# Calculating Carbon Emissions of the ICT Sector: Analyzing Key Drivers and Future Trends

Lappeenranta–Lahti University of Technology LUT & Aalborg University (Copenhagen)

Nordic Master's Programme in Sustainable ICT Solutions of Tomorrow, Master's thesis

2024

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Examiners: Professor Jari Porras (LUT University)

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# Abstract

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This research addresses the pressing issue of accurately calculating and predicting the carbon emissions of the information and communication technology (ICT) sector, a significant contributor to global greenhouse gas emissions. Despite increasing attention, the methodologies and factors influencing ICT's carbon footprint remain ambiguous. The study employs a mixed-methods approach, integrating a systematic literature review, time series analysis, and regression analysis, to identify significant factors and predict future emissions. Key findings reveal that electricity consumption is the most critical factor driving ICT emissions, along with device shipments and energy demand. Predictive models suggest a steady increase in carbon emissions, reaching 945 $MtCO_2e$ in 2030 and 991 $MtCO_2e$ by 2035, and highlight discrepancies with previous studies. The study emphasizes the need for standardized calculating methodologies and constant monitoring to inform policy and industrial actions successfully. Limitations include reliance on estimated past values and a broad approach that does not account for the entire life-cycle of ICT devices. Future research should focus on detailed data collection and ongoing collaboration to address the dynamic nature of technological advancements. This study provides a foundation for more accurate and informed strategies to mitigate the environmental impact of the ICT sector.

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A special thanks to all my family friends, colleagues, and teachers for their support throughout the challenging times. I am solely responsible for any form of errors found in this thesis, regardless of all the support and guidance throughout the work.

Akib Ahmed
Copenhagen, Denmark
August 09, 2024

# Declaration of AI Use

**Notice on the use of Artificial Intelligence**

As required by LUT University's academic regulations, I declare the use of the following Artificial Intelligence tools and systems in the development of the project:

- **Grammarly:** Proofread, correction of grammar, punctuation, and rephrase.
- **ChatGPT:** Help with latex syntax, understanding context, debugging code, and help with visualization.
- **Quillbot:** For improved writing, paraphrase and grammar check

I declare that all the AI tools used in the development of this thesis are in line with LUT University's standards and guidelines (LUT University 2023). The information provided above accurately reflects the extent and nature of AI usage in this work.

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# 1 Introduction

Modernization comes at a significant cost to the environment. Global temperature has been rising at a pace of 0.18°C each decade since 1981, up from an average of 0.08°C during 1880-1980 (Allen & Tildesley, 1987). Global warming is mostly caused by greenhouse gas emissions from burning fossil fuels, with $CO_2$ being the most significant contributor. About three-fourths of all emissions come from $CO_2$, which rose by 51% between 1990 and 2015 (US EPA, 2024). Global emissions of greenhouse gases are continually growing (NSW Government, 2024). Between 1990 and 2019, the overall warming impact of greenhouse gases produced by civilization on the Earth's atmosphere grew by 45% (US EPA, 2024). Rising GHG threatens the world's future by causing severe weather, rising sea levels, droughts, and health risks (Abdouli & Hammami, 2017). The economy, human health, and the environment are all significantly impacted by greenhouse gas emissions, underscoring the urgent need for international action to cut emissions and lessen the effects of climate change.

A small number of countries, particularly China, the United States, India, the European Union, Russia, and Brazil, are the main contributors to global greenhouse gas (GHG) emissions, collectively responsible for over 61% of global GHG emissions (Crippa et al., 2023). China, the United States, and India alone account for 42.6% of total emissions, whereas the bottom 100 countries contribute just 2.9% (Johannes Friedrich & Vigna, 2023). Per capita emissions are highest in the United States and Russia, and the largest per capita $CO_2$ emitters are typically major oil-producing nations with smaller populations (Ritchie & Roser, 2020). Thus, these nations are major targets for international initiatives to cut greenhouse gas emissions and address climate change since they contribute significantly to global emissions. Nearly three-quarters of global emissions come from the energy sector, with electricity and heat production being the most significant sources (Ritchie, Rosado & Roser, 2020).

The main contributors to global greenhouse gas (GHG) emissions are the energy sector, industry, buildings, waste management, agriculture, forestry, other land use, and transportation. Figure 1 shows the percentages for every sector. The energy sector is the largest source, responsible for 25–30% of emissions from heat and power generation, transportation, and industrial operations (Ritchie, Rosado & Roser, 2020; Climate Watch, 2022). Agriculture, including land use changes, animal production, deforestation, and crop cultivation, contributes 18–20% of global emissions. Industrial processes and product consumption account for around 9-10% of emissions, with buildings contributing 17-18% through the use of power, heat, and air conditioning. The transportation sector, comprising shipping, aviation, and road transport, accounts for 16-18% of global emissions, with road transport being the largest source (Climate Watch, 2022; Ritchie, Rosado & Roser, 2020). Waste management, including waste incineration, wastewater treatment, and solid waste disposal, contributes 3-4% of emissions (Ritchie, Rosado & Roser, 2020). Reducing emissions across these sectors is essential for addressing climate change.

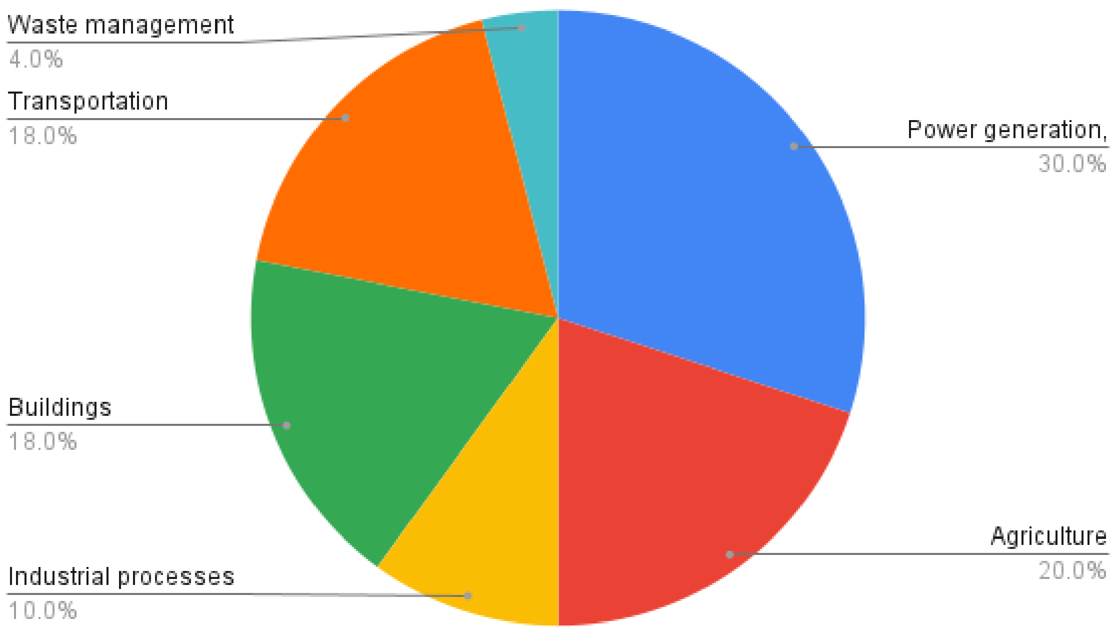



Figure 1: Main contributors to global greenhouse gas (GHG) emissions

Humanity must reduce its greenhouse gas (GHG) emissions by half every ten years to keep global warming to 1.5–2 degrees Celsius over pre-industrial levels. By 2050, these emissions should only make up a small portion of what they do presently (Rockström et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) of the United Nations estimates that to keep global average temperature increases below 2°C, global greenhouse gas emissions must be lowered by 40–70% by the year 2050 compared to 2010 (Pachauri & Meyer, 2014). Environmental organizations and researchers are exploring elements that might reduce carbon emissions while simultaneously promoting global economic growth.

The field of information and communication technology (ICT) has not only been expanding quickly at present but also has seen remarkable global advancements already. Figure 2 shows the growth of IT expenditure on enterprise software over the years. ICTs are pivotal in mitigating GHG emissions and combating climate change. The ICT sector can significantly reduce global GHG emissions, with the Global e-Sustainability Initiative (GeSI) indicating a potential 20% reduction by 2030 (United Nations Framework Convention on Climate Change (UNFCCC), 2016). ICT in total, aids in monitoring and mitigating climate change by tracking emissions and promoting energy-efficient practices, supporting the shift to a low-carbon economy. This sector is noteworthy due to its growth and ability to reduce greenhouse gas emissions in other industries by offering alternatives to transportation, travel, tangible commodities, and other related industries (Berkhout & Hertin, 2004; Hilty, Arnfalk, et al., 2006). Furthermore, this sector provides innovative solutions across various sectors, addressing the broader 97.5% of global emissions, and aligns with green transition initiatives like digital transformation for climate neutrality (International Telecommunication Union (ITU), 2014). The International Telecommunication Union (ITU) has established standards and methodologies to assess ICT's environmental impact, helping companies reduce emissions and achieve climate goals. In summary, ICT's role is crucial in emission reduction, climate monitoring, offering innovative solutions, supporting green transitions, and adhering to environmental standards.

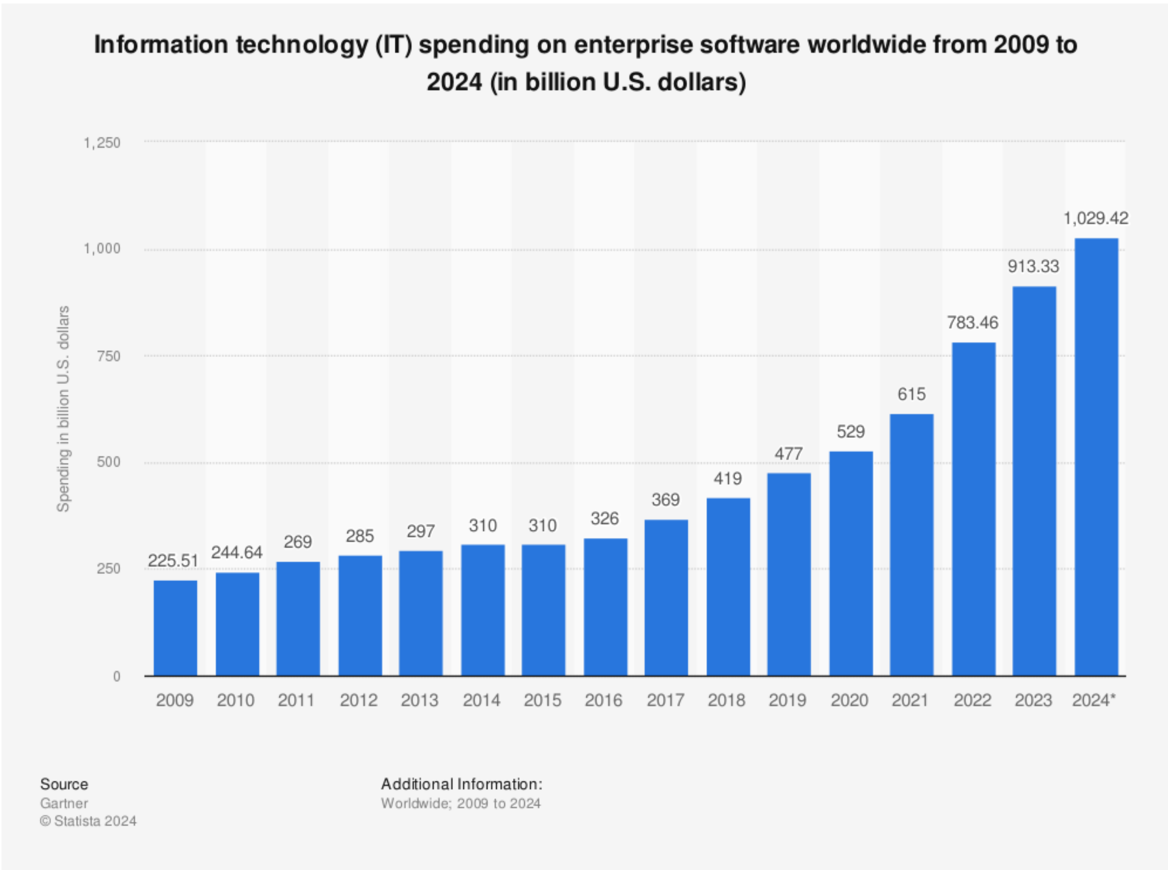



Figure 2: IT spending on enterprise software worldwide. Gartner, January 17, 2024

A framework for avoided emissions was presented by Mission Innovation, an initiative that supports global clean energy innovation that connects 23 nations with the EU. It encompasses ICT solutions and is meant to assist investors and decision-makers in promoting and accelerating the development of low-carbon solutions (Stephens & Thieme, 2018). The Paris Agreement, which "aims to strengthen the global response to the threat of climate change," has been approved by 195 member nations as of October 2017 (UNFCCC, 2015). $CO_2$

emissions are still rising in spite of the Paris Agreement and the Kyoto Protocol. Numerous research works concentrate on the connection between ICT and $CO_2$ emissions. Although ICT goods and services contribute to environmental degradation, they also have a great deal of potential to mitigate it by replacing environmentally unfriendly items with ICT products and streamlining manufacturing processes (Erdmann & Hilty, 2010; Arushanyan, Ekener-Petersen & Finnveden, 2014; Malmodin, Moberg, et al., 2010).

Digitalization through information and communication technologies (ICTs) affects several aspects of society and the economy, including power usage and $CO_2$ emissions. ICT has a significant influence on power usage and indirect $CO_2$ emissions (Danish, Khan, et al., 2018). Recent estimates (SG Andrae, 2020) indicate that ICT-related $CO_2$ emissions account for around 4% of total world emissions in 2020 and are anticipated to rise further. Based on statistics from 2007, the information and communications technology (ICT) industry accounts for 1.3% of worldwide greenhouse gas emissions (Malmodin, Moberg, et al., 2010). Furthermore, Mingay, 2007 notes that the ICT sector is responsible for 2% of global greenhouse gas emissions. According to an estimate, by 2020, the growth of the ICT sector would result in a 1.1 Gt carbon footprint (Malmodin, Bergmark & Lundén, 2013).

ICT may affect the environment in both beneficial and detrimental ways. ICT can significantly reduce global GHG emissions by up to 12,000 Mt-$CO_2$eq by 2030 across sectors like smart buildings and mobility, contributing over $11 trillion in economic benefits (X. Zhang et al., 2022). It enhances productivity, improves logistics efficiency, and supports sustainable production and consumption patterns (Higón, Gholami & Shirazi, 2017). ICT can offer some direction towards reducing how much human activity affects the environment. For example, by decreasing the requirement for transportation, e-commerce can help reduce the consumption of fuel (Yi & Thomas, 2007). However, the ICT's rising energy consumption and emissions are a growing concern. The growth of ICT has led to the proliferation of consumer electronics like PCs, smartphones, TVs, and home entertainment systems, as well as networking technologies such as wired networks and 3G/4G LTE, and the expansion of data centers. While ICT has enabled technologies such as cryptocurrency, AI, e-commerce, online entertainment, social networking, and cloud storage, it has also had a significant negative impact on the environment (Gupta et al., 2021). By 2030, ICT could account for up to 23% of global GHG emissions if not mitigated. Transitioning to renewable energy could reduce the sector's carbon footprint by over 80% (Ericsson IndustryLab, 2024).

