on a website must be sold in 100 ms. Otherwise, a blank space is shown to the end user, and a revenue loss will occur (Chen et al., 2016). Therefore, real-time bidding (RTB) is needed. RTB is the technology performing the massive aggregation and ad space bidding supported by targeting algorithms (Chen et al., 2016; Pujol et al., 2014). When RTB is used, a visit to a website generates a large number of background connections from that website (Pujol et al., 2014).

The effectiveness of an ad impression depends on a person's history data (Braun and Moe, 2013). There are several techniques to increase the effectiveness of an ad impression: 1) content integration, 2) search engine advertising, 3) display advertising (De Haan et al., 2016), 4) classified advertising and 5) tracking (Goldfarb, 2014). In content integration, the advertising is integrated into the content of the website (De Haan et al., 2016). A search is a statement or intent; in search engine advertising ads can be targeted effectively precisely when potential customers are looking for something. Display advertising includes banner ads, plain text ads, media-rich ads, video ads, and typical ads seen on Facebook for example. Classified advertisements are ads residing on websites that do not provide other media content or algorithmic search (Goldfarb, 2014). Tracking users at scale is not technically challenging (Chen et al., 2016). One website can contain as much as seven different trackers. Some trackers capture over 20% of a user's browsing behavior (Roesner et al., 2012). All of the techniques above are used on a massive scale: we claim the techniques are generating substantial network traffic end-to-end. Therefore, we estimate an advertising share of 50% for the traffic class *web, email, and data* in 2016, with an uncertainty range of [25%–75%]. The share is the same for both mobile and fixed traffic.

Unlike fixed-line online ads, mobile ads integrate with free applications. According to a Guardian 2016 article, up to 79% of data transferred is ads, and almost half of the data downloaded to smartphones were ads (The Guardian and Jackson, 2016). In September 2016, 73% of mobile applications were free. Ad-supported free apps receive 50 times more downloads and generate ten times the revenue compared to ad-free paid apps. Free apps cost more to end users than ad-free paid apps due to the notably higher advertising traffic (Chen et al., 2016). Therefore, we estimate the share of mobile video ads, including the free-apps advertising to be 14% in 2016, with an uncertainty range of [3%–25%]. The share of online ads was considered to be 10% for fixed network *video*, with an uncertainty range of [2%–18%]. The share of *video* traffic from global IP traffic is over 67%. We claim our estimation of the share of online advertising in *video* traffic is in the right magnitude, with the range of uncertainty taken into account.

For the *file sharing* and *online gaming* traffic classes, in both fixed and mobile networks, we will use 10% as an estimation of the share of ad traffic out of the total traffic, with an uncertainty range of [1%–19%]. Table 4 presents the shares of online advertising in each traffic class in 2016.

All of the estimations contain uncertainty. The actual shares of online advertising are not known precisely. In addition, the amount of uncertainty is not known. We will use larger ranges for uncertainty than the UNIDO method for uncertainty suggest, changing key parameters within the range of −20% to +20% (Berens and Havranek, 1995).

Generally, studies regarding online advertising contain

Table 4
The share of online advertising in each traffic class.

	Online ad share	Uncertainty	Reference
Fixed network			
Video	10.00%	[2%–18%]	Estimation
File sharing	10.00%	[1%–19%]	Estimation
Web, email, and data	50.00%	[25%–75%]	Estimation
Online Gaming	10.00%	[1%–19%]	Estimation
Mobile network			
Video	14.00%	[3%–25%]	Estimation
File sharing	10.00%	[1%–19%]	Estimation
Web, email, and data	50.00%	[25%–75%]	Estimation
Online Gaming	10.00%	[1%–19%]	Estimation

uncertainties: 1) external validity issues, 2) variable bias, 3) isolation difficulties of a single effect over multiple variables (Goldfarb, 2014), and 4) the flow of an ad through infrastructure is challenging to predict (Taylor and Koomey, 2008). Nevertheless, according to Koomey 2008, most Internet advertising flows can be well-represented by averages (Taylor and Koomey, 2008). Thus markets demand more reliable measurements (Wang et al., 2014).

We used the above information together with previous results and calculated the online advertising energy consumption for each traffic class separately. All the results presented in Table 3 were multiplied by the online advertising share percentages for each traffic class presented in Table 4. The energy consumption of fraudulent advertising is 23% (Botlab, 2017) of the total online advertising energy consumption.

2.10. Phase 7: calculating the carbon footprint

There is a direct link between Internet usage and CO_2e emissions. The grid mix is an essential factor when defining CO_2e emissions. About 80% of the energy generated in the OECD countries is done using non-renewable sources, resulting to an increase in CO_2e emissions (Salahuddin et al., 2016). Globally, the emissions from coal as a source of energy form more than 50% of the total emissions. In developing countries, the percentage is even higher (Li and Lin, 2017). Lambert et al., assumed CO_2e conversion to 500 g of CO_2e is produced per kWh (Lambert et al., 2012). The standard German electricity mix emission factor has been identified to be 0.5656 kg CO_2e/kWh (Kern et al., 2015). The latter result is used as a multiplying factor when we converted energy consumption of online advertising to CO_2e emissions on a global scale. It should be noted; the emission factor is context-, time-, and spatially-specific, as environmental characteristics and significance vary across countries over time (Del Campo, 2017). The emission factor is a source of uncertainty.

2.11. Phase 8: uncertainties in environmental impact assessment of online advertising

Uncertainty is a situation in which there is not sufficient information available to describe a situation being observed. EIA has guidelines to consider uncertainty and to point out sources of incomplete knowledge and a lack of data (Cardenas and Halman, 2016). Nevertheless, there is no common underlying conceptual framework for conducting uncertainty analysis (Leung et al., 2015). Uncertainty considerations are essential to ensure the quality of any impact assessment (Leung et al., 2015) and required in all stages of a decision-making process (Cardenas and Halman, 2016).

When investigating Internet energy consumption, there is a risk of relying more on assumptions than real data (Bull and Kozak, 2014). There are devices whose energy consumption scales with traffic, and devices that do not scale. This creates a methodological problem and is a source of uncertainty (Coroama and Hilty, 2014). Many of the studies conducted on the Internet domain assume a product as a functional unit, not the services the products are enabling. Used services reflect consumer behavior better than product-based analysis (Bull and Kozak, 2014). Internet energy intensity results vary significantly, depending on the assumptions, system boundary selection and the estimation of energy efficiency improvements (Schien and Preist, 2014). Due to the uncertainty and variability of results, the need for uncertainty analysis is widely acknowledged (Groen and Heijungs, 2017).

Top-down methods suffer from higher use phase estimations compared to the bottom-up or model-based approaches. This uncertainty can be reduced by smart system boundary selection (Schien and Preist, 2014). Models are inherently incomplete, as it is implausible that they fully encompass all relevant factors and their interconnected nature (Cardenas and Halman, 2016). In most impact assessment case studies that include uncertainty propagation, the correlation between the input parameters is ignored, even though the effect is unclear (Groen and Heijungs, 2017).

In our case study, uncertainties are found on all levels. The collection of Internet primary data is challenging, creating uncertainties (Schien and Preist, 2014). The year of the references and the amount of extrapolation are important sources of uncertainty. The ICT sector is evolving rapidly, and the equipment is becoming more energy efficient (Coroama and Hilty, 2014). Therefore, the energy consumption of devices provides uncertainty, as only average data is available (Schien and Preist, 2014).

Sensitivity analysis is used for assessing the interconnection between output and input variables (Cardenas and Halman, 2016). There are three ways to perform sensitivity analysis: 1) analyze a system or region characteristics which are influenced by change, 2) analyze resulting impacts, and 3) analyze the exposure, sensitivity, and interactions between components. In EIA, the aim is to identify areas with a high risk of being influenced by change (Del Campo, 2017).

We conducted an uncertainty and a sensitivity analysis to our results. First, we estimated the uncertainty of the infrastructure energy consumption. The uncertainty percentages of all the different technology domains are based on the reference years and the variation between previous studies results. As a rule of thumb, recent references result in smaller uncertainties. Then we calculated the impact of the minimum and maximum values in TWh to the output and summed up the percentages to get the total uncertainty impact to output. The results are presented in Appendix A Table A.5.

Similarly, we conducted an uncertainty analysis of the shares of traffic and the shares of online advertising in each traffic class. Uncertainty estimations for established protocols such as IPv4, TCP, and HTTP contain relatively small uncertainties as they are known from specific measures. The highest uncertainty is in the estimation of the shares of online advertising in each traffic class. The results are presented in Appendix A Table A.6. We calculated the effect of increasing every input factor by 1% on the corresponding output; the results can be found in Appendix A Fig. A.1. The share of the fixed network traffic class *web, email and data* with 1.77% increase for each percentage increase in the input, and the share of ads in the fixed network traffic class *video* with 3.22% increase have the highest impacts on the output. Overall, the uncertainty in the share of ads in each traffic class provides the highest impact on the output.