The main sources of carbon emissions in the ICT sector are network operations, data centers, and ICT equipment. When dividing emissions into usage and life cycle components, user devices such as mobile phones and computers account for the majority of emissions (Malmodin & Lundén, 2018). The energy requirements of data centers for operation and cooling, in addition to emissions from equipment manufacturing and transportation, make them a substantial contributor. Emissions are further increased by network operations, such as fixed and mobile access (Ayers et al., 2023). The industry's emissions have not changed despite an increase in data traffic, which emphasizes the need for greater energy efficiency and the use of renewable energy sources to lessen the impact on the environment (Carbon4Finance, 2023). As of 2020, the ICT sector accounted for 4-6% of global electricity usage, excluding TVs. This share is projected to increase over the next 5-10 years due to rising demand for digital services and technologies (Aimee Ross, 2022). Despite improvements in energy efficiency and renewable energy use, emerging technologies like 5G, AI, and cryptocurrencies are expected to drive a continued increase in electricity consumption (Gelenbe, 2023).

ICT goods raise $CO_2$ emissions at every stage of their life cycle—production, usage, and disposal—as confirmed by Danish, B. Zhang, et al., 2017. Dedrick, 2010 and Molla, Pittayachawan & Corbitt, 2009 underline the necessity for immediate measures to mitigate the negative environmental consequences of ICT. The ICT sector is frequently criticized for its exponential rise in energy use. Digital devices are becoming more and more necessary in present-day society. As a result, there has been an increase in energy consumption in the manufacturing sectors in recent years. The need for electricity to power ICT gadgets is the primary cause of the rise in $CO_2$ emissions. This has a direct impact on both global warming and greenhouse gas (GHG) emissions (Belkhir & Elmeligi, 2018). A significant amount of carbon emission of ICT comes from energy consumption through the ICT sector. Currently, the ICT industry accounts for around 8% of worldwide power consumption. The production of ICT goods is expected to rise over the next decade, potentially increasing energy consumption and GHG emissions, particularly in industries where electrical networks have a higher carbon intensity (Andrae & Edler, 2015; Andrae, Hu, et al., 2017).

The complexity and diversity of the ICT industry, which includes a wide range of products and services such as computer systems, data centers, and communication networks, make it difficult to calculate the sector's carbon emissions (Carbon4Finance, 2023; Data Bridge Market Research, 2023). Intricacy is increased by the lack of established procedures, inconsistent data quality, and several sources of emissions, including embodied, operational, and end-of-life emissions. Products' whole life cycle—from the extraction of raw materials to their disposal—must be taken into account (Jha et al., 2022). Accurate quantification is made more difficult by geographical differences and the rapid evolution of technology (Jha et al., 2022; Data Bridge Market Research, 2023). For instance, IoT testing solutions do not allow for detailed benchmarking of energy use and carbon emissions, hence removing the environmental impact from the testing (Beilharz et al., 2021). The difficulty of calculating correct estimates contributes to testing devices' failure to report energy and carbon emissions

(Trihinas et al., 2022). It might be challenging to estimate the sector's overall emissions impact when considering rebound effects, which occur when efficiency improvements result in higher demand (Freitag et al., 2021).

The Global eSustainability Initiative, which advocates for ICT companies, states in their report SMARTer 2030 (Global e-Sustainability Initiative (GeSI), 2015) that ICT could save 9.1 $GtCO_2e$ in 2020 and 12.08 $GtCO_2e$ in 2030 in other industries, including manufacturing, transportation, health, education, buildings, and agriculture—mostly as a result of increased efficiency. Keeping emissions at 2015 levels and severing the link between economic development and emissions increase, would enable a 20% decrease in global $CO_2$ emissions by 2030. In light of their projections of ICT's own emissions of 1.27 $GtCO_2e$ in 2020 and 1.25 $GtCO_2e$ in 2030, GeSI (Global e-Sustainability Initiative (GeSI), 2015) contends that ICT is carbon neutral and that public and private sectors need to increase their ICT spending. They claim that ICT reduced emissions by 1.5 times in just 2015. The GeSI report, sponsored by many significant ICT businesses, lacks transparency in its analysis, raising questions about potential conflicts of interest. Currently, there is limited data to support these predictions.

Reducing the adverse impact of ICT on the environment is the goal of the "green ICT" effort. With little to no negative environmental impact, green ICT epitomizes this industry's efficacy and efficiency (Askarzai, 2011). To create better transportation, energy, and industrial processes as well as cities, ICT is a crucial component (Danish, B. Zhang, et al., 2017).

## 1.1 Motivation

The information and communications technology (ICT) industry is essential to modern civilization as the foundation for international trade, communication, and information collaboration. Still, there are considerable environmental problems resulting from the rapid development and broad use of ICT, especially when considering carbon emissions. It is challenging to calculate the carbon emissions of the ICT industry because it requires knowledge of the different sources of emissions, the methodologies used to measure these emissions, and the complexities of the sector's operations.

The ICT sector's carbon footprint is a multifaceted issue that encompasses a wide range of activities, from the manufacturing and transportation of devices to the energy consumption and maintenance of data centers and networks. The sector's emissions are also influenced by factors such as the type and quality of energy used, the efficiency of devices and systems, and the overall scale of operations.

Despite the necessity of precisely quantifying ICT carbon emissions, the endeavor is riddled with difficulty. One of the key challenges is the complexity of the sector's operations, which include a wide range of technology, systems, and procedures. This complexity makes it difficult to precisely monitor emissions since it necessitates a thorough grasp of the sector's inner workings and the different elements that contribute to emission levels.

Another challenge in calculating ICT's carbon emissions is the lack of standardized methods and protocols. The ICT sector is characterized by a diverse range of activities, each with its unique set of emissions sources and factors. This diversity makes it difficult to develop a single, universally accepted method for calculating emissions, and instead, various approaches and frameworks have been developed to address specific aspects of the sector's emissions.

The absence of established procedures and protocols leads to heterogeneity in emissions estimates across research and reports. This variety can cause confusion and ambiguity, making it difficult to design effective emissions-reduction and sustainability plans in the ICT industry.

The purpose of this research is to assist in the advancement of a more precise and thorough knowledge of the carbon emissions associated with ICT. This study will use a numerical approach to calculate the carbon emission of ICT and compare the present-day values with those of previous studies.

## 1.2 Problem definition

The ICT sector's share of global GHG emissions ranges from approximately 1.8% to 3.9% according to various studies, with some estimates adjusting this figure upwards to account for the truncation of supply chain emissions (Freitag et al., 2021). The ICT sector's carbon footprint is comparable in size to that of the aviation industry in recent years (Avant Garde Group, 2021). This 2.1% difference makes a big difference while considering the global GHG emission. Therefore it is important to analyse with a more accurate and precise quantification to take further actions.

The GeSI report in 2008 predicted that the carbon emission of ICT would be 1470 $MtCO_2e$ in the year 2020. However, their later report in 2012 estimated the value is less than the previous prediction. There the mentioned value is estimated to be 1270 $MtCO_2e$. Also, another study by Andrae & Edler, 2015 showed several attributes and their values as well as estimates relating to electricity usage of ICT. But later on a study by Andrae, 2019 proposed new estimates for some of the attributes mentioning the previous study overestimated the values.

Also, the GeSI report considered the ICT devices in a different way than Malmodin's study. The GeSI calculation includes TV and paper media in their ICT sector but malmodin calculated separated the TV and media from the main ICT sector. Therefore, it is clear that there are obvious inconsistencies in the comparison done for the carbon emission of ICT. Thus, the problem statement for this research is defined by addressing the concern of the inconsistent definition of the ICT sector and the need for a standardized method.

The problem statement can be stated as follows:

> "Despite growing research on the environmental impact of Information and Communication Technologies (ICT), a clear understanding of ICT's global carbon dioxide emissions remains elusive. While some previous studies highlight detailed calculation methods for carbon emission of ICT, there is a lack of standardized methods and identifying factors. The unclear methods for predictions of the future values of carbon emission need to be addressed."

## 1.3 Research objectives and questions

From the previous studies and problem statement mentioned in the report, it is clear that there is certainly an ambiguity whilst calculating ICT's carbon emission. Also, the uncleared forecasting of future values needs to be studied further. Hence, the main question this project tries to answer is:

> "**How can the carbon emission of the ICT sector be calculated as well as forecasted?**"

The problem statement can further be broken down into sub-problems and smaller research questions that are stated below.

**Sub-problems/research questions:**

1. What significant factors need to be considered while calculating ICT's carbon emissions?
2. To what extent does electricity consumption impact the carbon footprint of the ICT sector?

## 1.4 Focus areas and expected outcomes

This paper addresses the gap mentioned in the problem statement by investigating the factors that affect the carbon dioxide emissions of ICT in a global context. This work will explore the previously conducted calculation methods and provide the latest analysis as well as predictions for the next decade. Firstly, a systematic literature review will be conducted to identify the current state and findings of recent studies in the field. After that, the findings will be sorted, analyzed, and outlined to answer the research goal.

To address the main research question of calculating carbon emissions of ICT, different machine learning algorithms will be used to calculate and predict future values. For that, the ICT sector will be defined and what each sector includes will be identified. Under each sector, there will be separate attributes contributing to the overall emission. Since the attributes used in this research are expected to be a training set for the outcomes. Thus, the prediction and other analyses are based on the model's learning techniques. Therefore, the features that will be selected will not predict the values based on basic arithmetic operations. Also, the factors contributing to the emission calculation will be identified through coding analysis.

The result is expected to be in the ranges mentioned in the previous estimations. This would clarify what considerations are taken into account and what is missing that could change the prediction. Also, the proof of being in the mentioned range will be able to validate the previous calculation to some extent. The outcome is significantly important to the ICT for Sustainability research field as predicting carbon footprint is quite challenging and has varied a lot previously.

## 1.5 Structure of the Thesis

In the first introductory chapter, an overview of the world's GHG emissions and relative studies are discussed by laying out the motivation of the research. Following that, the problem is defined by the importance of measuring carbon emissions in the ICT sector. After that, the appropriate research question along with the sub-questions is mentioned to help identify the methodology applied to conduct the research.

The background chapter discusses the role of ICT in sustainability research and how it is related to other fields. The extent of emissions in the ICT industry is extensively discussed with many sources of emitters. The impact of ICT on sustainability is discussed with some foundational models in this field that are widely talked about in this section. Following that, the state-of-the-art chapter discusses current studies that compute carbon emissions using a technique specific to the ICT industry. It also includes the methods that were followed by other authors to calculate as well as predict the values of carbon emission of ICT. The methodology chapter describes the strategy used to seek relevant literature and provide a concise response to the research topic. Here the methods followed in this research work are thoroughly mentioned with theoretical analysis.

The next chapter can be classified as calculation and analytical chapters. The first step is to calculate the carbon footprint of the ICT industry. This number is based on emissions from electronic devices, data centers, and network connections. The thorough strategy that was taken into account is described with references. The following part discusses a projection of future carbon emissions based on the techniques applied to predict the future. Finally, an explanation is presented that influenced the target value for specific years that helps the findings of important features.

The report concludes with a discussion comparing of the analytical results to the findings in the literature. This section also discusses the relevance of the results and the research problems that have been answered to some extent and with a new approach. In conclusion, the project's purpose, strategy, and findings are briefly described, and future work scopes are discussed.

# 2 Background

This chapter includes the related background concepts of carbon emission in the ICT sector by introducing sustainability in the context of ICT. It mentions frameworks proposed previously for understanding the environmental impacts of ICT. Furthermore, the sources of ICT emissions concerning the definition are discussed briefly with the scope of the emissions by category. Thus, this chapter sets a good foundation for providing the analysis of the conducted studies in the following chapters of this paper.

## 2.1 Sustainability and ICT

ICT is critical in promoting sustainability because it enables growth in impoverished areas, integrates ecological, social, and economic evaluations, and drives sustainable practices. The United Nations has recognized ICT as a catalyst for sustainable development, stating that technology helps bridge the digital divide, builds knowledge societies, and accelerates progress toward all 17 Sustainable Development Goals (SDGs) (The United Nations, 2016). ICT promotes sustainability by facilitating access to education, mobile banking, e-government services, and social media, thereby furthering goals such as education, gender equity, and infrastructure (Carrera & Kurnia, 2016). Overall, ICT is essential for creating a more sustainable and inclusive future.

### 2.1.1 Definition of Sustainability

Sustainability is a commonly used phrase that describes something's ability to endure over an extended period of time. Sustainability is the long-term goal of a healthy planet, while sustainable development is the process of achieving progress while respecting environmental limits. The two terminologies are connected because sustainable development can only happen on a foundation of sustainability. According to Penzenstadler & Fleischmann, 2011,

> "Sustainability is the capacity to endure and, for humans, the potential for long-term maintenance."

The authors also defined sustainable development as developing both a sustainable product and a product through a sustainable process. According to the Brundtland report from the United Nations, sustainable development is defined as follows:

> "Sustainable development is the development that meets the needs of the present without compromising the ability of future generations to meet their own needs." (WCED: World Commission on Environment and Development, 1987)

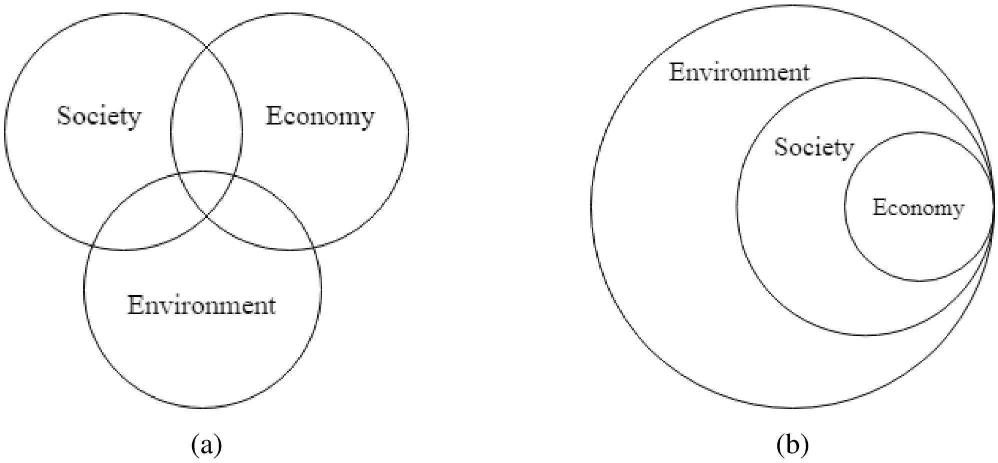



Figure 3: Different views of the environment, society, and the economy. (a). The general three-pillar model of sustainable development. (b). The nested three-pillar model of sustainable development (Hilty & Aebischer, 2015).

A metaphor that is frequently used to explain sustainable development is the idea of maintaining a “balance” between the environment, the economy, and society. Another name for this approach is the “three-pillar model” (Hilty & Aebischer, 2015).

The three-pillar concept of sustainable development includes environmental, economic, and social sustainability (Garbie, 2014; Purvis, Mao & Robinson, 2019). Environmental sustainability focuses on preserving natural resources and minimizing climate change. Economic sustainability emphasizes sustainable economic processes, employment enhancement, equitable remuneration, and the environmental effect of profit-driven tactics. Social sustainability seeks to provide a high quality of life, equal opportunity, and inclusion for everyone. To ensure long-term sustainability, each pillar must be considered collectively; no one pillar can be addressed alone (Thatcher, 2013). The approach arose from criticisms of economic practices and efforts to balance growth with social and environmental concerns.

Environmental and social interactions contribute to a “bearable” condition, in which a good environment promotes human well-being. Social and economic interactions promote “equitable” sustainability, which ensures equal resource allocation and economic possibilities. Economic and environmental connections foster “viable” sustainability by encouraging the responsible use of natural resources (Garbie, 2014; Purvis, Mao & Robinson, 2019). Integrating all three pillars yields “sustainable” development, which balances each component to suit current and future demands. Recognizing and managing these links is necessary for achieving sustainability.

To achieve balance, entities must be both independent and interlinked (Hilty & Aebischer, 2015). Diagrams like Figure 3a illustrate that the environment, economics, and society exist on the same level and are linked by overlapping regions. When the three systems are layered, as seen in Figure 3b, maintaining actions among the layers becomes difficult. The higher layer is achieved by considering the limitations of the lower ones. There cannot be a balance between parts and the whole.

### 2.1.2 Definition and Scope of ICT

Defining ICT entails comprehending its progression through three technical developments: communication technologies, storage technologies, and computing technologies (Aebischer & Hilty, 2015). The confluence of these advancements has resulted in a complex landscape of devices and infrastructures, making exact definitions difficult yet vital to prevent discrepancies in research, particularly those involving energy usage. Furthermore, the increasing integration of microprocessors into non-ICT devices, as well as the trend toward service-oriented ICT (such as cloud computing), complicate the boundaries and assessment of ICT's influence, emphasizing the importance of defined system boundaries in research (Aebischer & Hilty, 2015).

Information technology is "the study, design, development, implementation, support, or management of computer-based information systems, particularly software applications and computer hardware," according to the Information Technology Association of America (ITAA) (Veneri, 1999). On the other side, communication technology comprises the process of creating, building, and managing communication systems that are utilized to enable virtual communication between people or groups.

All technologies used to manage information and facilitate its transfer in a digital format-including production, collection, analysis, preservation, extraction, transmission, trading, and dissemination—are collectively referred to as information and communication technologies, or ICTs. ICT comprises both software and hardware. Hardware includes mobile phones, PDAs with pens, printers, wireless and mobile networks for telecommunication, wearable technology, desktop and laptop computers, and so on. Software includes related programs and services including videoconferencing, e-commerce, e-learning, decision support systems (DSS), service-oriented architecture (SOA), enterprise resource planning (ERP), and e-communities (virtual teams), among others (Bibri, 2009).

A 2008 report by the WWF identified ten ways information and communication technologies (ICT) can be used across different industries to boost energy savings and cut carbon dioxide emissions. Each approach has the potential to reduce emissions by over 100 million tons annually (Griffiths, 2008). Here's a breakdown of these methods based on You, Li & Waqas, 2024; British Telecommunication, 2016:

- **Smart Grid and Energy:** By putting smart grids into place, energy waste and emissions may be decreased by optimizing energy distribution and consumption. Smart grids are energy distribution and consumption systems that make better use of cutting-edge technology including automation, sensors, and data analytics.
- **Remote Work:** Leveraging the internet to work from a distance, reduces business travel and commutes. The requirement for travel, which contributes significantly to GHG emissions, may be minimized with the use of telepresence and video conferencing. Up to 1.5 million tons of $CO_2$ emissions can be avoided each year using this.
- **Smart Buildings:** Employing sensors and control systems to optimize efficiency in buildings. Smart homes may save energy by automating lighting, heating, and cooling systems. This can lower energy use and emissions by as much as 20%.
- **Digital Services:** Utilizing ICT to replace physical products and interactions (dematerialization). E-commerce and online purchasing can help eliminate the need for physical storefronts and transportation, resulting in lower emissions. This can save up to 1.2 million tonnes of $CO_2$ emissions yearly.
- **Industrial Optimization:** Using ICT to enhance operations and efficiency in production processes. Also, utilizing software to forecast, simulate, and analyze energy consumption within production processes.
- **Energy-Efficient Data Centers:** Data centers may be constructed and run more efficiently. This involves adopting energy-efficient servers, cooling systems, and power supply, with implementing virtualization and cloud computing to decrease energy use.
- **Renewable Energy Integration:** Utilizing simulation, analysis, and management tools to facilitate widespread adoption of renewable energy. Integrating renewable energy sources, such as solar and wind power, into the grid can help to reduce fossil fuel emissions. This can reduce up to 1.5 million tons of $CO_2$ emissions per year.
- **Intelligent Transport:** Implementing advanced sensors, data analysis, and widespread communication to enable cleaner transportation options. For instance, electric cars can lower transportation-related emissions by up to 70 percent. This can save up to 1.1 million tonnes of $CO_2$ emissions yearly.
- **Smart City Planning:** Employing simulation software to improve urban design for optimal energy efficiency.
- **Waste Reduction and Recycling:** Implementing waste reduction and recycling initiatives can minimize the quantity of garbage transported to landfills, hence decreasing emissions from waste breakdown. This can save up to 1.1 million tonnes of $CO_2$ emissions yearly.

### 2.1.3 Research fields relating ICT to sustainability

The ICT sector has significant and increasing greenhouse gas emissions, similar to the aviation industry. The UN has recognized its potential to drive sustainable development. There are no standard methods for fully calculating its carbon footprint (Carrera & Kurnia, 2016). The environmental impact of its various activities is complex. The need to balance economic, social, and environmental dimensions makes research on this relationship crucial (Jayaprakash & Radhakrishna Pillai, 2022). Achieving sustainability goals requires recognizing and reducing ICT's environmental effect, utilizing it in sustainable development, and creating all-encompassing methods.

Table 1 provides a general summary of the study topics related to ICT and sustainability, as well as their meaning, range based on primary approaches, and contributions to sustainable development. They are also mentioned briefly in this section of the background chapter.

#### Environmental Informatics

Environmental Informatics (EI) integrates computer science and information systems with environmental science and management to address specific information processing needs in environmental contexts. Emerging in the early 1990s, EI initially focused on public sector applications, later expanding to the private sector (Hilty & Rautenstrauch, 1997). Key methods in EI include modeling, simulation, and data integration. It aims to support sustainable development through shared data and transdisciplinary problem-solving. The field is documented through conferences like EnviroInfo and ISESS, and initiatives like the European ICT-ENSURE project have helped structure EI research (Hilty & Aebischer, 2015).

#### Computational Sustainability

Computational Sustainability (CompSust) is an interdisciplinary field founded in 2008 with support from the U.S. National Science Foundation (ICS, 2014). It applies computer and information science, applied mathematics, and statistics to balance environmental, economic, and societal needs for sustainable development (Gomes, 2009). CompSust focuses on providing decision support for managing natural resources, employing techniques like dynamic modeling, optimization, machine learning, and statistical modeling. While frequently emphasizing "balancing needs," the field lacks clarity on specific needs and approaches to addressing normative issues related to distributive justice (Hilty & Aebischer, 2015).

#### Sustainable HCI

Sustainable HCI is a sub-field of Human-Computer Interaction that explores how technology and human interaction can support sustainability. Originating in 2007 with E. Blevis's Sustainable Interaction Design (SID), it prioritizes sustainability in technology design alongside usability and robustness. SID emphasizes the entire lifecycle of a system, promoting longevity, transfer of ownership, and responsible disposal (Blevis, 2007). Mankoff et al., 2007 categorizes sustainability in HCI into "sustainability through design" and "sustainability in design." DiSalvo, Sengers & Brynjarsdóttir, 2010 identify five genres within Sustainable HCI research: persuasive technology, ambient awareness, sustainable interaction design, formative user studies, and pervasive and participatory sensing. Huang, 2011 highlights the need for Sustainable HCI to collaborate with other fields and real-world applications to effectively address sustainability challenges.

Green ICT

Green IT (or Green ICT) focuses on designing, using, and disposing of computing and telecommunications technology with minimal environmental impact (Murugesan, 2008). Popularized in 2007, it encompasses areas like energy-efficient computing, data center design, server virtualization, and responsible recycling (Mingay, 2007). It also involves using IT to promote environmental sustainability and awareness. The field differentiates between reducing ICT's environmental footprint ("Green in ICT") and using ICT to support broader sustainability goals ("Green by ICT"). Green Information Systems (Green IS) extend this by incorporating human activities within organizations, aiming for a holistic strategy to reduce environmental impacts through information systems (Loeser, Erek & Zarnekow, 2012).

ICT for Sustainability (ICT4S)

ICT for Sustainability (ICT4S) aims to harness the transformative power of information and communication technologies to foster sustainable production and consumption patterns. As articulated in the 2013 ICT4S conference in Zurich, this initiative highlights that simply increasing energy efficiency through technology does not inherently lead to sustainable development. Achieving true sustainability requires coordinated efforts from policymakers, industry, and consumers (Hilty, Aebischer, et al., 2013). ICT4S, which evolved from a conference rather than a research field, encompasses two main areas: making ICT products and services sustainable throughout their life cycle (Sustainability in ICT) and using ICT to promote sustainable behaviors and practices (Sustainability by ICT) (Hilty & Aebischer, 2015). While related to fields like Green ICT and Sustainable HCI, ICT4S uniquely emphasizes the societal impact of technological solutions, questioning whether they contribute to sustainable development at a broad societal level (Hilty & Aebischer, 2015). The field employs diverse methods, including life cycle assessment, technology assessment, social science research, scenario modeling, and interdisciplinary simulations, to study the interactions between tech-

Table 1: Overview of the research fields relating ICT to sustainability and their definition with scope based on main methods and contributions to sustainable development (Hilty & Aebischer, 2015).

| **Name of the Field of Study** | **Scope** |
|---|---|
| Environmental Informatics | In order to monitor the environment, comprehend complex processes, and promote data sharing and consensus-building, this area makes use of information systems, modeling and simulation, and geographic data processing. |
| Computational Sustainability | This discipline combines modeling, optimization, constraint reasoning, machine learning, and other techniques to provide decision assistance for natural resource management and dispute resolution. |
| Sustainable HCI | This approach supports a sustainable lifestyle, encourages sustainable behavior, and extends the life of gadgets through the application of design research, empirical HCI, and other methodologies. |
| Green IT/ICT | This field focuses on IT management, IT engineering, and software engineering to reduce the environmental impacts of ICT hardware and software. |
| ICT for Sustainability | This discipline relies on assessment methods (LCA, TA, and others), empirical methods (including social sciences), scenario development, modeling, and simulation to reduce ICT-induced energy and material flows, enable sustainable patterns of production and consumption, and comprehend and apply ICT as a transformational technology. |

nology and human behavior and to address complex dynamic systems.

## 2.2 Impact of ICT on Sustainability

Research conducted by the European Commission several years ago looked into the environmental impacts of society's rising reliance on information technology. The study, which employed social and economic models as well as simulations, found that while IT's overall environmental impact was minimal, it had both good and negative consequences in certain sectors. For instance, IT improved freight transit efficiency, resulting in increased demand, but simultaneously allowing for the dematerialization of goods, lowering the need for materials and transportation. These opposite effects frequently balance one other out. The key conclusion was that IT should not be simply labeled as beneficial or negative for the environment. Instead, particular rules are required to maximize the potential advantages while minimizing the negatives. A systematic approach, based on a framework such as the LES model proposed by Hilty & Aebischer, 2015, is critical for comprehending the complicated interaction between IT and sustainability and, ultimately, developing successful policies.

### 2.2.1 The Three-Levels Model

The Three-Levels Model categorizes the impacts of ICT into three orders: direct environmental effects from production and usage, indirect impacts on production processes and products, and indirect effects on lifestyles and value systems (Hilty & Aebischer, 2015). Initially introduced by Berkhout & Hertin, 2001 in an OECD report, this framework distinguishes between positive and negative impacts, labeling some as favorable for sustainability and others as not.

Figure-4 describes a framework for understanding the environmental impacts of Information and Communication Technology (ICT) (Hilty, 2008). The framework categorizes effects into three levels (Hilty & Aebischer, 2015):

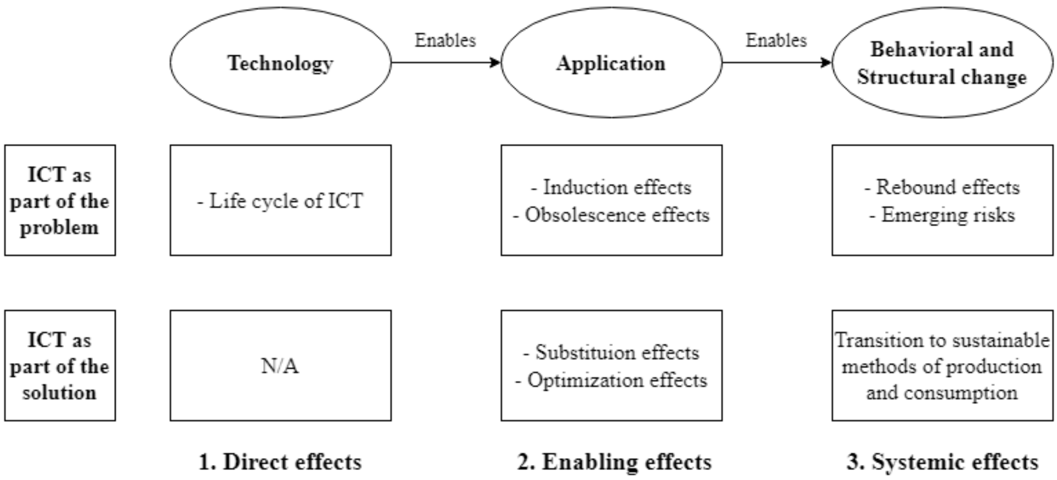



Figure 4: A matrix of ICT effects, based on (Hilty, 2008)

**Level 1- Direct effects (negative):** This level focuses on the direct material and energy costs of ICT, assessed via Life-Cycle Assessment. Since these consequences reflect the expense of delivering ICT services, they are altogether negative.

**Level 2- Enabling effects (mixed):** These effects depend on how ICT is used. Some can be positive, like replacing printed books with e-readers or using smart home technology to save energy. Others have negative impacts, such as increased paper use due to faster printing with ICT or devices becoming obsolete due to software incompatibility.

**Level 3- Systemic effects (mixed):** This level examines systemic effects, including behavioral and economic changes. Negative aspects include rebound effects, where efficiency gains lead to more consumption and new risks like ICT network vulnerabilities. Positive aspects involve promoting sustainable production and consumption.

Meanwhile, the model's use of abstraction levels and impact categories has been questioned.

While the micro-level effects (substitution, optimization) are obvious, the aggregated macro-level implications are unknown owing to market interactions (Hilty & Aebischer, 2015). As a result, analyzing ICT's sustainability necessitates a macro-level approach that ensures discrete acts are examined methodically.