The sensitivity of the output value to the input factors was investigated with a Monte Carlo simulation. We created the simulation with Python. The source code of the simulation is available at GitHub (2018). All input factors with uncertainties were simulated. All input variables in our Monte Carlo simulation are random variables. Expected values are calculated by utilizing references and extrapolation. All uncertainties are symmetrical, independent and identically distributed (IID). Probability theory states a sequence of random variables is IID, if each random variable has the same probability distribution as the other variables, and all variables are mutually independent. The variables in our assessment simulation fulfill these preconditions and are therefore assumed normally distributed random variables. An exception is the share of traffic classes in mobile and fixed networks. There are three input variables, whose expected value is close to zero, but still contain uncertainty to the extent that would result in a pessimistic scenario negative percentage values for traffic class share, if symmetrical uncertainty was used, which is not an intellectual scenario. Therefore, we have utilized triangular distribution on all traffic class share variables. When utilizing triangular distribution, the parameters for the random pick are minimum, maximum and peak value. The peak value is assumed to be the expected value. The simulation input factors and distributions are presented in Appendix A Table A.7. The central limit theorem states that the distribution of the sum or an average of many IID variables will be approximately normal, regardless of the underlying distribution (Siegrist, 2017). The simulation follows the calculation of online advertising energy consumption as described in previous sections. Each input factor with uncertainty is divided into 200 steps of

Table 5
The energy consumption of online advertising without uncertainties.

	Video	File sharing	Web, email, and data	Online gaming	Total
Devices (TWh)					
Smartphone	0.48	0.003	1.07	0.00	1.55
PC	3.62	0.62	3.20	0.09	7.53
Laptop	1.09	0.19	0.97	0.03	2.28
Tablet	0.46	0.08	0.40	0.01	0.95
Connectivity (TWh)					
RAN	7.91	0.04	17.46	0.00	25.41
PS-CORE	5.43	0.83	5.63	0.11	12.01
Fixed line CPE	7.74	1.33	6.86	0.18	16.12
Operator DC	1.09	0.17	1.13	0.02	2.40
Office networks	2.37	0.41	2.10	0.06	4.94
Internet core	0.66	0.10	0.68	0.01	1.46
Applications (TWh)	14.26	2.18	15.19	0.30	31.93
Total (TWh)	45.11	5.96	54.70	0.82	106.59

unique values being randomly picked for each round. This results in a massive amount of permutations. The simulation was run for million rounds, and the resulting distribution has 200 bins. We simulated the total infrastructure energy TWh and online advertising energy TWh.

3. Results

The total energy consumption of online advertising, without uncertainties, for each traffic class has been calculated according to the methods presented in Section 2. The results are presented in Table 5.

With our framework, system boundary, base value estimations, and assumptions: online advertising energy consumption in 2016 was 106.59 TWh. Web-browsing was the dominant source of online advertising and therefore consumed the highest amount of energy.

There are uncertainties in our estimation. Uncertainty analysis indicates the most influential infrastructure energy consumption input factors were application-, RAN-, and PC energy consumptions. Similarly, the most influential input factors for traffic were: share of ads in the fixed and mobile *video* traffic class, the share of ads in the fixed and mobile *web, email and data* traffic class, share of TCP, and the share of HTTP. We wanted to investigate the output of online advertising energy consumption when the input factors are randomly picked from the range of uncertainty for each input factor. We conducted a Monte Carlo simulation of the framework, with one million simulated rounds, and the distributions of results are presented in Fig. 6.

The online advertising energy consumption distribution (a) is a normal distribution; therefore, the mean value is also the expected value. The distribution for the total infrastructure energy consumption (b) is also normally distributed. The probability is more concentrated around the mean value in online advertising distribution, compared to the total infrastructure energy consumption.

Table 6
The online advertising energy consumption and CO_2 footprint.

Simulated results	Mean	Min value	Max value	Median	Standard deviation
Total infra energy TWh	1057.76	838.96	1278.44	1057.79	66.95
Ad energy TWh	111.82	36.138	222.4	110.98	23.44

Calculated results	Expected	Min value	Max value
Total infra energy TWh	1059.15	791.01	1334.29
Ad energy TWh	106.59	20.38	282.75

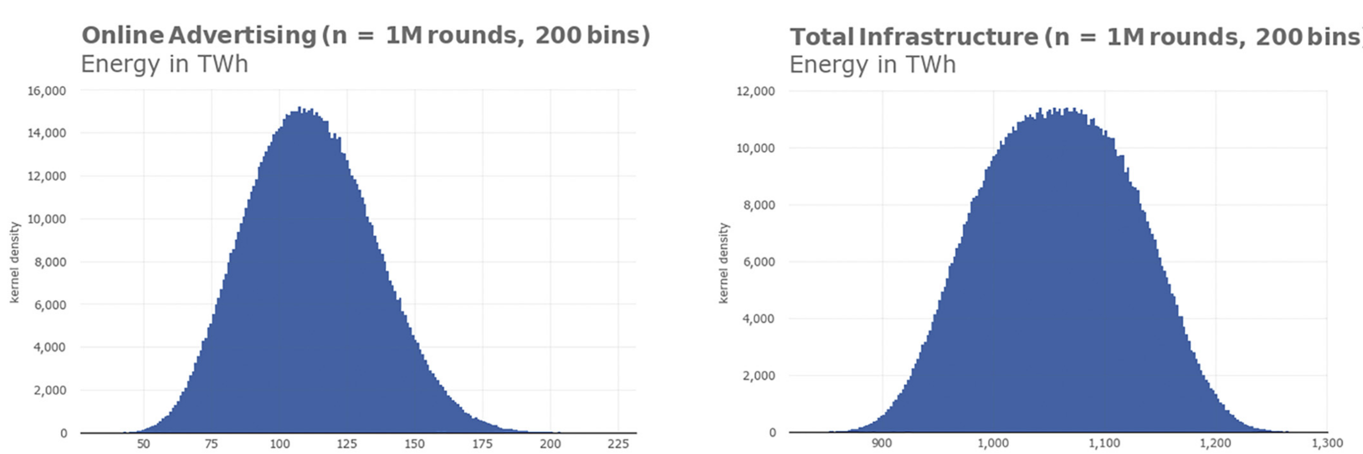
Ads energy consumption TWh expected [min, max]	106.59 [20.38, 282.75]
Ads CO_2 (million tons CO2e.) emissions expected [min, max]*	60.28 [11.53, 159.93]
Advertising fraud CO_2 (million tons CO2e) emissions expected [min, max]**	13.87 [2.65, 36.78]

* Emission factor 0,5656 kg CO2e/kWh (Kern et al., 2015).
** Advertising fraud percentage 23% (Botlab, 2017).

As a summary, we calculated the online advertising energy consumption and the total infrastructure energy consumption with uncertainties. The simulated results show 5 TWh higher mean values for online advertising, compared to the calculated results, because of the simplifications of the framework made in the simulation. The whole distribution is within the range of calculated results as expected. The results are presented in Table 6.

The results must be viewed with uncertainties taken into account. As a result, in 2016, online advertising consumed 20–282 TWh of energy. In the same year, the total infrastructure consumption was from 791 to 1334 TWh. With extrapolated 2016 input factor values without uncertainties, online advertising consumed 106 TWh of energy and the infrastructure 1059 TWh. We calculated the carbon emissions of online advertising and found it produced 60 Mt CO_2e (between 12 and 159 Mt of CO_2e when considering uncertainty). The share of fraudulent online advertising traffic was 13.87 Mt of CO_2e emissions (between 2.65 and 36.78 Mt of CO_2e when considering uncertainty).

Using the emission factor simplifies the calculation but at the same time creates uncertainties, as the grid mix varies between different geographical locations and as a function of time (there can be changes



(a) (b)

Fig. 6. Online advertising energy consumption TWh distribution (a), and total infrastructure energy consumption TWh distribution (b).

in the grid mix daily). For our purposes the average is sufficient. Online advertising CO_2e emissions are 10% of the total infrastructure emissions and therefore a significant contributor to the environmental impact of the Internet ecosystem. Advertising fraud can be considered a total waste of resources, both economically and environmentally. Our framework-based EIA of online advertising contains significant uncertainties but even with uncertainties included, the range of values indicates our results are significant.

4. Discussion and recommendations

Growing energy consumption is a global problem. The ICT industry enables substantial energy savings in many industries through automation, for example. Nonetheless, the ICT industry should also reduce its energy consumption and CO_2e emissions. Electricity price is predicted to rise, as it has risen for decades. It will be interesting to observe at which price point the ICT industry becomes more enthusiastic about energy efficiency.

According to Cisco, data flows of the Internet are expected to grow by 42% annually until 2020 (Aslan et al., 2017). In addition, leading OECD countries are funding Internet rollouts with billions of dollars to increase the Internet use and digitalization (Salahuddin et al., 2016). The growth of energy consumption in ICT is increasing despite technological disruptions such as cloud computing, high connection speeds, wireless access, and smartphones and tablets (Salahuddin et al., 2016). A 2012 study estimated an increasing need for more powerful and energy consuming infrastructure to support the steeply expanding amount of traffic (Gosselin et al., 2012). Meilson et al. present results of 20% annual energy efficiency improvement, and a more recent 2014 study done by Tamm et al., indicates the improvement rate has leveled to 10% per annum (Schien and Preist, 2014). Cisco and Juniper report overall capacity increments of 54% per annum for core routers, with annual energy efficiency improvement of 18% (Schien and Preist, 2014).