### 2.2.2 The LES Model

the LES model, which is an improvement upon previous approaches. It avoids normative assumptions and focuses on descriptive analysis, connecting well with production and sociological theories. The model comprises three levels of impact: Life-cycle, Enabling, and Structural impacts (Hilty & Aebischer, 2015). The LES model (shown in figure-5), an improved framework for assessing ICT impacts, categorizes effects into three levels:

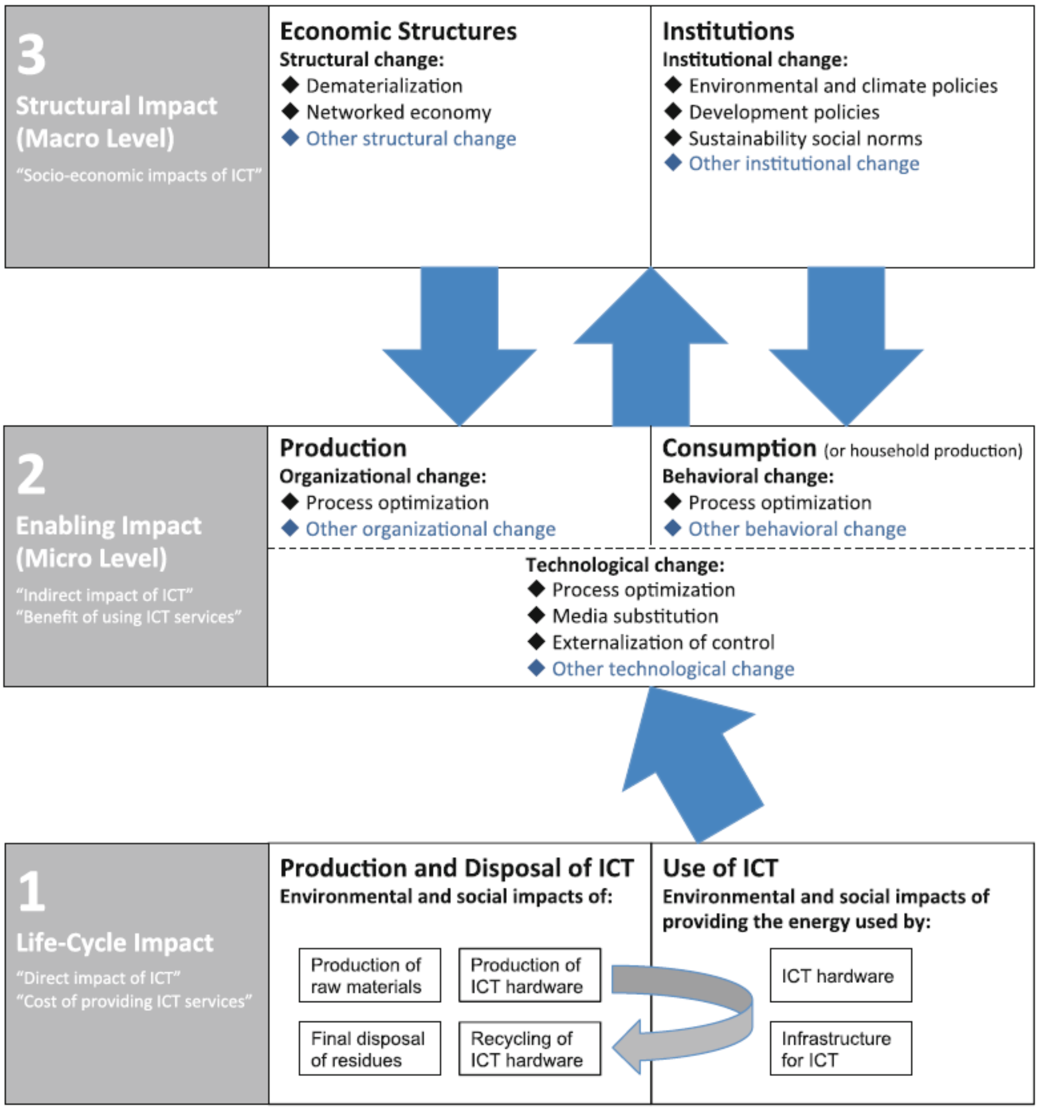



Figure 5: The LES model, based on (Hilty & Aebischer, 2015)

**Level 1 (Life-Cycle Impact):** Life-Cycle Impact covers the environmental effects throughout the ICT hardware lifecycle, including raw material extraction, production, energy use, recycling, and disposal. Life-cycle assessment (LCA) is used for evaluation, often focusing on energy consumption during use.

**Level 2 (Enabling Impact):** Enabling Impact includes actions enabled by ICT, categorized into process optimization, media substitution, and externalization of control. These impacts are viewed as types of resource substitution, aiming to reduce material resource use.

**Level 3 (Structural Impact):** Structural Impact refers to long-term, macro-level changes, such as economic structures and institutions influenced by ICT. This includes dematerialization (reducing material use) and the networked economy (individual-based production), as well as the role of ICT in environmental monitoring and shaping policies.

Overall, the LES model is significant given that it provides a full investigation of the effects of Information and Communication Technology (ICT) on sustainability. It provides a systematic framework that takes into account environmental consequences, societal changes, and economic effects, while also integrating well with current concepts. However, its complexity, data needs, and interpretation difficulties are disadvantages. Despite this, the model provides useful insights into the complex interaction between ICT and sustainability, nevertheless,its practical application may necessitate careful evaluation of its limits.

## 2.3 Sources of ICT sector emissions

Different sorts of data are required in the ICT sector to manage energy consumption and reduce emissions. Data on energy usage is useful to national governments for resource management and policy creation aimed at reducing the sector's carbon impact. At the moment, only a few countries have detailed country-level ICT emissions statistics accessible. Since the industry operates internationally, regional data is equally vital, and worldwide data is necessary to comprehend the industry's broad scope and long-term growth. Targeted actions are further informed by data on ICT subsectors, such as electronic devices, data centers, and connection networks. Depending on how each nation fits within the ICT value chain, the distribution of emissions varies (Ayers et al., 2023). For example, the emissions resulting from the production of devices are centered in a few nations, and the locations of major data centers are also restricted. Figure-6 shows the main sources that contribute to ICT's carbon emission.

### 2.3.1 ICT Products and Devices

ICT products and devices can be classed based on their functionality, application, and technology (Luo & Lei, 2012; Gowri, 2016; Spiezia, 2008). Computers and associated equip-

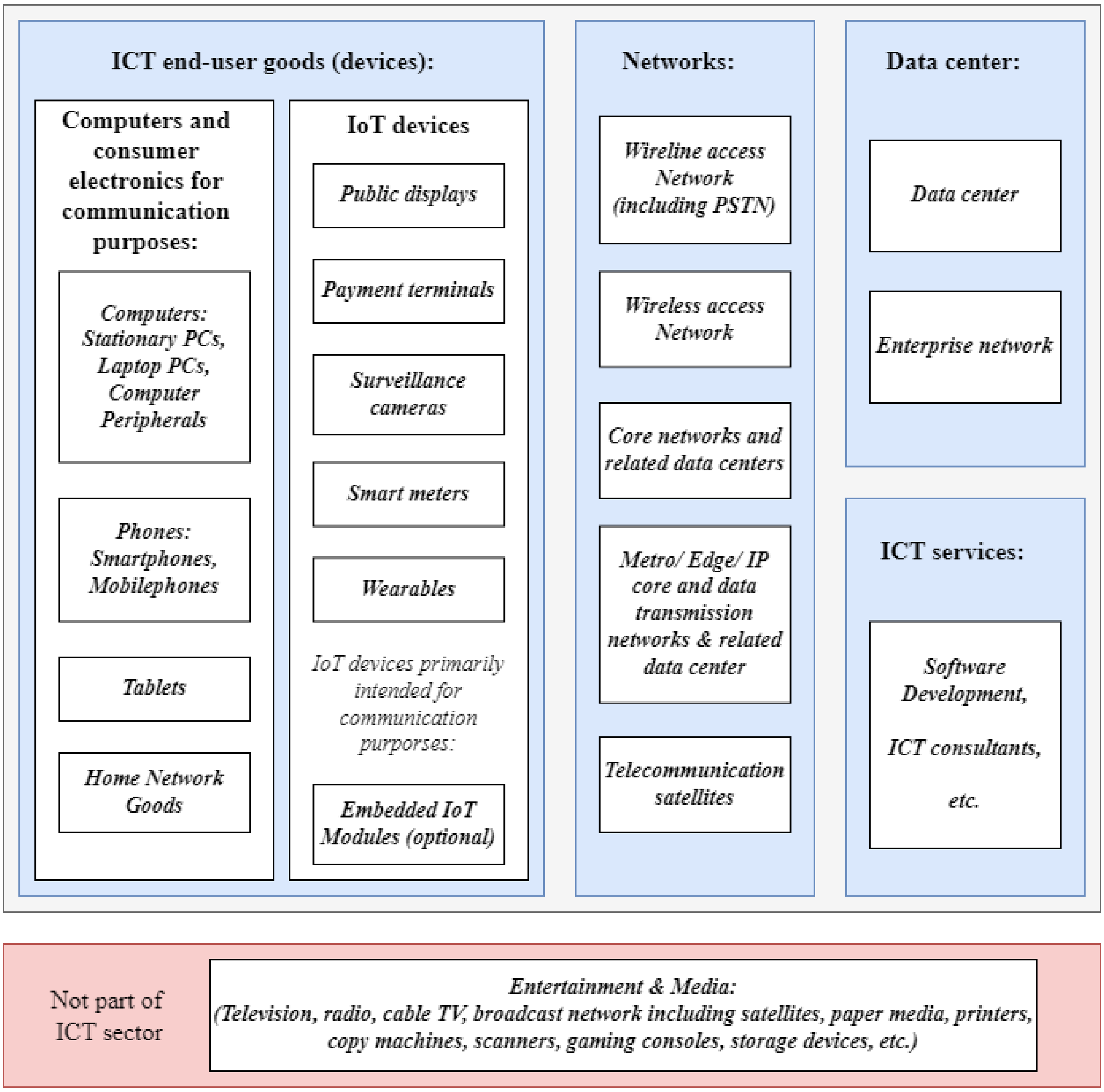



Figure 6: ICT sector boundaries based on ITU-T L.1450 Annex-A (International Telecommunications Union, 2018).

ment include desktops, laptops, tablets, and other information processing and storage devices. Smartphones, smartwatches, and fitness trackers serve as data transport and communication devices. Consumer devices, such as MP3 players, e-readers, and gaming consoles, provide amusement. Miscellaneous ICT components encompass a wide range of accessories, including USB flash drives and storage devices (Luo & Lei, 2012).

Business and productivity software, such as word processing and data analysis programs, help with organizational duties. Business demands are satisfied by information technology advice and services, which include IT consulting, software development, and data management. Telecommunications services include internet, phone, and data access to facilitate communication. Leasing and rental services provide ICT equipment for temporary commercial or personal usage (Luo & Lei, 2012; Spiezia, 2008). Finally, other ICT services like IT support, maintenance, and repair guarantee that these technologies run well within enterprises.

Due to their promotion of worldwide connection, ICT goods, and gadgets have had a profound impact on global communication and data transmission. They offer unmatched information access, enabling people to learn and access resources from almost anyplace. The emergence of Internet services and e-commerce has completely changed how businesses and consumers purchase. These technologies have also made it easier to collaborate virtually and work remotely, which has increased productivity and flexibility (Luo & Lei, 2012). ICT products are revolutionizing the way people engage in recreational activities by providing a variety of digital alternatives for leisure and relaxation in the entertainment sector.

When considering sources of ICT sector emissions, ICT devices encompass various components that contribute to the sector's environmental impact. These components include (Data Bridge Market Research, 2023):

- **Computing Devices:** This category includes desktop and laptop computers, along with associated CRT and LCD displays, as well as handheld devices like tablets and smartphones. These devices consume energy during production, usage, and disposal, contributing to emissions.
- **Infrastructural Facilities:** Data centers are a critical part of the ICT sector and contain servers, networking gear, power and cooling equipment, and communication networks. These components consume energy and contribute to emissions, particularly in data processing activities and networking operations.
- **Operational Activities:** The operational activities within ICT devices, such as data processing, communication, and networking, also contribute to emissions. The energy consumption of these activities, along with the production and disposal of ICT equipment, impacts the sector's carbon footprint.
- **User Devices:** User devices, including smartphones, tablets, laptops, and desktop PCs, account for a significant portion of the total carbon footprint of the ICT sector. The emissions from user devices are related to both usage and other lifecycle stages, highlighting the importance of considering the entire life cycle of ICT devices when assessing emissions.
- **Electricity Consumption:** The electricity consumption of ICT devices, networks, and data centers is a major source of emissions within the sector. User devices, networks, and data centers account for a substantial amount of electricity consumption, with user devices representing the highest electricity consumption among these categories.

In summary, when considering sources of ICT sector emissions, it is essential to recognize the components and activities within ICT devices, data centers, and operational processes that contribute to the sector's environmental impact. Understanding these sources is crucial for developing strategies to reduce emissions and promote sustainability within the ICT sector.

### 2.3.2 Data Center

Data centers, essential for remote data access, are complex, high-security structures dedicated to housing IT hardware. The definition of a data center is mentioned by Hintemann & Fichter, 2012 and stated as follows:

> "A data center is a building or space which houses the central data processing technology of one or more organizations. It must consist at least of a room of its own with a secure electricity supply as well as climate control."

They can operate under various business models, such as co-location centers, where third parties place their servers, or fully managed centers offering cloud services. Reliability, including security and availability, drives their complexity and cost. Security measures protect against digital and physical threats, while redundant systems ensure continuous operation during power outages or hardware failures. These redundancies and security features significantly increase both the acquisition and operational costs of data centers (Schomaker, Janacek & Schlitt, 2015). All this equipment and redundancy require a significant amount of energy, making data centers energy-intensive facilities.

Data centers are categorized based on their server capacity and power input. Small data centers house 100–500 servers with around 50 kW of power input. Medium-sized data centers accommodate 500–5,000 servers, consuming about 240 kW. Large data centers, which host over 5,000 servers, can have a power input of approximately 2.5 MW or more (Schomaker, Janacek & Schlitt, 2015). Other than these three types of data centers, Hintemann, 2015 mentioned two more categories based on data center size. They are server closets (up to 10 $m^2$), server rooms (11-100 $m^2$), small data centers (101-500 $m^2$), medium-sized data centers (501-5000 $m^2$), and large data centers (more than 5000 $m^2$).

Data centers consume a significant portion of global electricity. In 2010, they accounted for 1.1-1.5% of global, 1.7-2.2% of US, and 1.8% of Germany's electricity consumption (Hintemann & Fichter, 2013). Their energy use increased by 56% from 2005 to 2010 (Koomey et al., 2011). Large data centers, such as those operated by Facebook and Microsoft, can exceed 50 MW (Hintemann, 2015). The evolution and distribution of data centers, driven by trends like cloud computing and virtualization, significantly impact overall energy consumption

(Hintemann, 2015). Analyzing this is complicated by varied definitions, rapid technological advancements, and limited data availability.

When considering the sources of ICT sector emissions, data centers contain various components and activities that contribute to the sector's emissions. These include (Data Bridge Market Research, 2023; IEA, 2023):

- **Servers:** Data centers house numerous servers that store and process data, consuming significant amounts of energy and contributing to emissions (Data Bridge Market Research, 2023; IEA, 2023).
- **Networking Gear:** This includes routers, switches, and other networking equipment that enable data transmission within the data center and to external networks, consuming energy and contributing to emissions (Data Bridge Market Research, 2023; IEA, 2023).
- **Power and Cooling Equipment:** Data centers require power for operation and cooling systems to maintain optimal temperatures for equipment, both of which consume energy and contribute to emissions (Data Bridge Market Research, 2023).
- **Communication Networks:** These networks include customer premises access equipment (CPAE) and other infrastructure that facilitate communication and data transfer, consuming energy and contributing to emissions (IEA, 2023).
- **Data Processing Activities:** The processing of vast amounts of data within data centers requires significant computational power, leading to high energy consumption and emissions (Data Bridge Market Research, 2023; IEA, 2023).
- **Waste Disposal:** The disposal of electronic waste from outdated or decommissioned data center equipment contributes to the sector's emissions and environmental impact (Data Bridge Market Research, 2023).
- **Mining for Earth Metals:** The production of ICT equipment involves mining for rare earth metals, which has environmental consequences and contributes to the carbon footprint of the ICT sector.