We created a framework for assessing energy consumption and CO_2e emissions for the EIA of the Internet service. We scoped out economic and social impact analysis. As a justification of our framework, we utilize the framework to assess online advertising energy consumption and suggest that a substantial portion of HTTP traffic is ad related. Even with uncertainties taken into account, online advertising consumes vast amounts of energy.

All traffic classes presented in this paper include online advertising to some extent. In the *web, email, and data* traffic class the amount of online advertising ranges from 25 to 75% of the traffic, being significantly less in other classes. The impact of the share of online advertising creates the most significant systemic uncertainties, which is not surprising, as it is in the highest level of abstraction on top of the infrastructure, protocols and traffic classes. The results can be repeated easily and changing any of the input parameters is possible, including the percentage of online advertising for each traffic class. We also created a Python simulation, which allows future researchers to investigate any Internet service by changing the input parameters. The source code of the simulation is available at GitHub (GitHub, 2018).

The main factors affecting the output results are: 1) share of online advertising in each traffic class 2) uncertainty based on the base value year, and 3) the inclusion of DCs and end devices in the system boundary. We have added CDNs into our system boundary, as they have technologically reduced the network resource consumption of favorite sites. CDNs ensure content is downloaded from a server (cache) close by to the end-user and therefore also improve the end-user experience. At the same time, CDNs reduce the need for expensive Tier-1 transit capacity needed for intercontinental traffic.

The share of ICT energy consumption from the total energy consumption has been studied during the last few decades. A 2008 study indicates a conservative estimate of 3% of the total global energy consumption for the ICT, with the system boundary of cellular, PSTN and the Internet core, without DCs (Fettweis and Zimmermann, 2008). The share of global energy consumption of ICT has increased from 3.9% (2007) to 4.6% (2012) (Salahuddin et al., 2016; Aslan et al., 2017). According to the IAE report, the total global electricity consumption in 2015 was 24,344 TWh (International Energy Agency, 2017b). The 2016 figures were not available, therefore as an indicative result, we used the 2015 global electricity consumption value and calculated the shares with our results. The results were in the range of 3.2–5.4% of the total global consumption (the results were somewhat lower with the 2016 figures, as global electricity consumption is increasing).

When analyzing the results, it should be taken into account that many of the most widely used Internet services are free, as the business logic is based on advertising, rather than pay-as-you-use. Changing this business model would increase energy efficiency, but at the cost of lower adaptation level for services. According to a web publication (Venturebeat and Protalinski, 2015), Netflix's share of the total downstream traffic in America is 37.05%. Let's assume this is their global share. If Netflix changed its business model to that of Spotify, which is free to use if the user accepts advertisements, the effect on the Internet energy consumption would be substantial. If an additional 10% is assumed as the advertising *video* traffic, based on our framework, on a global level additional 42.02 TWh of energy would be consumed, and 23.76 million tons of CO_2e emitted (without taking uncertainties into account).

Our recommendations for future research include applying inventory-based bottom-up analysis to all technology domains, to increase the accuracy of results, and to remove uncertainties as much as possible. The same applies to traffic classes. The role of software in energy efficiency improvement initiatives should also be investigated further. There are reference models for greener software (Kern et al., 2015). They are not widely applied. In addition, the trend towards smartphones, smart TVs, and clouds shift computing and storage to service provider data centers, therefore potentially decreasing energy consumption through scale and resource utilization rate improvement. None of the energy consumption improvements happen by accident; instead, they are a result of systematic energy efficiency improvement initiatives at all levels of the ICT industry.

5. Conclusions

The Internet consumes vast amounts of energy and creates CO_2e emissions of global significance. The exact figures are challenging to calculate due to the enormous complexity of the Internet. Our framework is sufficient to conclude that improving the energy efficiency of the Internet is a relevant matter. By utilizing our framework, we aimed to identify the part of energy consumption related to online advertising, and the amount consumed by fraudulent online advertising.

Reducing online advertising traffic will improve the energy efficiency of the Internet. The impact will not manifest immediately, but somewhat gradually. While the impact of invalid online advertising significantly affects the advertising economy in monetary terms, it also consumes lots of energy and has a hefty carbon footprint. The current trend of the CO_2e emissions will continue to grow over time in many industries. It is essential industries leveraging the Internet technologies take the necessary steps to stop this trend and to ultimately decrease the CO_2e emissions as early as possible. Awareness of the problem is the first step towards more concrete actions.

Our framework contributes to the discussion of EIA assessments of Internet services. It is a collection of best practices and methods joined together into a layered and modular structure and fits into any level of detail or abstraction locally or globally across technologies.