Understanding the components and activities within data centers that contribute to emissions is essential for developing strategies to reduce the environmental impact of the ICT sector and promote sustainability in data center operations.

### 2.3.3 Network Infrastructure

Network infrastructure in the context of ICT sector emissions refers to the interconnection of devices and systems within the ICT infrastructure that enable data transmission, communication, and resource-sharing.

Computer networks can be classified according to variables such as geographical dispersion, user count, and communication protocols utilized by devices. The four major types of networks are Personal Area Network (PAN), Local Area Network (LAN), Metropolitan Area Network (MAN), and Wide Area Network (WAN) (ALferjani, 2021; Ali, 2014). PANs link personal devices such as cellphones and headphones, commonly via Bluetooth. LANs cover specific regions, such as homes or workplaces, and link many devices via Ethernet or Wi-Fi. MANs encompass cities, connecting several LANs with high-bandwidth technologies such as fiber optics. WANs cover huge geographic regions, linking networks across continents, with the internet being the largest WAN (Ali, 2014).

Another approach to categorize networks is by architecture, such as Peer-to-Peer (P2P) and Client/Server models (Leibnitz et al., 2007; Maly et al., 2003). On one hand, P2P networks, which are ubiquitous in file-sharing networks, allow devices to interact directly without the necessity of a central server. On the other hand, Client/Server networks employ a central server to manage communication and services for client devices, similar to how a central server handles user accounts and file storage in corporate networks. Understanding various network types and designs aids in the selection of the best network for a given situation, taking into account aspects such as user numbers, geographical coverage, and functional requirements.

Networks have had a significant impact on the world in a variety of ways. They have encouraged globalization by allowing for seamless communication and collaboration across international borders, effectively downsizing the world into a global village (Federal Communications Commission, 2013). The internet, a critical component of network systems, has enabled unprecedented access to information and knowledge, revolutionizing how individuals learn and exchange information. This digital connectivity has also resulted in the development of several online services, such as e-commerce, social networking, and cloud computing, which have revolutionized sectors and personal lifestyles (Castells, 2014). Furthermore, network technologies have had a big influence on work culture by enabling remote work, increasing flexibility, and raising productivity because workers may now work from anywhere. Another notable development is the expansion of the Internet of Things (IoT), which connects a growing number of objects to networks, resulting in breakthroughs in smart homes, smart cities, and industrial automation. These developments not only improve ease and efficiency but also pave the way for increasingly interconnected and intelligent systems throughout the world.

When considering sources of ICT sector emissions, network connectivity encompasses various components and activities that contribute to the sector's environmental impact. These components include (Data Bridge Market Research, 2023; Ali, 2014):

- **Network Interface Cards (NICs):** NICs enable devices to connect to a network and facilitate data transmission, consuming energy and contributing to emissions (Data Bridge Market Research, 2023).
- **Hubs:** Hubs are basic networking devices that allow multiple devices to communicate with each other. They receive data packets from one device and broadcast them to all other devices connected to the hub, sharing bandwidth and contributing to emissions (Data Bridge Market Research, 2023).
- **Switches:** Switches are more advanced networking devices than hubs, connecting multiple devices on a network. They contain updated tables that determine where data is transmitted, delivering messages to the correct destination based on physical addresses and reducing unnecessary data broadcasts, thus improving network efficiency and reducing emissions (Ali, 2014).
- **Routers:** Routers connect multiple networks together, allowing them to communicate with each other. Routers operate at the network level and play a crucial role in directing data packets to their intended destinations, optimizing data transmission, and reducing emissions (Ali, 2014).
- **Modems:** Modems facilitate the transmission of data over communication networks, converting digital signals to analog signals for transmission over telephone lines or digital signals for transmission over cable or fiber optics, contributing to energy consumption and emissions (Ali, 2014).
- **Bridges:** Bridges connect two or more network segments, allowing devices on different segments to communicate with each other. They operate at the Data Link layer of the OSI model and use MAC addresses to forward data packets between network segments, improving network performance and security while contributing to emissions (Data Bridge Market Research, 2023; Ali, 2014).

Network connectivity components play a vital role in the ICT sector's emissions by enabling data transmission, communication, and resource-sharing. Understanding the environmental impact of these components is essential for developing strategies to reduce emissions and promote sustainability in network operations within the ICT sector.

## 2.4 GHG Emission Scopes in ICT sector

The Greenhouse Gas Protocol (GHG Protocol) divides the ICT sector's carbon impact into three categories. These areas are critical to identifying and reducing the sector's environmental effects. Understanding and precisely measuring these emissions is critical for the ICT sector's capacity to design successful strategies for minimizing environmental impact and meeting sustainability goals. The categories based on Sipilä, Partanen & Porras, 2023, WRI & WBCSD, 2004 and Greenhouse Gas Protocol Team, 2011 are pictured in the figure-7.

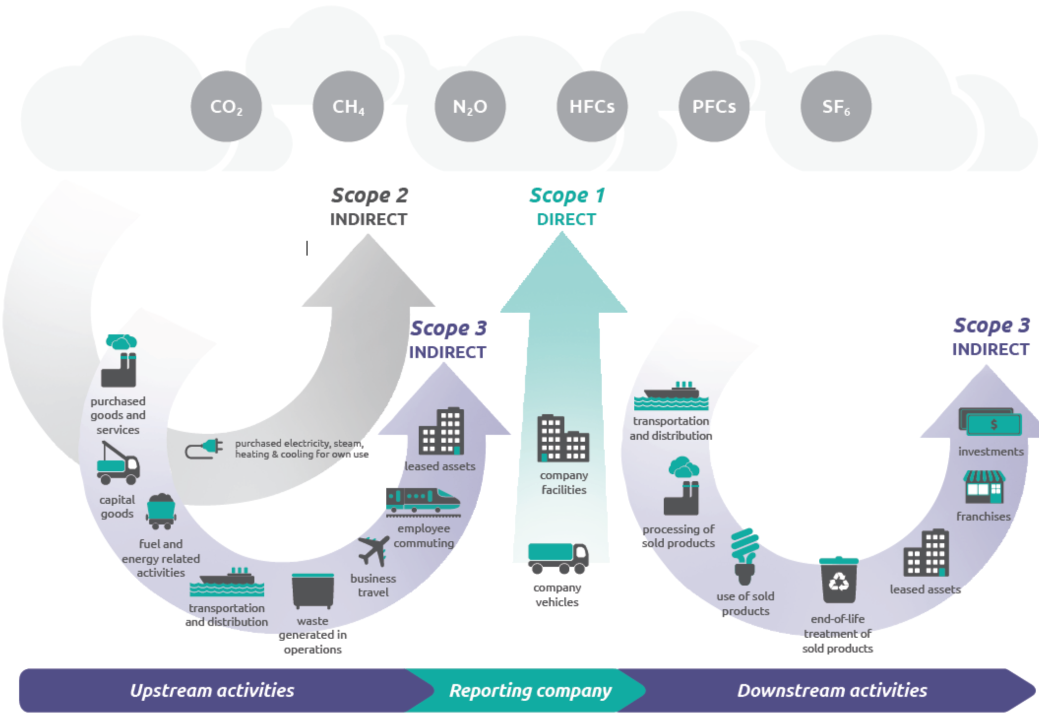



Figure 7: Overview of Scope 1,2, and 3 emission Categories.

### 2.4.1 Scope-1 emission

Scope 1 emissions within the ICT sector denote direct emissions originating from sources owned or managed by the entity. These emissions stem from activities like generating energy for heating, cooling, and powering company vehicles. In the context of the ICT sector, Scope 1 emissions encompass direct energy consumption from owned or controlled sources such as data centers, offices, and other facilities, including heating, cooling, lighting, and equipment power usage (Jha et al., 2022; Avantgarde Group, 2021). Additionally, emissions from company-owned vehicles utilized for business purposes contribute to Scope 1 emissions, particularly if they are not electric or hybrid. The measurement and reporting of Scope 1 emissions in the ICT sector typically adhere to established frameworks such as the GHG Protocol Corporate Standard. Calculating the carbon footprint of an ICT company involves quantifying these direct emissions from owned or controlled sources, which include energy consumption and emissions from company-owned vehicles. Moreover, companies are obligated to report Scope 1 emissions as part of their sustainability reporting and carbon footprint assessments (Lamers & Vrisekoop, 2022; Ayers et al., 2023; Jha et al., 2022).

To mitigate Scope 1 emissions, various best practices can be adopted within the ICT sector. Implementing energy-efficient practices and technologies is one such strategy, which can significantly reduce energy consumption and, consequently, Scope 1 emissions. Transitioning to electric or hybrid company-owned vehicles also presents an opportunity to reduce emissions from transportation. Furthermore, utilizing renewable energy sources for powering data centers and facilities can effectively reduce Scope 1 emissions originating from energy consumption. Encouraging sustainable transportation options, such as public transport or carpooling, can further contribute to reducing Scope 1 emissions from company-owned vehicles (Lamers & Vrisekoop, 2022; Ayers et al., 2023). In summary, comprehending and measuring Scope 1 emissions from owned or controlled sources is vital for ICT companies to diminish their environmental impact and attain sustainability objectives.

### 2.4.2 Scope-2 emission

Scope 2 emissions within the ICT sector pertain to indirect emissions arising from the consumption of purchased electricity, steam, heating, and cooling by the organization. These emissions are not under the direct control of the ICT company but result from the energy usage associated with its operations (Jha et al., 2022; Avantgarde Group, 2021). For instance, electricity consumption is a significant contributor to Scope 2 emissions, encompassing the energy required to power various facilities like data centers and offices. Similarly, heating and cooling energy consumption, along with steam usage, also contributes to Scope 2 emissions, reflecting the energy demands of these operational aspects.

To assess and address Scope 2 emissions, established frameworks such as the GHG Protocol Corporate Standard are commonly utilized for measurement and reporting. Calculating the carbon footprint of an ICT company involves quantifying these indirect emissions from purchased energy sources. Compliance with reporting requirements mandates companies to disclose Scope 2 emissions as part of sustainability reporting and carbon footprint assessments (Ayers et al., 2023).

Efforts to mitigate Scope 2 emissions in the ICT sector involve implementing best practices focused on energy efficiency, renewable energy adoption, and effective energy management. Strategies like utilizing renewable energy sources for powering facilities and implementing sustainable operations practices contribute to reducing energy consumption and associated emissions (Ayers et al., 2023). Understanding and managing Scope 2 emissions are integral steps for companies aiming to minimize their environmental impact and meet sustainability objectives.

### 2.4.3 Scope-3 emission

Scope 3 emissions within the ICT sector encompass the indirect emissions occurring throughout the organization's value chain, excluding those captured in Scope 2 emissions. These emissions stem from sources outside the direct control of the company, such as suppliers, customers, and other business partners. Recognizing and managing Scope 3 emissions is paramount for companies striving to thoroughly evaluate their environmental footprint and advance sustainability objectives (GSMA, GeSI, ITU, 2023; Avantgarde Group, 2021).

In the ICT sector, Scope 3 emissions span a broad spectrum, including various indirect emissions associated with the entire lifecycle of ICT products and services. This encompasses activities like raw material extraction, manufacturing, transportation, product usage, and end-of-life disposal. However, reporting these emissions poses challenges due to the intricate nature of the sector's value chain. The involvement of numerous suppliers, partners, and global operations complicates the accurate quantification and tracking of all indirect emissions (Jha et al., 2022; GSMA, GeSI, ITU, 2023).

Moreover, there exists considerable diversity in how Scope 3 emissions are reported among ICT companies, both in terms of coverage and transparency. This variability impedes the derivation of trends and general conclusions regarding the distribution of emissions across Scope 1, 2, and 3 categories in the sector. To address these challenges, standardized methods and guidance provided by frameworks like the GHG Protocol and ISO standards are crucial (GSMA, GeSI, ITU, 2023). These standards aid telecommunication operators in assessing and reporting their Scope 3 GHG emissions, enhancing coverage, transparency, and consistency in reporting practices across the sector.

Furthermore, many ICT companies are committing to reducing not only their Scope 1 and 2 emissions but also their Scope 3 emissions, including those originating from their supply chain and customers. This commitment is vital for achieving Science-Based Targets and aligning with broader sustainability initiatives (GSMA, GeSI, ITU, 2023). In summary, understanding, measuring, and mitigating Scope 3 emissions are integral steps for ICT companies to comprehensively evaluate their environmental impact and contribute to global efforts aimed at reducing greenhouse gas emissions.

## 2.5 Decomposing ICT's emissions into embodied and use stage contributions

The embodied emissions and usage phase emissions are important components of the environmental effect of the ICT sector. Use phase emissions are those originating from the energy used and the functioning of these systems, whereas embodied emissions are those linked to the manufacturing and disposal of ICT products as well as infrastructure.

### 2.5.1 Embodied emission of ICT

Embodied emissions refer to the total greenhouse gas emissions generated throughout an ICT product or infrastructure's entire lifespan, encompassing every stage from raw material extraction and processing to final product production, transportation, and eventual disposal (Andersson & Jullien, 2023). This broad scope includes emissions from manufacturing processes as well as from the creation of components like metals, semiconductors, and polymers, which are integral to ICT products.

IT facilities and merchandise have substantial and varying embodied emissions across different industries. For example, in the production of personal computers, significant emissions are generated during the extraction of raw materials such as aluminum, copper, and rare earth metals used in components like the motherboard, hard drives, and processors. Companies like Apple, Dell, and HP, which produce millions of laptops and desktops annually, contribute notably to these embodied emissions. Apple, for instance, reported that around 74% of its carbon footprint for a MacBook comes from manufacturing, highlighting the significant role of embodied emissions in the lifecycle of ICT products [1]. Similarly, the creation of mobile devices such as smartphones involves substantial embodied emissions, particularly due to the energy-intensive processes involved in producing semiconductors and other electronic components. For instance, the production of an iPhone involves the extraction and processing of over 60 different metals, including cobalt, lithium, and gold, which contribute significantly to its overall carbon footprint. Samsung, another major smartphone manufacturer, faces similar challenges. According to a study by Fairphone, a sustainable smartphone company, the production of a single smartphone can generate between 16 to 95 kg of $CO_2e$ (carbon dioxide equivalent), depending on the complexity and materials used [2].

Moreover, the energy required for the production and transportation of these devices further exacerbates their embodied emissions (Andersson & Jullien, 2023). For instance, the global logistics involved in shipping millions of electronic devices from manufacturing hubs in Asia to consumers worldwide adds another layer of environmental impact. According to Dong, Jiang & Wang, 2021, the transportation of ICT products contributes to approximately 10-15% of their total embodied emissions, depending on the mode of transportation and the distance covered.

Given the significant contribution of embodied emissions to the overall carbon footprint of

[1] Apple sustainability report. https://www.apple.com/environment/
[2] Fairphone sustainability report. https://www.fairphone.com/en/impact-report/

ICT products, there is a growing need for manufacturers to adopt more sustainable practices. This includes using recycled materials, improving energy efficiency during manufacturing, and optimizing supply chains to reduce transportation-related emissions. Companies like Fairphone and Dell have started to implement such strategies by increasing the use of recycled materials and designing products that are easier to repair and upgrade, thereby extending their lifespan and reducing the need for frequent replacements.

Furthermore, there is a critical need for industry-wide transparency regarding embodied emissions. Consumers and regulators are increasingly demanding that manufacturers disclose the carbon footprint of their products, including the embodied emissions, to make informed choices and promote sustainability. Initiatives like the Carbon Trust's "Product Carbon Footprint" certification are steps in the right direction, as they provide a standardized way to measure and communicate the environmental impact of ICT products [3].

In conclusion, addressing the embodied emissions of ICT products is essential for reducing the overall carbon footprint of the sector. By focusing on sustainable manufacturing practices, using eco-friendly materials, and optimizing supply chains, the ICT industry can significantly mitigate its environmental impact and contribute to global carbon reduction efforts.

### 2.5.2 Use phase emission of ICT

Use phase emissions refer to the greenhouse gas emissions that result from the energy consumption of ICT devices and infrastructure during their operational life. This includes the energy required to power laptops, smartphones, data centers, servers, and other infrastructure involved in processing, storing, and transmitting data. Unlike embodied emissions, which occur during the production of ICT products, use-phase emissions are generated during the actual usage of these technologies. These emissions are heavily influenced by the energy sources used to generate electricity, which often rely on nonrenewable resources such as coal, natural gas, and, in some cases, oil (Andersson & Jullien, 2023).

The energy usage of laptops and smartphones, while generally lower compared to larger ICT infrastructure like data centers, is still significant due to the sheer number of devices in operation globally. For instance, the energy consumption of a typical laptop is estimated to be around 50-100 kWh per year, depending on usage patterns and efficiency settings. Smartphones, on the other hand, consume less energy individually, with an estimated annual consumption of around 2-4 kWh. However, given the billions of smartphones in use worldwide, this adds up to a substantial amount of energy.

[3] https://www.carbontrust.com/en-eu/what-we-do/product-carbon-footprint-labelling/product-carbon-footprint-label

To put this into perspective, if a laptop consumes 75 kWh per year and is used in a country like Germany[4], where the electricity mix is about 30% coal and 40% renewable energy sources, the resulting emissions would be approximately 32 kg of $CO_2$e annually. In contrast, in Norway[5], where almost all electricity is generated from hydropower, the same laptop would generate less than 1 kg of $CO_2$e per year due to the nearly carbon-neutral electricity grid. This stark difference underscores how different countries' energy production profiles significantly impact ICT devices' use phase emissions. Comparing this to the manufacturing emissions of a laptop, which can range between 200 to 300 kg of $CO_2$e, it becomes evident that the use phase emissions, though ongoing throughout the device's lifespan, are still generally lower annually compared to the one-time embodied emissions. However, over a typical 3-5 years lifespan of a laptop, the cumulative use phase emissions can rival or even exceed the embodied emissions, especially in countries with high-carbon electricity grids.

The growing demand for ICT services, especially with the rise of cloud computing, streaming services, and the proliferation of mobile devices, is driving up use phase emissions. Data centers, in particular, have become significant contributors to global energy consumption. Given the variability in energy production profiles across different regions, the environmental impact of ICT use phase emissions can vary widely. In countries with a high reliance on renewable energy, the use phase emissions of ICT devices are relatively low. Conversely, in regions where coal and natural gas dominate the energy mix, these emissions are much higher. This highlights the importance of energy efficiency measures and the adoption of renewable energy sources to mitigate the environmental impact of ICT operations. Moreover, the comparison between the use phase and embodied emissions highlights a critical aspect of sustainable ICT practices. While reducing embodied emissions through improved manufacturing processes and materials is essential, efforts to lower use phase emissions—such as by improving the energy efficiency of devices, optimizing data center operations, and transitioning to renewable energy sources—are equally important. For example, tech giants like Google[6] and Microsoft have committed to running their data centers on 100% renewable energy, significantly reducing the use phase emissions associated with their services.

In conclusion, managing use phase emissions is crucial for the overall sustainability of the ICT sector. As the demand for digital services continues to grow, so too will the energy consumption associated with these technologies. Therefore, ICT companies and policymakers must prioritize energy efficiency and the use of clean energy to minimize the environmental impact of this increasingly essential sector.

[4] Germany electricity sources. https://www.iea.org/countries/germany/electricity
[5] Norway electricity sources. https://energifaktanorge.no/
[6] https://www.google.com/about/datacenters/cleanenergy/

# 3 State-of-the-art

This chapter highlights recent research that calculated or estimated the ICT sector's carbon emissions from numerous perspectives. First, the carbon footprint of ICT using the used method is briefly reviewed, followed by an emission estimate per category. While energy is one of the primary contributors to ICT carbon emissions, a thorough study is provided. Finally, several types of GHG emissions in the ICT industry are investigated.

## 3.1 Measuring ICT's carbon emission

One of the main reasons for varied emission values is the use of different calculation methods. In this section, two calculations are described from the Global e-Sustainability Initiative (GeSI), 2012 and Malmodin, Lövehagen, et al., 2024 studies. They provide a full calculation for the ICT sector for a specific year. Firstly, the definition of the ICT sector varied in both studies. The ICT sector is discussed in the first part of this chapter. Then the calculation method is mentioned.

### 3.1.1 Define ICT sector

The table 2 derived from Global e-Sustainability Initiative (GeSI), 2012, organizes ICT carbon emissions into three primary categories: End Use Devices, Telecommunication Networks, and Data Centers. End-user devices encompass items like PCs (desktops and laptops), mobile devices (smartphones and tablets), and various peripherals (monitors, printers, set-top boxes, and home routers). Telecommunication Networks are divided into fixed lines and wireless networks, while Data Centers include critical infrastructure components such as servers, storage systems, and cooling systems. This structured categorization highlights the key areas within the ICT sector that contribute to carbon emissions.

| **Category** | **Details** |
|---|---|
| **End Use Devices** | PCs (Desktop, Laptop), Mobile devices (Smartphone, other mobile devices, tablets), Peripherals (Monitor, printer, set-top box, home router) |
| **Telecommunication Networks** | Fixed lines, Wireless |
| **Data Centers** | Servers, Storage Systems, Cooling Systems |

Table 2: ICT sector defined by Global e-Sustainability Initiative (GeSI), 2012

The ICT sector's boundary used by Malmodin, Lövehagen, et al., 2024 is very similar to International Telecommunications Union, 2018) with a wide range of categories considered while calculating the carbon emission of ICT. Their scopes of the ICT sector is shown in table 3. The table 3 breaks down the ICT sector into four main areas: Devices, Networks, Data Centers, and Enterprise Networks. Devices include everything from desktop and laptop computers, peripherals like monitors and keyboards, and various types of phones, to tablets, VR headsets, smart speakers, wearables, and smart home gadgets. Networks cover both fixed broadband and mobile networks (like 2G-5G), along with core networks, data transmission, and telecommunication satellites. Data Centers focus on electricity usage and emissions from industrial data centers, while Enterprise Networks include local area networks (LAN) and wireless local area networks (WLAN). This summary provides an overview of the key components in the ICT sector that contribute to energy use and emissions.

| **Category** | **Details** |
|---|---|
| **Devices** | Computers: Desktop PCs, Laptop PCs; Computer peripherals: PC monitors, mouse, keyboard, external webcam; Phones: Smartphones, Feature phones; Fixed phones incl. DECT; Tablets, VR headsets, Smart speakers, Headphones/Hearables; CPE (routers, modems); Displays: Commercial displays, Other displays; Projectors, Payment terminals, Surveillance cameras; Smart meters, Wearables (watches, rings); IoT/M2M communication modules; Smart home devices (monitoring/security, lighting, thermostats, plugs, gateways/CPE) |
| **Networks** | Fixed broadband access networks, PSTN; Wireless Access networks: Mobile (2G-5G); Core networks and data transmission; Telecommunication satellites |
| **Data Centers** | Data center electricity usage and scope-wise emission data from industries |
| **Enterprise networks** | LAN, WLAN |

Table 3: ICT sector defined by Malmodin, Lövehagen, et al., 2024

With the sector defined, the next part of this section will focus on how these components are being used to calculate the emission of ICT.

### 3.1.2 Emission calculation formula

Based on the ICT sector definition the carbon emission of ICT differs. In this section, two of the studies are being focused on to describe the whole calculation strategy. They are described below with some brief details. The figures and the table describe the underlying broad formula to achieve the target result. Each of the terminology can be further divided for more clarification. However, in this research work, these in-depth calculations are not used. Thus, the calculation method can be considered from a higher level

Calculation method applied in Global e-Sustainability Initiative (GeSI), 2012 report:

The formulas used by Global e-Sustainability Initiative (GeSI), 2012 are shown in the figures 8 to 11. Figure 8 outlines a method to calculate the carbon emissions of ICT devices by considering two main components: usage footprint and embodied carbon emissions.

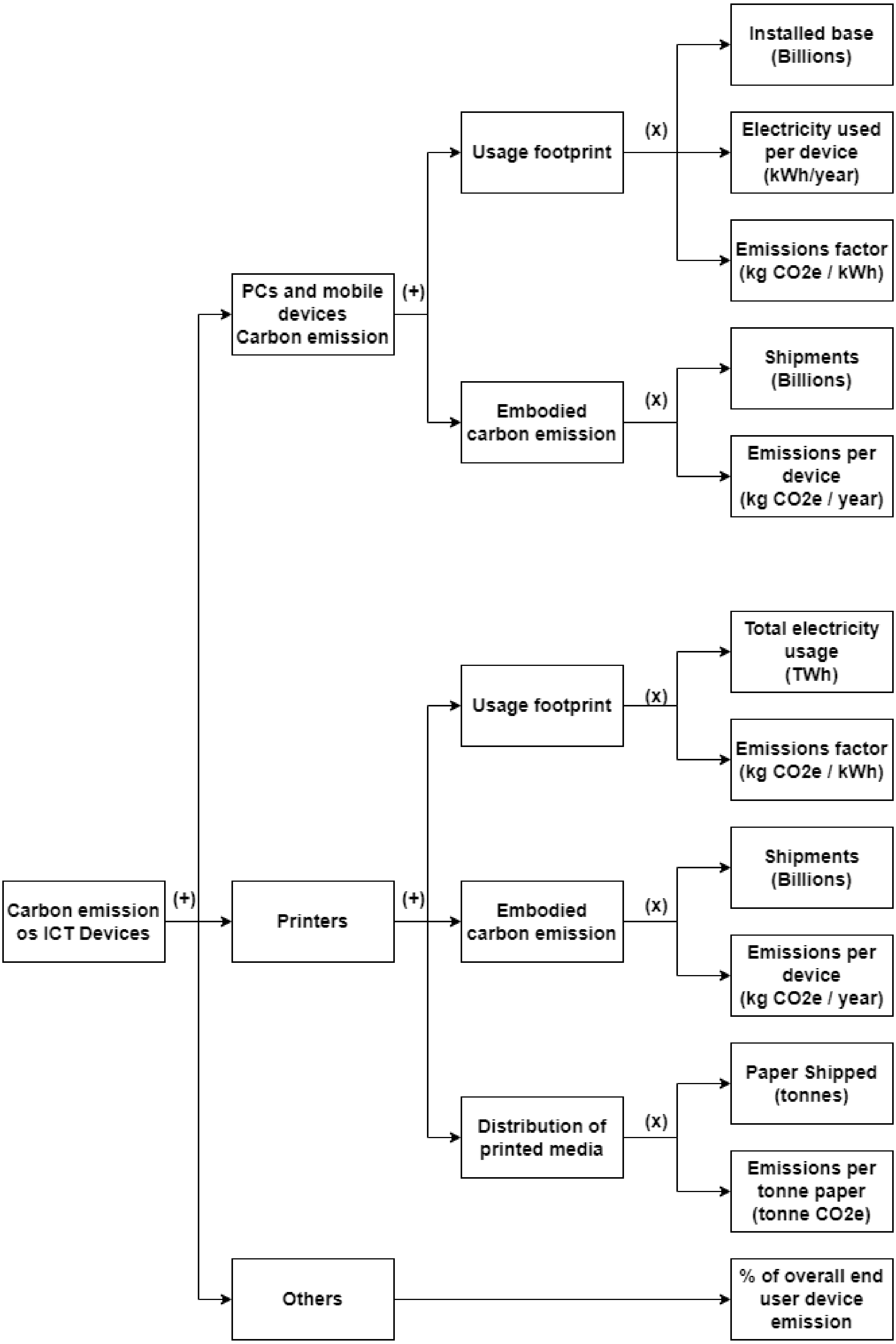



Figure 8: ICT devices emission calculation by GeSI.

For usage footprint, the method multiplies the installed base of devices by the electricity used per device and the emissions factor (kg $CO_2$e/kWh). This provides the total emissions due to the energy consumption of the devices during their operational phase. For embodied carbon emissions, the method multiplies the number of devices shipped by the emissions per device (kg $CO_2$e/year). This calculation captures the emissions related to the manufacturing and distribution of the devices. For printers, the method includes an additional step to account for the carbon emissions from the distribution of printed media. This is calculated by multiplying the amount of paper shipped by the emissions per tonne of paper. Finally, the total carbon emissions for ICT devices are obtained by adding the usage footprint and embodied carbon emissions for all relevant devices.

The data center's carbon emission calculation may not seem complex with the method mentioned in the figure 9. Here the usage footprint is calculated directly from the electricity consumed by data centers. However, this data is derived from other studies and reports as mentioned in their work. Also, the embodied emission data is gathered from other collaborative data from various data centers. There are no details about the data centers that are being considered for each of these factors. Therefore, the calculation follows a black-box approach which makes it more ambiguous and assumption-based.

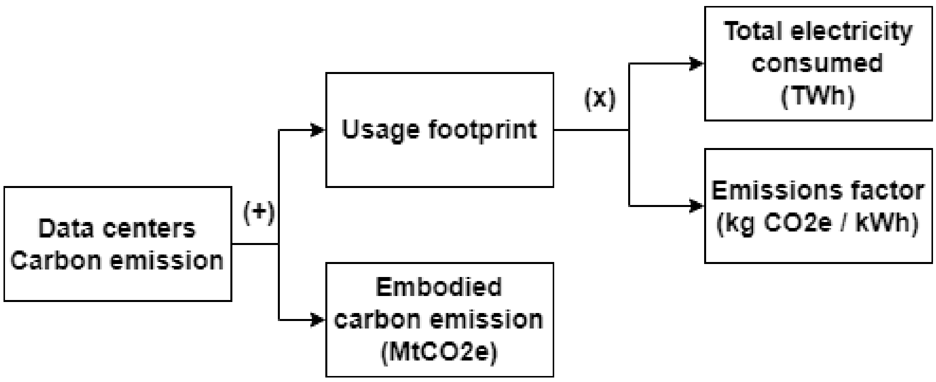



Figure 9: Data center emission calculation by GeSI.

Similarly, the network emission is shown in two different figures 10, 11. Figure 10 illustrates a method for calculating carbon emissions from wireless and home access networks. For each network type, the calculation begins with the usage footprint, which is determined by multiplying the electricity used per subscriber by the number of subscribers, the emissions factor, and the operations overhead percentage. Additionally, the embodied carbon emissions are calculated by multiplying the number of subscribers by the emissions per subscriber. For wireless networks, diesel usage is also included in the total emissions. The total emissions for each network type are obtained by summing the usage footprint, embodied carbon emissions, and for wireless networks, the diesel usage.