Appendix A. Appendix

Table A.1
Total energy consumption.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Reference
Internet users (millions)	1024	1151	1365	1561	1751	2019	2224	2594	2705	2937	3173	3555	3758	3929	4086	4229	(Vlachos, 2016)
Growth%		12.40 %	18.59 %	14.36 %	12.17 %	15.31 %	10.15 %	16.64 %	4.28 %	8.58 %	8.04 %	12.04 %	5.71 %	4.55 %	4.00 %	3.50 %	
Devices																	
Smartphone devices (millions)	90	150	190	237	304	431	687	1031	1457	1850	2222	2562	2890	3150	3402	3640	(Meeker, 2017; Statista, 2018a)
Growth%		66.67 %	26.67 %	24.74 %	28.27 %	41.78 %	59.40 %	50.07 %	41.32 %	26.97 %	20.11 %	15.30 %	12.80 %	9.00 %	8.00 %	7.00 %	
Smartphone avg energy / device (kWh)	4.62	4.49	4.36	4.23	4.11	3.99	3.87	3.76	3.65	3.54	3.44	3.34	3.24	3.14	3.05	2.96	(Canstar Blue, 2016)
Growth%	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*		*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	(Andrae and Edler, 2015)
Smartphone total energy (TWh)	0.42	0.67	0.83	1.00	1.25	1.72	2.66	3.88	5.32	6.56	7.64	8.56	9.36	9.90	10.37	10.76	
Growth%		*61.81 %*	*22.98 %*	*21.10 %*	*24.53 %*	*37.65 %*	*54.75 %*	*45.70 %*	*37.20 %*	*23.27 %*	*16.61 %*	*11.94 %*	*9.42 %*	*5.73 %*	*4.76 %*	*3.79 %*	
PC devices (millions)	*493*	*440*	*400*	*370*	*349*	*336*	*329*	*326*	*322*	*322*	*325*	*325*	*322*	*319*	*315*	*312*	(Statista., 2018b)
Growth%	*12.00 %*	*10.00 %*	*8.00 %*	*6.00 %*	*4.00 %*	*2.00 %*	*1.00 %*	*-0.5 %*	*-1.23 %*	*0.00 %*	*0.93 %*	*0.00 %*	*-1.00 %*	*-1.00 %*	*-1.00 %*	*-1.00 %*	
PC avg energy / device (kWh)	*266*	*263*	*260*	*257*	*254*	*251*	*248*	*245*	*242*	*239*	*236*	*233*	*230*	*227*	*224*	*221*	(Van Heddeghem et al., 2014)
Growth%		*-1.13 %*	*-1.14 %*	*-1.15 %*	*-1.17 %*	*-1.18 %*	*-1.20 %*	*-1.21 %*	*-1.22 %*	*-1.24 %*	*-1.26 %*	*-1.27 %*	*-1.29 %*	*-1.30 %*	*-1.32 %*	*-1.34 %*	
PC total energy (TWh)	*131.04*	*115.68*	*103.96*	*95.15*	*88.72*	*84.30*	*81.66*	*79.87*	*77.92*	*76.96*	*76.70*	*75.73*	*74.00*	*72.31*	*70.64*	*68.99*	
Growth%		*-11.72 %*	*-10.13 %*	*-8.48 %*	*-6.76 %*	*-4.98 %*	*-3.13 %*	*-2.19 %*	*-2.44 %*	*-1.24 %*	*-0.34 %*	*-1.27 %*					
Laptop devices (millions)	*20*	*30*	*45*	*80*	*135*	*200*	*258*	*316*	*374*	*432*	*490*	*548*	*606*	*664*	*722*	*780*	(Andrae and Edler, 2015)
Growth%		*50.00 %*	*50.00 %*	*77.78 %*	*68.75 %*	*48.15 %*	*29.00 %*	*22.48 %*	*18.35 %*	*15.51 %*	*13.43 %*	*11.84 %*	*10.58 %*	*9.57 %*	*8.73 %*	*8.03 %*	
Laptop avg energy / device (kWh)	*61.6*	*59.8*	*58.0*	*56.2*	*54.4*	*52.6*	*50.8*	*49.0*	*47.2*	*45.4*	*43.6*	*41.8*	*40.0*	*38.2*	*36.4*	*34.6*	(Van Heddeghem et al., 2014)
Growth%		*-2.91 %*	*-3.01 %*	*-3.10 %*	*-3.20 %*	*-3.31 %*	*-3.42 %*	*-3.54 %*	*-3.67 %*	*-3.81 %*	*-3.96 %*	*-4.13 %*	*-4.31 %*	*-4.50 %*	*-4.71 %*	*-4.95 %*	
Laptop total energy (TWh)	*1.23*	*1.79*	*2.61*	*4.50*	*7.34*	*10.52*	*13.11*	*15.48*	*17.65*	*19.61*	*21.36*	*22.91*	*24.24*	*25.36*	*26.28*	*26.99*	
Growth%		*45.63 %*	*45.49 %*	*72.26 %*	*63.35 %*	*43.25 %*	*24.59 %*	*18.14 %*	*14.01 %*	*11.10 %*	*8.93 %*	*7.22 %*	*5.82 %*	*4.64 %*	*3.61 %*	*2.69 %*	
Tablet devices (millions)						*16*	*61*	*147*	*276*	*427*	*585*	*742*	*889*	*1021*	*1133*	*1224*	(TekCarta., 2018)
Growth%							*281.13 %*	*142.08 %*	*88.07 %*	*54.69 %*	*37.16 %*	*26.70 %*	*19.91 %*	*14.76 %*	*11.00 %*	*8.00 %*	
Tablet avg energy / device (kWh)						15.4	15.0	14.5	14.1	13.7	13.3	12.9	12.5	12.1	11.8	11.4	(www.zdnet.com, 2016)
Growth%						*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*		*-3.00 %*	*-3.00 %*	*-3.00 %*	*-3.00 %*	(Andrae and Edler, 2015)
Tablet total energy (TWh)						0.24	0.91	2.13	3.89	5.84	7.78	9.57	11.13	12.39	13.34	13.97	
Growth%							*270.03 %*	*135.03 %*	*82.59 %*	*50.19 %*	*33.17 %*	*23.01 %*	*16.32 %*	*11.32 %*	*7.67 %*	*4.76 %*	
Connectivity (TWh)																	
RAN	245	235	225	215	205	200	190	180	170	160	150	140	130	120	110	100	(Andrae and Edler, 2015)
Growth%		*-4.08 %*	*-4.26 %*	*-4.44 %*	*-4.65 %*	*-2.44 %*	*-5.00 %*	*-5.26 %*	*-5.56 %*	*-5.88 %*	*-6.25 %*	*-6.67 %*	*-7.14 %*	*-7.69 %*	*-8.33 %*	*-9.09 %*	
PS-CORE	38	43	48	55	63	71	81	92	104	117	131	146.7	164	184	206	231	(Han et al., 2011)
Growth%	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*		*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	(Pickavet et al., 2008)
Fixed line CPE	481	438	398	362	329	299	272	247	222	200	180	162	146	131	118	106	(Andrae and Edler, 2015)
Growth%	*10.00 %*	*10.00 %*	*10.00 %*	*10.00 %*	*10.00 %*	*10.00 %*	*10.00 %*		*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	(Andrae and Edler, 2015)
Operator DC	8	9	10	11	13	14	16	18	21	23	26	29.3	33	37	41	46	(Han et al., 2011)
Growth%	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*	*-12.00 %*		*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	*12.00 %*	(Pickavet et al., 2008)
Office networks	22.9	25.4	27.8	30.2	32.7	35.1	37.5	40.0	42.4	44.8	47.2	49.7	52.1	54.5	57.0	59.4	(Lambert et al., 2012)
Growth%		*10.59 %*	*9.58 %*	*8.74 %*	*8.04 %*	*7.44 %*	*6.93 %*	*6.48 %*	*6.08 %*	*5.73 %*	*5.42 %*	*5.14 %*	*4.89 %*	*4.66 %*	*4.46 %*	*4.27 %*	
Internet core	93.50	85.00	76.50	68.85	61.97	55.77	50.19	45.17	40.66	36.59	32.93	29.64	26.67	24.01	21.61	19.45	(Taylor and Koomey, 2008)
Growth%	*10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	*-10.00 %*	(Schien and Preist, 2014)
Applications (TWh)	152.50	182.22	211.94	241.66	271.38	301.10	315.10	329.10	343.10	357.10	371.10	385.04	398.90	412.67	426.31	439.82	(Koomey et al., 2011b; Whitehead et al., 2014)
Growth%		*19.49 %*	*16.31 %*	*14.02 %*	*12.30 %*	*10.95 %*	*4.65 %*	*4.44 %*	*4.25 %*	*4.08 %*	*3.92 %*	*3.76 %*	*3.60 %*	*3.45 %*	*3.31 %*	*3.17 %*	
Total Energy Consumption	1173	1135	1105	1084	1072	1073	1060	1053	1048	1048	1052	1059	1069	1083	1101	1123	

Peer-reviewed base values

Estimation

Table A.2
Traffic shares.

Traffic in Exabytes (EB)	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Reference
IP Traffic	29.11	47.90	77.16	119.12	172.97	242.36	329.80	522.84	614.02	749.74	852.00	1152.65	1460.33	1810.92	2237.44	2737.30	(Vlachos, 2016; Cisco Systems, 2017a)
Growth%		*64.55 %*	*61.07 %*	*54.39 %*	*45.20 %*	*40.12 %*	*36.07 %*	*58.53 %*	*17.44 %*	*22.10 %*	*13.64 %*	*35.29 %*	*26.69 %*	*24.01 %*	*23.55 %*	*22.34 %*	
Fixed network IP traffic	*24.66*	*40.07*	*62.63*	*91.67*	*128.11*	*179.15*	*247.61*	*376.06*	*419.42*	*505.43*	*606.05*	*791.09*	*1000.45*	*1235.52*	*1524.10*	*1861.45*	(Vlachos, 2016; Cisco Systems, 2017a)
Growth%		*62.48 %*	*56.30 %*	*46.37 %*	*39.76 %*	*39.84 %*	*38.21 %*	*51.88 %*	*11.53 %*	*20.51 %*	*19.91 %*	*30.53 %*	*26.47 %*	*23.50 %*	*23.36 %*	*22.13 %*	
Share of total IP traffic	*84.71 %*	*83.64 %*	*81.17 %*	*76.95 %*	*74.07 %*	*73.92 %*	*75.08 %*	*71.93 %*	*68.31 %*	*67.41 %*	*71.13 %*	*68.63 %*	*68.51 %*	*68.23 %*	*68.12 %*	*68.00 %*	
Mobile network IP traffic	*0.01*	*0.05*	*0.18*	*0.46*	*1.10*	*3.07*	*7.16*	*10.62*	*17.76*	*30.98*	*52.04*	*86.41*	*134.20*	*199.75*	*290.64*	*412.58*	(Vlachos, 2016; Cisco Systems, 2017a)
Growth%		*344.44 %*	*275.00 %*	*153.33 %*	*142.11 %*	*178.26 %*	*133.20 %*	*48.24 %*	*67.23 %*	*74.46 %*	*67.97 %*	*66.04 %*	*55.30 %*	*48.85 %*	*45.50 %*	*41.96 %*	
Share of total IP traffic	*0.04 %*	*0.10 %*	*0.23 %*	*0.38 %*	*0.64 %*	*1.27 %*	*2.17 %*	*2.03 %*	*2.89 %*	*4.13 %*	*6.11 %*	*7.50 %*	*9.19 %*	*11.03 %*	*12.99 %*	*15.07 %*	
CDN IP traffic	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*158.10*	*209.86*	*284.44*	*460.08*	*646.66*	*874.72*	*1171.63*	*1521.52*	(Vlachos, 2016; Cisco Systems, 2017a)
Growth%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*32.74 %*	*35.54 %*	*61.75 %*	*40.55 %*	*35.27 %*	*33.94 %*	*29.86 %*	
Share of total IP traffic	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*27.99 %*	*33.38 %*	*39.92 %*	*44.28 %*	*48.30 %*	*52.36 %*	*55.58 %*	

Peer reviewed value

Estimation

Table A.3
The share of traffic classes 2013-2016.

Traffic class	2013				2014				2015				2016			
	Fixed EB/year	Share %	Mobile EB/year	Share %	Fixed EB/year	Share %	Mobile EB/year	Share %	Fixed EB/year	Share %	Mobile EB/year	Share %	Fixed EB/year	Share %	Mobile EB/year	Share %
Consumer video	202.04	60.39 %	7.60	53.24 %	245.82	64.93 %	13.67	55.56 %	324.13	68.65 %	21.07	58.01 %	460.43	72.84 %	43.92	61.48 %
Consumer file sharing	72.53	21.68 %	0.49	3.45 %	72.53	19.16 %	0.55	2.24 %	71.30	15.10 %	0.26	0.73 %	79.19	12.53 %	0.35	0.49 %
Consumer web, email, and data	59.27	17.71 %	6.18	43.31 %	60.22	15.91 %	10.38	42.20 %	75.72	16.04 %	14.98	41.23 %	81.54	12.90 %	27.16	38.01 %
Consumer Online Gaming	0.74	0.22 %	0.00	0.00 %	0.01	0.003 %	0.00	0.0 %	0.98	0.21 %	0.012	0.033 %	10.98	1.74 %	0.012	0.02 %
Consumer Total Internet Traffic	334.58	100.00 %	14.27	100.00 %	378.58	100.00 %	24.60	100.00 %	472.14	100.00 %	36.32	100.00 %	632.14	100 %	71.44	100 %

Cisco Systems, 2014, 2015, 2016, 2017a.

Table A.4
Traffic share by protocol.

Traffic share by protocol	2010	2011	2012	2013	2014	2015	2016	Reference
IP								
IPv4	NA	NA	NA	99.40 %	99.00 %	98.75 %	98.50 %	(Czyz et al., 2014; Pujol et al., 2014)
IPv6	NA	NA	NA	0.60 %	1.00 %	1.25 %	1.50 %	(Czyz et al., 2014; Pujol et al., 2014)
TCP	80.77 %	82.27 %	83.77 %	85.27 %	86.77 %	88.27 %	89.77 %	(Pujol et al., 2014)
UDP	19.23 %	17.73 %	16.23 %	14.73 %	13.23 %	11.73 %	10.23 %	(Pujol et al., 2014)
HTTP(S)	64.20 %	65.87 %	67.53 %	69.20 %	70.87 %	72.53 %	74.20 %	(Czyz et al., 2014)
Fixed network								
Video	NA	NA	NA	60.39 %	64.93 %	68.65 %	72.84 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
File sharing	NA	NA	NA	21.68 %	19.16 %	15.10 %	12.53 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
Web, email, and data	NA	NA	NA	17.71 %	15.91 %	16.04 %	12.90 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
Online Gaming	NA	NA	NA	0.22 %	0.003 %	0.21 %	1.74 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
Mobile network								
Video	NA	NA	NA	53.24 %	55.56 %	58.01 %	61.48 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
File sharing	NA	NA	NA	3.45 %	2.24 %	0.73 %	0.49 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
Web, email, and data	NA	NA	NA	43.31 %	42.20 %	41.23 %	38.01 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)
Online Gaming	NA	NA	NA	0.00 %	0.0 %	0.033 %	0.02 %	(Cisco Systems, 2014; Cisco Systems, 2015; Cisco Systems, 2016; Cisco Systems, 2017a)

Peer-reviewed value

Estimation

Table A.5
The uncertainty of infrastructure energy consumption.

	2016 TWh	Share of total	Ref. Year	Uncertainty	Min	Max	Min value	Max value	Min impact	Max impact
Devices (TWh)										
Smartphone devices (millions)	2562		2017	10 %	2306	2818	106.43	106.74	-0.155	0.155
Smartphone avg. kWh / device	3.34		2016	30 %	2.34	4.34	106.12	107.05	-0.466	0.466
Smartphone total energy (TWh)	8.56	0.81 %					106.01	107.25	-0.575	0.668
PC devices (millions)	325		2018	10 %	293	358	105.83	107.34	-0.753	0.753
PC avg. kWh / device	233.00		2014	30 %	163.10	302.90	104.33	108.85	-2.260	2.260
PC total energy (TWh)	75.73	7.15 %					103.80	109.82	-2.787	3.239
Laptop devices (millions)	548		2015	10 %	493	603	106.36	106.81	-0.228	0.228
Laptop avg. kWh / device	41.80		2014	30 %	29.26	54.34	105.90	107.27	-0.683	0.683
Laptop total energy (TWh)	22.91	2.16 %					105.74	107.57	-0.843	0.980
Tablet devices (millions)	742		2018	10 %	668	816	106.49	106.68	-0.095	0.095
Tablet avg. kWh / device	12.90		2016	30 %	9.03	16.77	106.30	106.87	-0.285	0.285
Tablet total energy (TWh)	9.57	0.90 %					106.23	106.99	-0.352	0.409
Connectivity (TWh)										
RAN	140.00	13.22 %	2015	20 %	112.00	168.00	101.50	111.67	-5.082	5.082
PS-CORE	146.65	13.85 %	2011	25 %	109.99	183.32	103.58	109.59	-3.002	3.002
Fixed line CPE	162.06	15.30 %	2015	20 %	129.65	194.47	103.36	109.81	-3.224	3.224
Operator DC	29.33	2.77 %	2011	25 %	22.00	36.66	105.99	107.19	-0.600	0.600
Office networks	49.67	4.69 %	2012	25 %	37.25	62.09	105.35	107.82	-1.235	1.235
Internet core	29.64	2.80 %	2008	40 %	17.78	41.49	106.00	107.17	-0.583	0.583

(continued on next page)

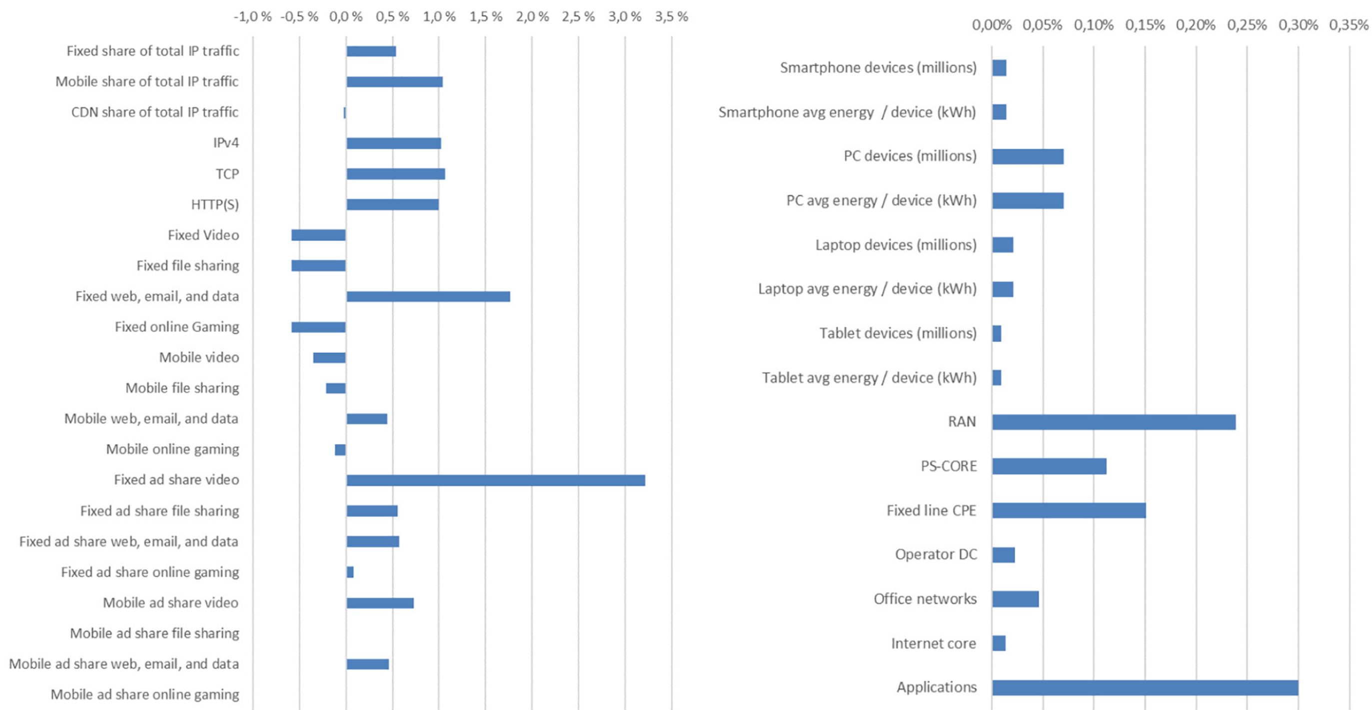
Table A.5 (*continued*)

	2016 TWh	Share of total	Ref. Year	Uncertainty	Min	Max	Min value	Max value	Min impact	Max impact
Applications (TWh)	385.04	36.35 %	2014	25 %	288.78	481.30	98.60	114.57	-7.984	7.984
Total	**1059**	**100.00 %**							**-26.266**	**27.005**

Table A.6
The uncertainty of traffic shares.