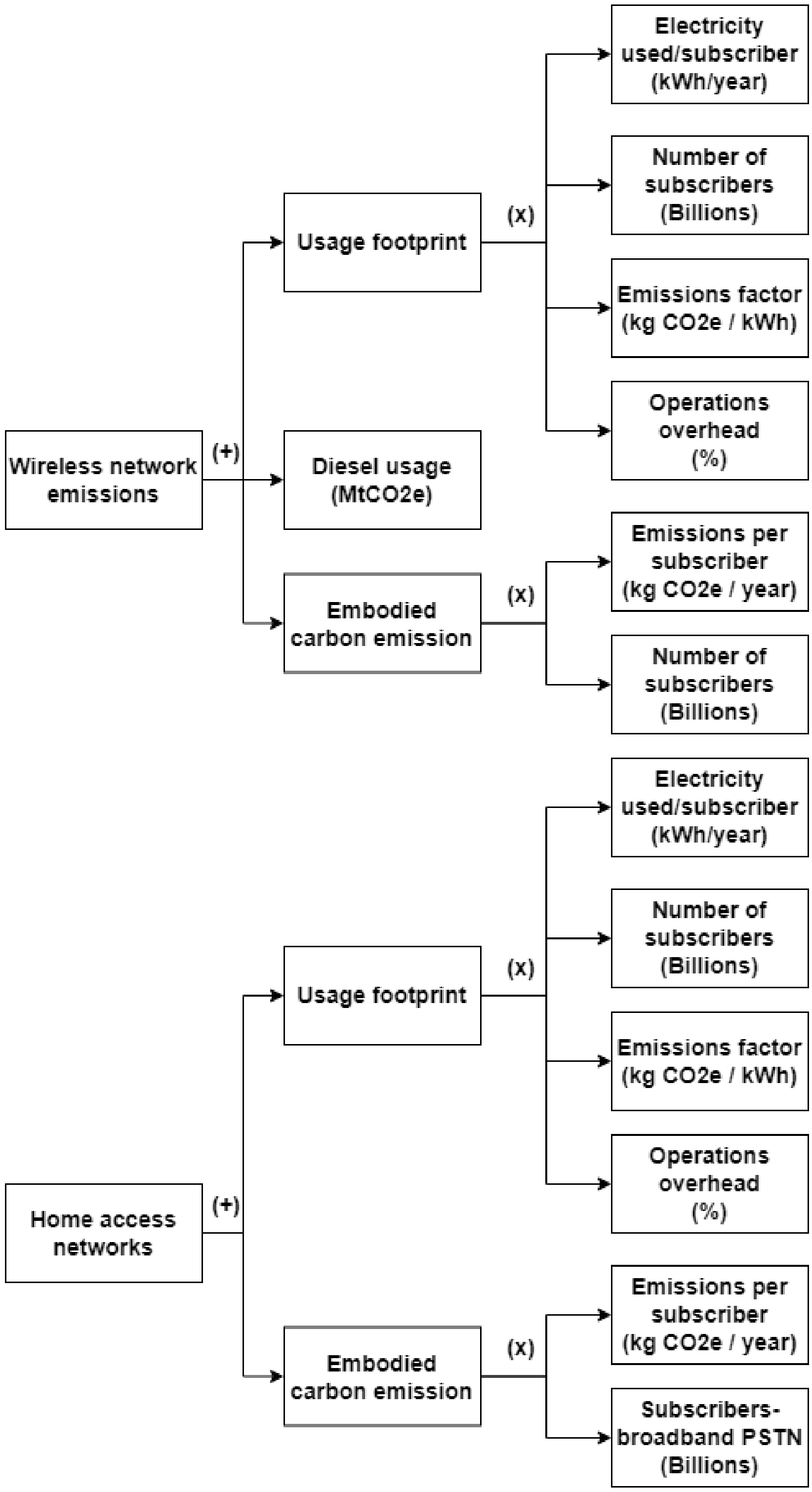



Figure 10: Network emission calculation by GeSI.

As shown and described before, figure 11 outlines a method for calculating carbon emissions from enterprise networks and data transport. For enterprise networks, the total emissions are determined by calculating the usage footprint, which involves multiplying the electricity used per office PC by the number of enterprise PCs, the emissions factor, and the overhead for hubs, routers, and switches. The embodied carbon emissions are also calculated separately. For data transport, the emissions are calculated by multiplying the total electricity used by the emissions factor. The final emissions for each category are obtained by summing the usage footprint and the embodied carbon emissions.

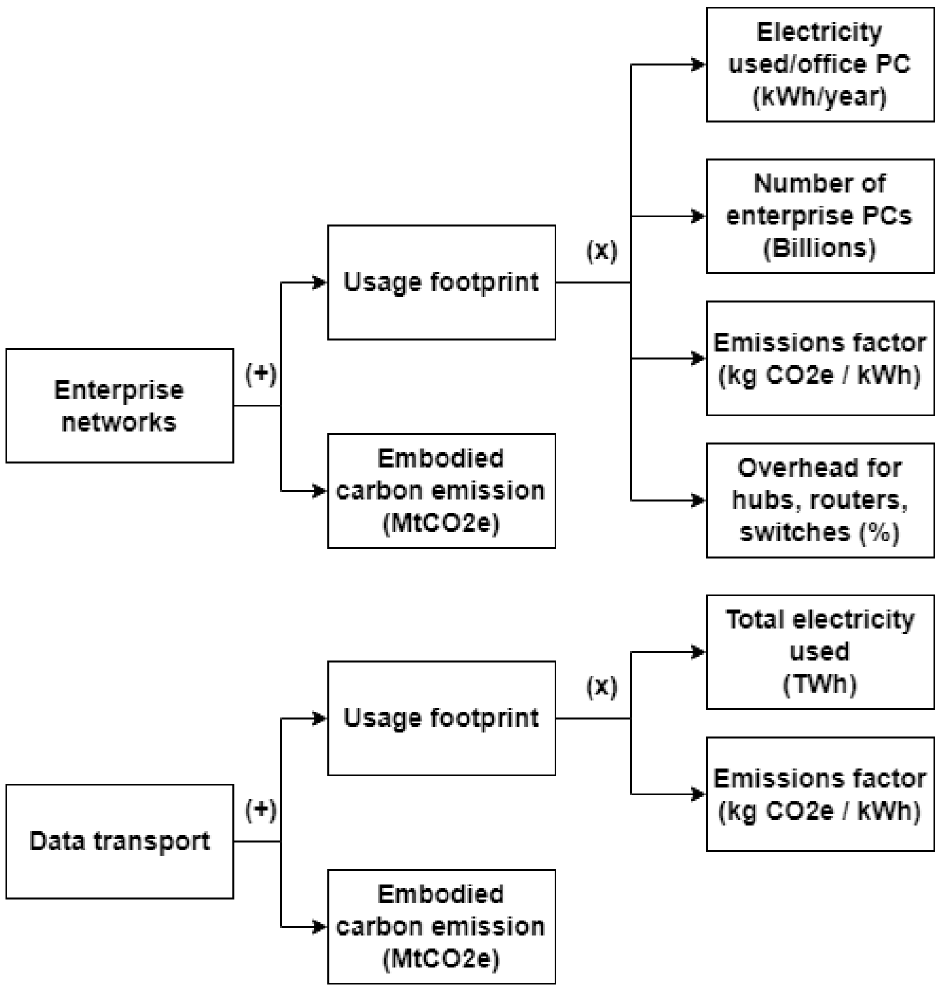



Figure 11: Enterprise network emission calculation by GeSI.

After looking into the category-wise calculation by Global e-Sustainability Initiative (GeSI), 2012, it is clear that the data provided in the report follows a black-box approach. The macro-level analysis is tough with this study approach. Malmodin, Lövehagen, et al., 2024 in a recent study published a very detailed approach to calculating the carbon emission of ICT. This approach is described in the next part of this chapter.

Calculation method applied by Malmodin, Lövehagen, et al., 2024:

After defining the ICT sector, the carbon emissions of four main categories are calculated by dividing those into two parts which are use stage and embodied. The broader approach for calculation is shown in table 4. In this table, the equations mentioned are also from a wide view, and each of the factors is dependent on many other attributes. In this section, the value derivation of these attributes is discussed briefly.

| Category | Carbon Emission Calculation |
|---|---|
| **User Devices carbon emission calculation** | |
| *Use stage carbon emission* | Electricity consumption of a device (TWh) X Installed base (Millions) X Emission factor (kg $CO_2$e/kWh) |
| *Embodied carbon emission* | Emission of a device (From PCF/LCA) X Total shipments |
| **Data center's carbon emission calculation** | |
| *Use stage carbon emission* | (Scope 1 + Scope 2) emission + Fuel supply + Transportation + Renewable electricity supply chain |
| *Embodied carbon emission* | Electronics Equipment Emissions + Building Construction Emissions |
| **Network infrastructure carbon emission calculation** | |
| *Use stage carbon emission* | (Scope 1 + Scope 2) emission + Fuel and energy supply + Transportation + Renewable electricity supply chain |
| *Embodied carbon emission* | Electronics Equipment Emissions (Networks) + Construction and Deployment Emissions (Networks) |
| **Enterprise network carbon emission calculation** | |
| *Use stage carbon emission* | Total Use Stage Electricity (TWh) X Emission Factor (kg $CO_2$e/kWh) |
| *Embodied carbon emission* | Total Units Shipped (millions) X Embodied GHG per Unit (kg $CO_2$e) |

Table 4: Carbon Emission Calculations for ICT by Malmodin, Lövehagen, et al., 2024

The methodology for calculating the use-stage carbon emissions of ICT user devices by focusing on electricity consumption. The process involves gathering data on device power, average daily usage, and the impact of different modes (active, idle, sleep) to estimate total electricity consumption per device type. Additional data is collected on the installed base, annual shipments, and estimated device lifetimes to calculate annual electricity consumption across different product types. This data is then used to estimate the total annual electricity consumption of ICT devices, which is further analyzed for sensitivity to different parameters. For embodied emissions, the estimation is based on the total carbon footprint of the entire electronics industry, incorporating data from manufacturers across the supply chain, including integrated circuits, printed circuit boards, display manufacturers, and other electronics manufacturing services. Key user devices also account for material and mechanical components, with results cross-checked against life cycle assessments and scaled by the number of devices sold in a specific year. This comprehensive approach ensures that both use-stage and embodied emissions are accurately reflected for ICT user devices.

The operational carbon emissions of data centers are calculated by integrating electricity consumption data with associated greenhouse gas emissions, using a comprehensive method that draws from academic studies, server shipment analysis, and reports from data center companies. This approach starts with establishing baseline electricity consumption, which is adjusted for server deployment growth and activity levels. Data from numerous companies, including their reported electricity usage and renewable energy adoption, is crucial, with estimates made to cover any gaps. The methodology also includes applying global emission factors for unreported data. It considers regional differences in electricity consumption and emissions across key global regions, providing a detailed estimate of the global carbon footprint of data centers.

The calculation of network operational electricity and carbon emissions is based on a detailed methodology that involves estimating electricity usage across different regions and applying emission factors from reliable sources like ITU-T, 2020 and studies by Lundén et al., 2022. The approach incorporates adjustments for underreported emissions, off-grid electricity, and additional supply chain-related emissions. It also factors in the specific energy mixes and supply chain losses in each region. Data coverage percentages are carefully considered, and assumptions are made about the extent of data center usage and renewable energy integration. This comprehensive analysis ensures that the emission estimates are aligned with established international standards and reflect regional variations in electricity consumption and carbon intensity.

The calculation of embodied emissions for networks and data centers relies on a combination of direct measurements, estimations, and scaling methodologies, drawing on various data sources. For data centers, emissions from electronic equipment are derived by assessing the carbon footprint of the electronics industry, with allocations based on product-specific data from companies like Dell and HP. Construction-related emissions are calculated using corporate reports, such as those from Google, and adjusted for global energy consumption. For networks, similar methods are applied to estimate emissions from both mobile and fixed equipment, along with infrastructure like fiber optic cables and towers. These estimates are validated through comparisons with other studies and industry reports, ensuring accuracy and a comprehensive understanding of the carbon impact of ICT infrastructure.

The calculation of emissions from enterprise networks is also based on two primary categories: operational and embodied emissions. Operational emissions are estimated by calculating the total electricity consumption of network components such as WLAN access points, switches/routers, and small cells, and then applying a global emission factor derived from industry standards. For embodied emissions, the focus is on the production and deployment of network equipment, with the number of units shipped and their associated greenhouse gas emissions per unit being used to estimate the total embodied impact. The combined emissions from both categories provide a comprehensive assessment of the network's overall environmental impact.

### 3.1.3 Future value prediction

A very few studies where future prediction of the carbon emission of ICT with a detailed approach is discussed. Global e-Sustainability Initiative (GeSI), 2015 mentioned their approach to making future predictions. In their approach to calculating for a future year's values remains the same for the year of studies calculation. For instance, the factors for the years 2011 and 2020 were the same. The future values at that time were considered to be growing at the same rate as the base year. Many times, the values remained the same throughout the years. Another example is the printer's emissions per year remained the same from 2007 to 2020. In summary, Global e-Sustainability Initiative (GeSI), 2015 report's predictions are mostly based on assumptions, constant growth, and using the previous values as they are.

Andrae & Edler, 2015 projected the future carbon emission values of ICT from a wide range of 2010 to 2030. In their studies, they also provided a wide range of factors and gave a detailed prediction for all the factors. However, their prediction method is not described in detail. It is also seen that the predictions are mainly exponentially growing. These predictions are mentioned to be overestimated by a later study by Andrae, 2019. The new study also lacks a description of the method used to predict those values.

## 3.2 Electricity consumption of ICT sector

From the previous sections, it is clear that to measure the carbon emission of ICT, the electricity consumption of it is the most important factor. In many studies, the use stage emission of ICT is directly derived from electricity usage. Therefore, a clear understanding of electricity usage and the factors that play pivotal roles is needed. In this section, previously calculated values as well as some of the future estimations are discussed.

The electricity consumption trends of the ICT sector from 2010 to 2030, across different scenarios, reveal substantial growth, with varying degrees of increase depending on the scenario as shown in 12. This study was conducted by Andrae & Edler, 2015. In the best-case sce-

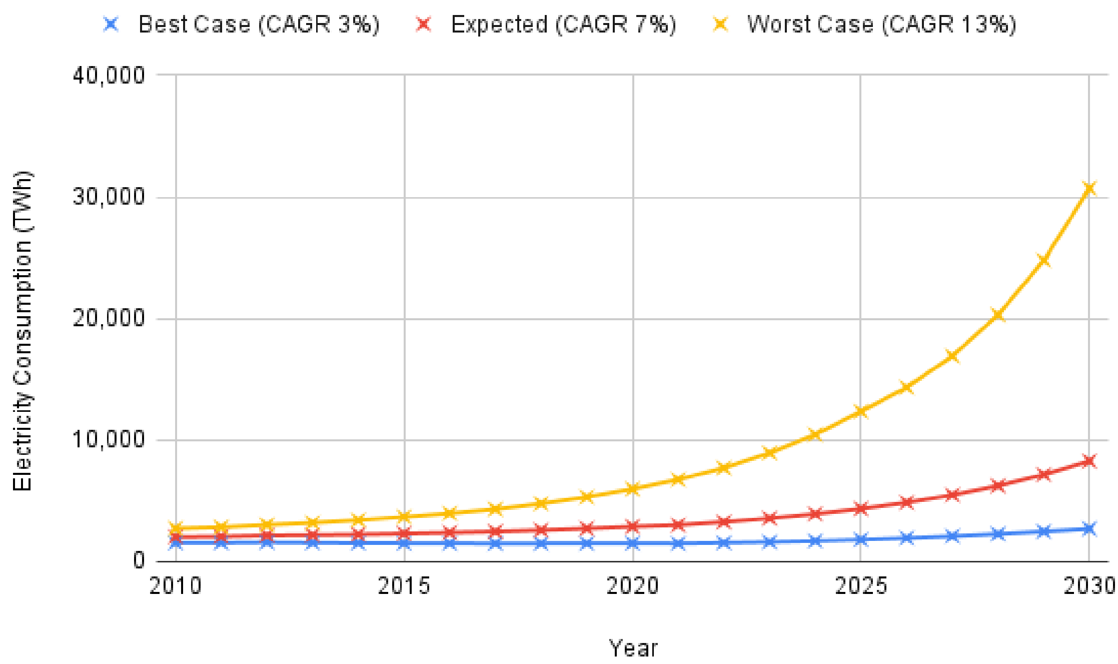



Figure 12: Electricity footprint (TWh) of Communication Technology 2010-2030.

nario, consumption remains relatively stable from 2010 to 2020, with a slight decrease from 1,538 TWh/year in 2010 to 1,507 TWh/year in 2020. However, a marked rise begins thereafter, reaching 1,810 TWh/year by 2025 and surging to 2,698 TWh/year by 2030, indicating a significant increase of 79% over the 20-year period. The expected scenario shows a more pronounced increase, starting at 2,037 TWh/year in 2010 and climbing to 2,878 TWh/year by 2020. This upward trend accelerates further, reaching 4,350 TWh/year in 2025 and nearly quadrupling to 8,265 TWh/year by 2030. In the worst-case scenario, the growth is exponential, with consumption escalating from 2,723 TWh/year in 2010 to 5,976 TWh/year by 2020. By 2025, the figure more than doubles to 12,352 TWh/year, and by 2030, it skyrockets to 30,715 TWh/year, representing an over tenfold increase from 2010. These trends highlight the dramatic rise in electricity demand within the ICT sector, emphasizing the urgent need for energy-efficient technologies and sustainable practices to manage the sector's environmental impact.