	2016	Reference year	Uncertainty %	Uncertainty in value	Min	Max	Min value	Max value	Min impact	Max impact
Fixed network IP traffic										
Share of total IP traffic	68.63 %	2017	10 %	6.86 %	61.77 %	75.50 %	102.63	110.54	-3.951	3.951
Mobile network IP traffic										
Share of total IP traffic	7.50 %	2017	10 %	0.75 %	6.75 %	8.25 %	105.76	107.41	-0.829	0.829
CDN IP traffic										
Share of total IP traffic	39.92 %	2017	10 %	3.99 %	35.92 %	43.91 %	106.68	106.49	0.097	-0.097
IP										
IPv4	98.50 %	2014	0.5 %	0.49 %	98.01 %	98.99 %	106.05	107.12	-0.533	0.533
TCP	89.77 %	2014	5.0 %	4.5 %	85.28 %	94.26 %	101.46	111.71	-5.129	5.129
HTTP(S)	74.20 %	2014	13.4 %	10.0 %	64.22 %	84.18 %	95.93	117.24	-10.659	10.659
Fixed network*										
Video	72.84 %	2017	4.12 %	3.00 %	69.84 %	75.84 %	108.47	104.71	1.884	-1.880
File sharing	12.53 %	2017	23.95 %	3.00 %	9.53 %	15.53 %	108.47	104.71	1.884	-1.880
Web, email, and data	12.90 %	2017	23.26 %	3.00 %	9.90 %	15.90 %	100.94	112.23	-5.645	5.649
Online Gaming**	1.74 %	2017	173 %	3.00 %	0.00 %	4.74 %	107.68	104.71	1.092	-1.880
Mobile network *										
Video	61.48 %	2017	4.88 %	3.00 %	58.48 %	64.48 %	107.06	105.45	0.479	-1.136
File sharing**	0.49 %	2017	715.83 %	3.00 %	0.00 %	3.49 %	106.70	105.91	0.112	-0.676
Web, email, and data	38.01 %	2017	7.89 %	3.00 %	35.01 %	41.01 %	105.21	108.00	-1.378	1.417
Online Gaming**	0.02 %	2017	17959 %	3.00 %	0.00 %	3.02 %	106.59	106.22	0.003	-0.369
Online ad share										
Fixed network										
Video	10.00 %	Estimate	80 %	8.00 %	2.00 %	18.00 %	79.17	134.00	-27.419	27.419
File sharing	10.00 %	Estimate	90 %	9.00 %	1.00 %	19.00 %	101.28	111.89	-5.305	5.305
Web, email, and data	50.00 %	Estimate	50 %	25.00 %	25.00 %	75.00 %	91.41	121.76	-15.174	15.174
Online Gaming	10.00 %	Estimate	90 %	9.00 %	1.00 %	19.00 %	105.85	107.32	-0.736	0.736
Mobile network										
Video	14.00 %	Estimate	78.57 %	11.00 %	3.00 %	25.00 %	98.07	115.10	-8.517	8.517
File sharing	10.00 %	Estimate	90 %	9.00 %	1.00 %	19.00 %	106.53	106.64	-0.055	0.055
Web, email, and data	50.00 %	Estimate	50 %	25.00 %	25.00 %	75.00 %	94.41	118.76	-12.174	12.174
Online Gaming	10.00 %	Estimate	90 %	9.00 %	1.00 %	19.00 %	106.58	106.59	-0.002	0.002

[*] Total sum must be 100%, in Min/Max Impact the reduced or added percentages are divided equally to other classes.
[**] Min value with uncertainty cannot go below zero.



(a) (b)

Figure A.1. One percentage increase in input effect on online advertising TWh output percentage.

Table A.7
Monte Carlo simulation input factors and uncertainties.

Simulation input factor	Value	Uncertainty	Unit	Distribution
Infrastructure factors				
smartphone_dev_millions	2565	0.1	Millions	Normal
smartphone_avg_energy	3.34	0.3	kWh	Normal
pc_dev_millions	325	0.1	Millions	Normal
pc_avg_energy	233	0.3	kWh	Normal
laptop_dev_millions	548	0.1	Millions	Normal
laptop_avg_energy	41.8	0.3	kWh	Normal
tablet_dev_millions	742	0.1	Millions	Normal
tablet_avg_energy	12.9	0.3	kWh	Normal
ran	140	0.2	TWh	Normal
ps_core	146.65	0.25	TWh	Normal
fixed_line_cpe	162.06	0.2	TWh	Normal
operator_dc	29.33	0.25	TWh	Normal
office_network	49.67	0.25	TWh	Normal
internet_core	29.64	0.4	TWh	Normal
applications	385.04	0.25	TWh	Normal
Traffic share factors				
fixed_ip	0.6863	0.1	%	Normal
mobile_ip	0.075	0.1	%	Normal
cdn_ip	0.3992	0.1	%	Normal
Smartphone usage factor				
smarphone_usage	1	0	%	Normal
pc_usage	1	0	%	Normal
laptop_usage	1	0	%	Normal
tablet_usage	1	0	%	Normal
Protocol factors				
ipv4	0.985	0.005	%	Normal
tcp	0.8977	0.05	%	Normal

(continued on next page)

Table A.7 (*continued*)

Simulation input factor	Value	Uncertainty	Unit	Distribution
http	0.742	0.1	%	Normal
Traffic class factors				
fixed_video*	0.7284	0.03	%	Triangular
fixed_file*	0.1253	0.03	%	Triangular
fixed_web*	0.129	0.03	%	Triangular
fixed_gaming*	0.0174	0.03	%	Triangular
mobile_video*	0.6148	0.03	%	Triangular
mobile_file*	0.0049	0.03	%	Triangular
mobile_web*	0.3801	0.03	%	Triangular
mobile_gaming*	0.0002	0.03	%	Triangular
Ads share factors				
fixed_video	0.1	0.8	%	Normal
fixed_file	0.1	0.9	%	Normal
fixed_web	0.5	0.5	%	Normal

* Uncertainty +/- value, Min value cannot go below zero.

References

Aisch, G., et al., 2015. The New York Times. Available online at: https://www.nytimes.com/interactive/2015/10/01/business/cost-of-mobile-ads.html (Accessed 14.8.2018).

Alcatel-Lucent, 2015. White Paper. Available online at:. https://media-bell-labs-com.s3.amazonaws.com/pages/20150114_1907/GWATT_WhitePaper.pdf (Accessed 28.04.2018).

Andrae, A.S., Edler, T., 2015. On global electricity usage of communication technology: trends to 2030. Challenges 6 (1), 117–157.

Arushanyan, Y., Ekener-Petersen, E., Finnveden, G., 2014. Lessons learned–review of LCAs for ICT products and services. Comput. Ind. 65 (2), 211–234.

Aslan, J., Mayers, K., Koomey, J.G., France, C., 2017. Electricity intensity of Internet data transmission: untangling the estimates. J. Ind. Ecol.

Badic, B., O'Farrell, T., Loskot, P., He, J., 2009. Energy efficient radio access architectures for green radio: large versus small cell size deployment. In: Vehicular Technology Conference Fall (VTC 2009-Fall), 2009 IEEE 70th. IEEE, pp. 1–5.

Balasubramanian, N., Balasubramanian, A., Venkataramani, A., 2009. Energy consumption in mobile phones: a measurement study and implications for network applications. In: Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement. ACM, pp. 280–293.

Baliga, J., Ayre, R.W., Hinton, K., Tucker, R.S., 2011. Green cloud computing: balancing energy in processing, storage, and transport. Proc. IEEE 99 (1), 149–167.

Berens, V., Havranek, P.M., 1995. Guidelines for Evaluating the Effectiveness of Investments. INFRA-M, Moscow, pp. 528.

Bidstrup, M., Kørnøv, L., Partidário, M.R., 2016. Cumulative effects in strategic environmental assessment: the influence of plan boundaries. Environ. Impact Assess. Rev. 57, 151–158.

Canstar Blue., 2016, The surprising cost of charging your phone. Available online at:https://www.canstarblue.com.au/energy/electricity/surprising-cost-charging-phone/ (Accessed 28.04.2018).

Bond, A., Retief, F., Cave, B., Fundingsland, M., Duinker, P.N., Verheem, R., Brown, A.L., 2018. A contribution to the conceptualisation of quality in impact assessment. Environ. Impact Assess. Rev. 68, 49–58.

Botlab, 2017. An Entropy-Based Methodology for Detecting Online Advertising Fraud at Scale. Available online at: http://botlab.io/wp-content/uploads/2017/08/v1_anonymous_no_tags-1.pdf [Accessed 28.04.2018].

Braun, M., Moe, W.W., 2013. Online display advertising: modeling the effects of multiple creatives and individual impression histories. Mark. Sci. 32 (5), 753–767.

Bull, J.G., Kozak, R.A., 2014. Comparative life cycle assessments: the case of paper and digital media. Environ. Impact Assess. Rev. 45, 10–18.

Cardenas, I.C., Halman, J.I., 2016. Coping with uncertainty in environmental impact assessments: open techniques. Environ. Impact Assess. Rev. 60, 24–39.

Chen, G., Cox, J.H., Uluagac, A.S., Copeland, J.A., 2016. In-Depth survey of Digital Advertising Technologies. IEEE Commun. Surv. Tutorials 18 (3), 2124–2148.

Cisco Systems, 2014. Cisco Visual Networking Index: Forecast and Methodology, 2013–2018 (White paper. Available online at). http://www.anatel.org.mx/docs/interes/Cisco_VNI_Forecast_and_Methodology.pdf (Accessed 28.04.2018).

Cisco Systems, 2015. Cisco Visual Networking Index: Forecast and Methodology, 2014–2019. White paper. Available online at:. http://s2.q4cdn.com/230918913/files/doc_downloads/report_2014/white_paper_c11-481360.pdf (Accessed 28.04.2018).

Cisco Systems, 2016. Cisco Visual Networking Index: Forecast and Methodology, 2015–2020 (White paper. Available online at). https://static1.squarespace.com/static/54496f89e4b0ad2be6456bc7/t/57b386f8e4fcb59cf4894907/1471383319341/Cisco+Forecast+2015-2020.pdf (Accessed 28.04.2018).

Cisco Systems., 2017a. Cisco Visual Networking Index: Forecast and Methodology, 2016–2021. White paper. Available online at:https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/complete-white-paper-c11-481360.html (Accessed 28.04.2018).

Cisco Systems., 2017b. The Zettabyte Era: Trends and Analysis. White paper. Available online at:http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/vni-hyperconnectivity-wp.html (Accessed 28.04.2018).

Coroama, V.C., Hilty, L.M., 2014. Assessing Internet energy intensity: a review of methods and results. Environ. Impact Assess. Rev. 45, 63–68.

Coroama, V. C., Schien, D., Preist, C., & Hilty, L. M., 2015. The energy intensity of the Internet: home and access networks. ICT Innov. Sustain. (pp. 137–155). Springer, Cham.

Czyz, J., Allman, M., Zhang, J., Iekel-Johnson, S., Osterweil, E., Bailey, M., 2014. Measuring ipv6 adoption. In: ACM SIGCOMM Computer Communication Review. vol. 44. ACM, pp. 87–98 No. 4.

Dalessandro, B., Hook, R., Perlich, C., Provost, F., 2015. Evaluating and optimizing online advertising: forget the click, but there are good proxies. Big Data 3 (2), 90–102.

De Haan, E., Wiesel, T., Pauwels, K., 2016. The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. Int. J. Res. Mark. 33 (3), 491–507.

Del Campo, A.G., 2017. Mapping environmental sensitivity: a systematic online approach to support environmental assessment and planning. Environ. Impact Assess. Rev. 66, 86–98.

Ebrahimi, K., Jones, G.F., Fleischer, A.S., 2014. A review of data center cooling technology, operating conditions and the corresponding low-grade waste heat recovery opportunities. Renew. Sust. Energ. Rev. 31, 622–638.

Englehardt, S., Narayanan, A., 2016. Online tracking: A 1-million-site measurement and analysis. In: Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security. ACM, pp. 1388–1401.

ETSI ES 203 199 V1.3.1, 2015. Environmental Engineering (EE); Methodology for Environmental Life Cycle Assessment (LCA) of Information and Communication Technology (ICT) Goods, Networks and Services. Available online at: https://www.etsi.org/deliver/etsi_es/203100_203199/203199/01.03.01_60/es_203199v010301p.pdf (Accessed 20.07.2018).

Facebook, 2017. 2017 Q1 Quarterly Report (04 May 2017). Available online at:. http://d18rn0p25nwr6d.cloudfront.net/CIK-0001326801/2309fab3-1f67-46bc-8d66-7039bc4a0e68.pdf (Accessed 28.04.2018).

Falaki, H., Mahajan, R., Kandula, S., Lymberopoulos, D., Govindan, R., Estrin, D., 2010. Diversity in smartphone usage. In: Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services. ACM, pp. 179–194.

Fettweis, G., Zimmermann, E., 2008. ICT energy consumption-trends and challenges. In: Proceedings of the 11th International Symposium on Wireless Personal Multimedia Communications. Vol. 2. pp. 6 No. 4.

Frank, B., Poese, I., Lin, Y., Smaragdakis, G., Feldmann, A., Maggs, B., ... Weber, R., 2013. Pushing CDN-ISP collaboration to the limit. ACM SIGCOMM Comput. Commun. Rev. 43 (3), 34–44.

García-Dorado, J.L., Finamore, A., Mellia, M., Meo, M., Munafo, M., 2012. Characterization of isp traffic: Trends, user habits, and access technology impact. IEEE Trans. Netw. Serv. Manag. 9 (2), 142–155.

GitHub, 2018. Energy Sim simulation code. Available online at: https://github.com/3mission/energysim (Accessed 07.05.2018).

Goldfarb, A., 2014. What is different about online advertising? Rev. Ind. Organ. 44 (2), 115–129.

Google, 2017. 2016 Annual report. Available online at: https://abc.xyz/investor/pdf/2016_google_annual_report.pdf (Accessed 28.04.2018).

Gosselin, S.W., Saliou, F., Bourgart, F., Le Rouzic, E., Le Masson, S., Gati, A., 2012. Energy consumption of ICT infrastructures: an operator's viewpoint. In: European Conference

and Exhibition on Optical Communication. Optical Society of America (We-1).
Gozalvez, J., 2012. Wireless Connections Surpass 6 billion Mark [Mobile Radio]. IEEE Veh. Technol. Mag. 7 (4), 13–17.
Groen, E.A., Heijungs, R., 2017. Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: what is the risk? Environ. Impact Assess. Rev. 62, 98–109.
Gupta, A., Vanbever, L., Shahbaz, M., Donovan, S.P., Schlinker, B., Feamster, N., Katz-Bassett, E., 2015. Sdx: a software defined internet exchange. ACM SIGCOMM Comput. Commun. Rev. 44 (4), 551–562.
Han, C., Harrold, T., Armour, S., Krikidis, I., Videv, S., Grant, P.M., ... Le, T.A., 2011. Green radio: radio techniques to enable energy-efficient wireless networks. IEEE Commun. Mag. 49 (6).
Haverinen, H., Siren, J., Eronen, P., 2007. Energy consumption of always-on applications in WCDMA networks. In: Vehicular Technology Conference. VTC2007-Spring. IEEE 65th. IEEE, pp. 964–968.
Heller, B., Seetharaman, S., Mahadevan, P., Yiakoumis, Y., Sharma, P., Banerjee, S., McKeown, N., 2010. ElasticTree: Saving Energy in Data Center Networks. Nsdi, vol. 10. pp. 249–264.
Hilty, L. M., & Page, B., 2015. Information technology and renewable energy–modelling, simulation, decision support and environmental assessment.
ICT Sector Guidance built on the GHG Protocol Product Life Cycle Accounting and Reporting Standard., 2017, Available online at:https://ghgprotocol.org/sites/default/files/GHGP-ICTSG%20-%20ALL%20Chapters.pdf (Accessed 20.07.2018).
Ihm, S., Pai, V.S., 2011. Towards understanding modern web traffic. In: Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference. ACM, pp. 295–312.
IHS Technology, 2015. Paving the Way: How Online Advertising Enables the Digital Economy of the Future. Technical Report. Available online at: https://www.iabeurope.eu/files/9614/4844/3542/IAB_IHS_Euro_Ad_Macro_FINALpdf.pdf (Accessed 28.04.2018).
International Energy Agency, 2017a. Key World Energy Statistics. International Energy Agency, Paris Available online at: https://www.iea.org/publications/freepublications/publication/KeyWorld2017.pdf (Accessed 28.04.2018).
International Energy Agency, 2017b. Key World Energy Statistics. International Energy Agency, Paris Available online at: http://www.iea.org/statistics/statisticssearch/report/?country=WORLD&product=electricityandheat&year=2015 (Accessed 28.04.2018).
Internet World Stats, 2017. Usage and Population Statistics. Available online at. http://www.internetworldstats.com/stats.htm.
Ishii, K., Kurumida, J., Sato, K.I., Kudoh, T., Namiki, S., 2015. Unifying top-down and bottom-up approaches to evaluate network energy consumption. J. Lightwave Technol. 33 (21), 4395–4405.
Jagroep, E., Broekman, J., van der Werf, J.M.E., Brinkkemper, S., Lago, P., Blom, L., van Vliet, R., 2017. Awakening awareness on energy consumption in software engineering. In: Proceedings of the 39th International Conference on Software Engineering: Software Engineering in Society Track. IEEE Press, pp. 76–85.
Jesdabodi, C., Maalej, W., 2015. Understanding usage states on mobile devices. In: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, pp. 1221–1225.
Ji, C., Hong, T., 2016. New Internet search volume-based weighting method for integrating various environmental impacts. Environ. Impact Assess. Rev. 56, 128–138.
Jones, M., Morrison-Saunders, A., 2017. Understanding the long-term influence of EIA on organisational learning and transformation. Environ. Impact Assess. Rev. 64, 131–138.
Kern, E., Dick, M., Naumann, S., Hiller, T., 2015. Impacts of software and its engineering on the carbon footprint of ICT. Environ. Impact Assess. Rev. 52, 53–61.
Koomey, J.G., 2007. Estimating Total Power Consumption by Servers in the US and the World.
Koomey, J.G., 2008. Worldwide electricity used in data centers. Environ. Res. Lett. 3 (3), 034008.
Koomey, J., 2011. Growth in data center electricity use 2005 to 2010. A report by Analytical Press, completed at the request of The New York Times, 9.
Koomey, J., Berard, S., Sanchez, M., Wong, H., 2011. a. Implications of historical trends in the electrical efficiency of computing. IEEE Ann. Hist. Comput. 33 (3), 46–54.
Koomey, J., Chong, H., Loh, W., Nordman, B., Blazek, M., 2004. Network electricity use associated with wireless personal digital assistants. J. Infrastruct. Syst. 10 (3), 131–137.
Korotky, S.K., 2013. Semi-empirical description and projections of internet traffic trends using a hyperbolic compound annual growth rate. Bell Labs Tech. J. 18 (3), 5–21.
Koutitas, G., Demestichas, P., 2010. A review of energy efficiency in telecommunication networks. Telfor J. 2 (1), 2–7.
Lambert, S., Van Heddeghem, W., Vereecken, W., Lannoo, B., Colle, D., Pickavet, M., 2012. Worldwide electricity consumption of communication networks. Opt. Express 20 (26), B513–B524.
Lee, Y., Lee, Y., 2013. Toward scalable internet traffic measurement and analysis with Hadoop. ACM SIGCOMM Comput. Commun. Rev. 43 (1), 5–13.
Leung, W., Noble, B., Gunn, J., Jaeger, J.A., 2015. A review of uncertainty research in impact assessment. Environ. Impact Assess. Rev. 50, 116–123.
Li, J., Lin, B., 2017. Environmental impact of electricity relocation: a quasi-natural experiment from interregional electricity transmission. Environ. Impact Assess. Rev. 66, 151–161.
Loomis, J.J., Dziedzic, M., 2018. Evaluating EIA systems' effectiveness: a state of the art. Environ. Impact Assess. Rev. 68, 29–37.
Meeker, M., 2017. Internet trends 2017-code conference. Glokalde 1 (3).
Mills, M.P., 2013. The cloud begins with coal. In: Digital Power Group, Available online at: http://www.tech-pundit.com/wp-content/uploads/2013/07/Cloud_Begins_With_Coal.pdf (Accessed 28.04.2018).
Minovski, D., Rondeau, E., Georges, J.P., 2016. Using ICT Energy consumption for monitoring ICT usage in an enterprise. In: Future Internet of Things and Cloud (FiCloud), 2016 IEEE 4th International Conference on. IEEE, pp. 393–398.
Moberg, Å., Borggren, C., Ambell, C., Finnveden, G., Guldbrandsson, F., Bondesson, A., ... Bergmark, P., 2014. Simplifying a life cycle assessment of a mobile phone. Int. J. Life Cycle Assess. 19 (5), 979–993.
More, N.S., Ingle, R.B., 2017. Challenges in green computing for energy saving techniques. In: Emerging Trends & Innovation in ICT (ICEI), 2017 International Conference on. IEEE, pp. 73–76.
Morgan, R.K., 2017. Conceptualising best practice in impact assessment. Environ. Impact Assess. Rev. 66, 78–85.
Obile, W., 2016. Ericsson Mobility Report. Available online at:https://www.ericsson.com/res/docs/2016/ericsson-mobility-report-2016.pdf (Accessed 28.04.2018).
Pang, C., Hindle, A., Adams, B., Hassan, A.E., 2016. What do programmers know about software energy consumption? IEEE Softw. 33 (3), 83–89.
Pickavet, M., Vereecken, W., Demeyer, S., Audenaert, P., Vermeulen, B., Develder, C., ... Demeester, P., 2008. Worldwide energy needs for ICT: The rise of power-aware networking. In: Advanced Networks and Telecommunication Systems, 2008. ANTS'08. 2nd International Symposium on. IEEE, pp. 1–3.
Pope, J., Bond, A., Morrison-Saunders, A., Retief, F., 2013. Advancing the theory and practice of impact assessment: setting the research agenda. Environ. Impact Assess. Rev. 41, 1–9.
Pujol, E., Richter, P., Chandrasekaran, B., Smaragdakis, G., Feldmann, A., Maggs, B.M., Ng, K.C., 2014. Back-office web traffic on the Internet. In: Proceedings of the 2014 Conference on Internet Measurement Conference. ACM, pp. 257–270.
PwC, 2017. IAB internet advertising revenue report 2016 full year results. Technical Report. Available online at: https://www.iab.com/wp-content/uploads/2016/04/IAB_Internet_Advertising_Revenue_Report_FY_2016.pdf (Accessed 28.04.2018).
Roesner, F., Kohno, T., Wetherall, D., 2012. Detecting and defending against third-party tracking on the web. In: Proceedings of the 9th USENIX Conference on Networked Systems Design and Implementation. USENIX Association, pp. 12.
Salahuddin, M., Alam, K., Ozturk, I., 2016. The effects of Internet usage and economic growth on CO_2 emissions in OECD countries: a panel investigation. Renew. Sust. Energ. Rev. 62, 1226–1235.
Schien, D., Preist, C., 2014. A Review of Top-Down Models of Internet Network Energy Intensity. ICT4S.
Siegrist, K., 2017. Probability, Mathematical Statistics, Stochastic Processes. Available online at:http://www.randomservices.org/random/sample/CLT.html (Accessed 27.07.2018).
Silva, F.A., Domingues, A.C., Silva, T.R., 2018. Discovering mobile application usage patterns from a large-scale dataset. ACM Trans. Knowl. Discov. Data (TKDD) 12 (5), 59.
Simons, R.J.G., Pras, A., 2010. The Hidden Energy Cost of Web Advertising.
Solarwinds., 2018. Available online at:https://royal.pingdom.com/2018/05/21/trackers-impact-performance/ (Accessed 14.8.2018).
Statista, 2018a. The Statistics Portal. Available online at: https://www.statista.com/statistics/371889/smartphone-worldwide-installed-base/ (Accessed 28.04.2018).
Statista, 2018b. The Statistics Portal. Available online at: https://www.statista.com/statistics/541339/worldwide-pc-market-installed-base-by-type/ (Accessed 28.04.2018).
Taylor, C., Koomey, J., 2008. Estimating energy use and greenhouse gas emissions of internet advertising. Network.
TekCarta., 2018. Tablet installed base by OS worldwide 2010–2018. Available online at: https://www.nakono.com/tekcarta/market-forecasts/tablets-installed-base/tablet-installed-base-by-os-worldwide/ (Accessed 28.04.2018).
The Guardian, Jackson, J., 2016. Adblocking: Advertising 'accounts for Half of Data Used to Read articles'. Available online at: https://www.theguardian.com/media/2016/mar/16/ad-blocking-advertising-half-of-data-used-articles (Accessed 28.04.2018).
The Independent, Bawden, T., 2016. Global Warming: Data Centres to Consume Three Times as Much Energy in Next Decade, Experts Warn. Available online at: http://www.independent.co.uk/environment/global-warming-data-centres-to-consume-three-times-as-much-energy-in-next-decade-experts-warn-a6830086.html (Accessed 28.04.2018).
Valliyammai, C., Uma, S., Surya, P., 2014, April. Efficient energy consumption in green cloud. In: Recent Trends in Information Technology (ICRTIT), 2014 International Conference on. IEEE, pp. 1–4.
Van Heddeghem, W., Lambert, S., Lannoo, B., Colle, D., Pickavet, M., Demeester, P., 2014. Trends in worldwide ICT electricity consumption from 2007 to 2012. Comput. Commun. 50, 64–76.
Venturebeat, Protalinski, Emil, 2015. Streaming Services Now Account for over 70% of Peak Traffic in North America, Netflix Dominates with 37%. Available online at: https://venturebeat.com/2015/12/07/streaming-services-now-account-for-over-70-of-peak-traffic-in-north-america-netflix-dominates-with-37/ (Accessed 28.04.2018).
Vlachos, N., 2016. Internet Traffic Volumes Characterization and Forecasting (Doctoral dissertation). Heriot-Watt University.
Wahlroos, M., Pärssinen, M., Manner, J., Syri, S., 2017. Utilizing data center waste heat in district heating–Impacts on energy efficiency and prospects for low-temperature district heating networks. Energy 140, 1228–1238.
Wang, L., 2016. On Providing Energy-efficient Data Transmission to Mobile Devices. Available online at:https://aaltodoc.aalto.fi/bitstream/handle/123456789/19830/isbn9789526066868.pdf?sequence=1&isAllowed=y. (Accessed 14.8.2018).
Wang, P., Liu, Y., Meytlis, M., Tsao, H.Y., Yang, J., Huang, P., 2014. An efficient framework for online advertising effectiveness measurement and comparison. In: Proceedings of the 7th ACM International Conference on Web Search and Data Mining. ACM, pp. 163–172.

Wang, Y., Xiang, Y., Zhang, J., Zhou, W., Wei, G., Yang, L.T., 2014. Internet traffic classification using constrained clustering. IEEE Trans. Parallel Distribut. Syst. 25 (11), 2932–2943.
Whitehead, B., Andrews, D., Shah, A., Maidment, G., 2014. Assessing the environmental impact of data centres part 1: Background, energy use and metrics. Build. Environ. 82, 151–159.
Whitehead, B., Andrews, D., Shah, A., Maidment, G., 2015. Assessing the environmental impact of data centres part 2: Building environmental assessment methods and life cycle assessment. Build. Environ. 93, 395–405.
Yang, J., Qiao, Y., Zhang, X., He, H., Liu, F., Cheng, G., 2015. Characterizing user behavior in mobile internet. IEEE Trans. Emerg. Top. Comput. 3 (1), 95–106.
ZDNet, Kingsley-Hughes, Adrian, 2016. How Much Does it Cost to Charge an iPhone for a Year? Available online at: http://www.zdnet.com/article/how-much-does-it-cost-to-charge-an-iphone-for-a-year/ (Accessed 28.04.2018).
Zhao, B., Hu, W., Zheng, Q., Cao, G., 2015. Energy-aware web browsing on smartphones. IEEE Trans. Parallel Distribut. Syst. 26 (3), 761–774.