The provided figure 13 reveals a concerning trend in the electricity consumption of the ICT sector across three categories: ICT device production, data centers, and networks. All three categories show a potential for significant growth in electricity use over the years, with varying degrees of severity.

The production of ICT devices is expected to decrease by around 18 TWh. The expected case scenario of ICT device production suggests a steady increase, with consumption nearly

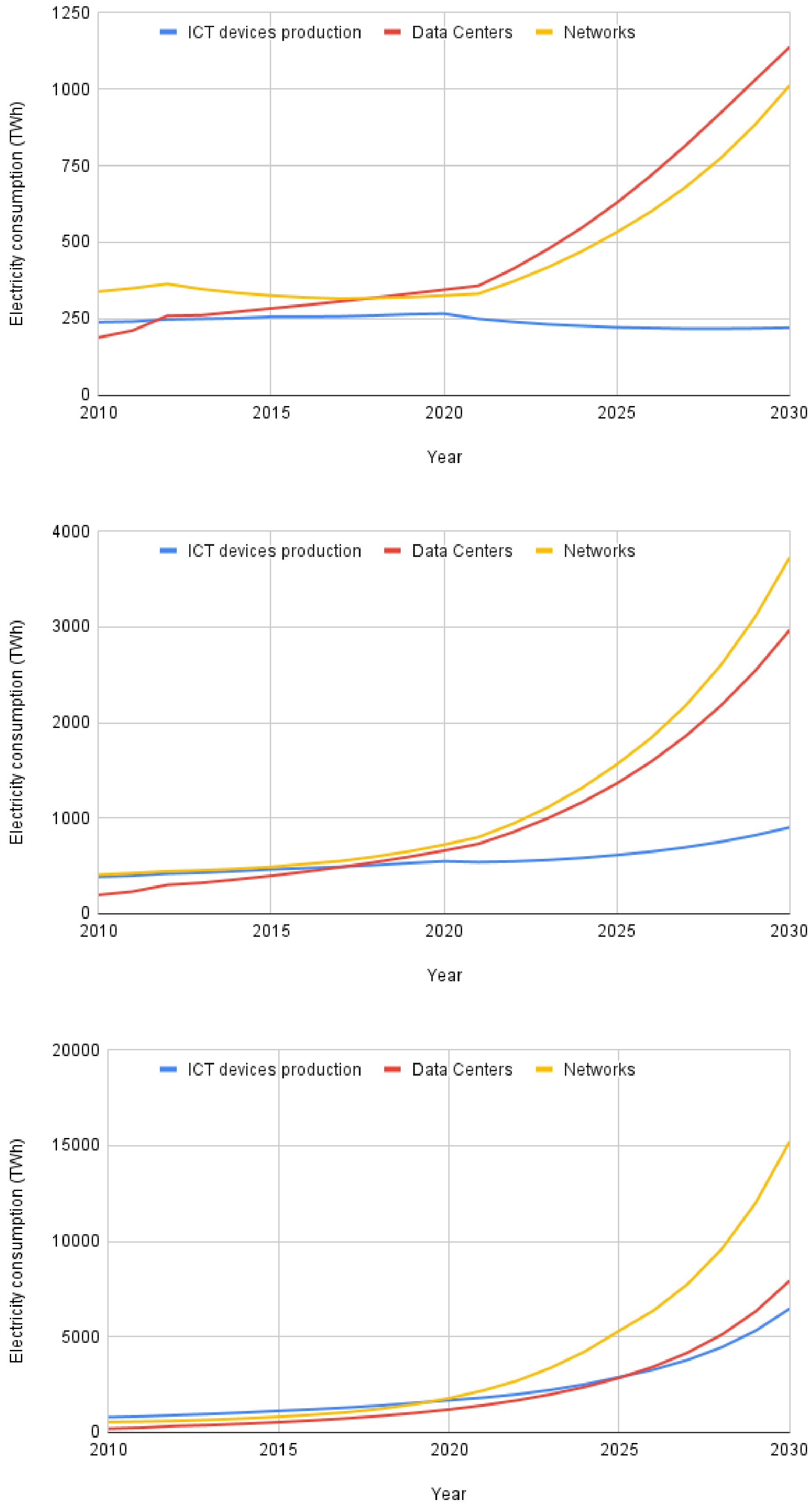



Figure 13: Electricity consumption, ICT- best, expected, and worst cases (from top).

doubling from 2010 to 2030 (387 TWh in 2010 to 903 TWh in 2030). However, the worst-case scenario paints a more alarming picture, with a potential eightfold increase by 2030 (800 TWh in 2010 to 6,467 TWh in 2030). Similar to ICT device production, data centers exhibit a potential for substantial growth. In the best case, the electricity consumption in 2030 is supposed to be almost six times of 2010. The expected case anticipates a near-fifteenfold increase by 2030 (196 TWh in 2010 to 2,967 TWh in 2030). The worst-case scenario presents an even steeper trajectory, with a potential forty-fold increase by 2030 (from 199 TWh to 7,933 TWh). While networks also show growth potential, the increase appears less dramatic compared to the other categories. In the best case, the electricity consumption in 2030 is supposed to be almost three times of 2010. The expected case suggests a nearly tenfold increase by 2030 (from 408 TWh to 3,725 TWh), with the worst-case scenario reaching a potential forty-fourfold increase (546 TWh in 2010 to 15,208 TWh in 2030).

In conclusion, the data suggests a critical need for sustainable practices within the ICT sector to mitigate the potential surge in electricity consumption across all three categories.

## 3.3 Global carbon emission of the ICT sector

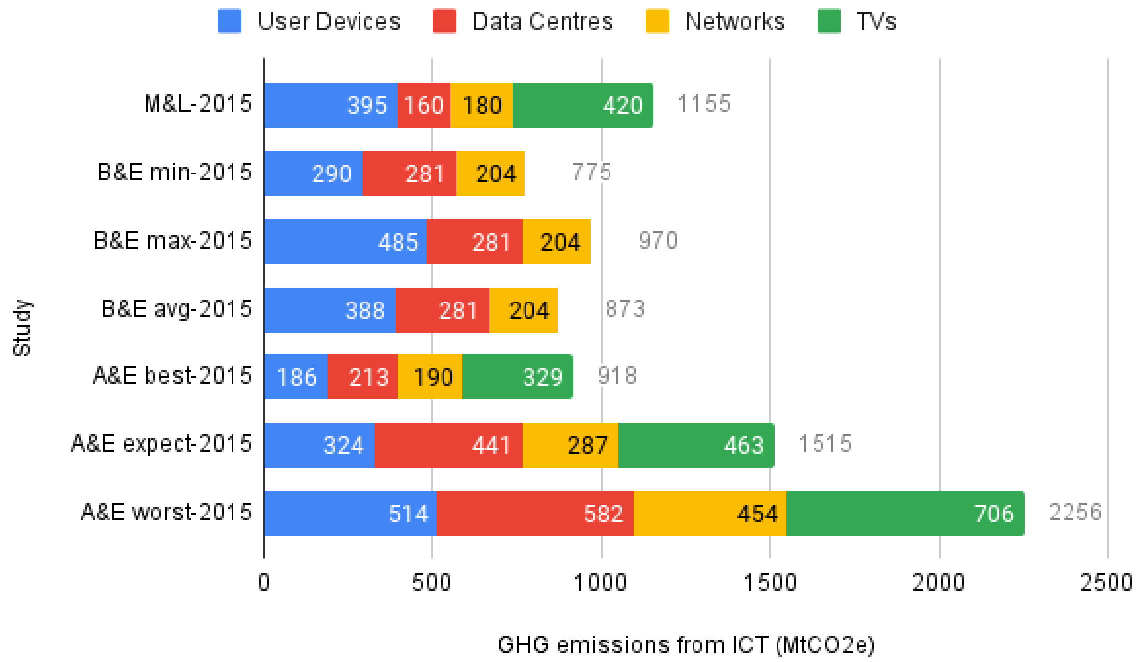
It is difficult to gather country-wise detailed data regarding all the factors influencing carbon emissions. Thus, this paper focuses on the global data only and this section peaks into the global carbon emission values from the previously calculated studies. This part of the paper looks into the categories of emission first, followed by the scope emissions and usage-embodied phase emissions. Finally, the calculated total emission values are represented in a brief discussion.

### 3.3.1 Emissions by category

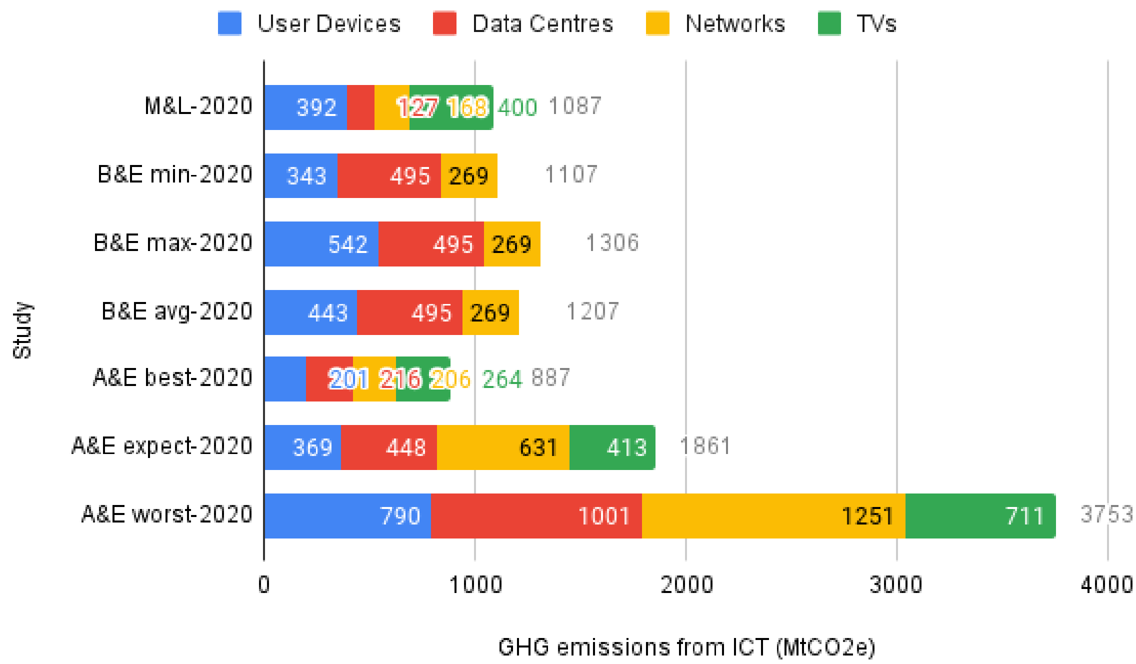
The ICT sector is categorized into three parts for most of the studies. Although some of the papers add a separate category for the enterprise network, most of the studies focus on three types of categorizations.

The data from figure 14 shows the evolution of emissions from user devices, data centers, networks, and TVs from 2015 to 2020 across various studies, revealing trends and changes in different scenarios.

In the study by Malmodin & Lundén, 2018, user device emissions slightly decreased by 0.8%, from 395 to 392 $MtCO_2e$. Data center emissions saw a more significant reduction of 20.6%, dropping from 160 to 127 $MtCO_2e$. Network emissions decreased by 6.7%, from 180 to 168 $MtCO_2e$. Emissions from TVs also decreased by 4.8%, from 420 to 400 $MtCO_2e$.




(a)




(b)

Figure 14: GHG footprint (Mt $CO_2$e) of ICT from different categories for years (a) 2015 and (b) 2020 (Freitag et al., 2021; Jha et al., 2022).

The Belkhir & Elmeligi, 2018 study provides three scenarios. In the minimum scenario, user device emissions increased by 18.3%, from 290 to 343 $MtCO_2e$. Data center emissions rose substantially by 76.2%, from 281 to 495 $MtCO_2e$. Network emissions increased by 31.9%, from 204 to 269 $MtCO_2e$. TV emissions are not available in this scenario. In the Belkhir & Elmeligi, 2018 maximum scenario, user device emissions saw a similar increase of 11.8%, from 485 to 542 $MtCO_2e$. Data center emissions showed the same significant rise of 76.2%, from 281 to 495 $MtCO_2e$. Network emissions also increased by 31.9%, from 204 to 269 $MtCO_2e$. As in the minimum scenario, TV emissions are not reported. Calculating the Belkhir & Elmeligi, 2018 average scenario, user device emissions increased by 14.2%, from 388 to 443 $MtCO_2e$. Data center emissions again rose substantially by 76.2%, from 281 to 495 $MtCO_2e$. Network emissions showed a similar increase of 31.9%, from 204 to 269 $MtCO_2e$.

The Andrae & Edler, 2015 study presents three scenarios as well. In the best case, user device emissions increased by 8.1%, from 186 to 201 $MtCO_2e$. Data center emissions saw a slight increase of 1.4%, from 213 to 216 $MtCO_2e$. Network emissions increased by 8.4%, from 190 to 206 $MtCO_2e$. TV emissions, however, decreased by 19.8%, from 329 to 264 $MtCO_2e$. In the expected case, user device emissions increased by 13.9%, from 324 to 369 $MtCO_2e$. Data center emissions rose slightly by 1.6%, from 441 to 448 $MtCO_2e$. Network emissions saw a dramatic increase of 119.9%, from 287 to 631 $MtCO_2e$. TV emissions increased by 21.6%, from 463 to 413 $MtCO_2e$. In the worst case, user device emissions saw a dramatic increase of 53.7%, from 514 to 790 $MtCO_2e$. Data center emissions rose significantly by 72.0%, from 582 to 1,001 $MtCO_2e$. Network emissions also saw a substantial increase of 175.5%, from 454 to 1,251 $MtCO_2e$. TV emissions remained relatively stable, with a slight increase of 0.7%, from 706 to 711 $MtCO_2e$.

These analyses highlight significant variations in emissions trends across different scenarios and components, with notable increases in data center and network emissions in most cases, while TV emissions show mixed trends and user devices exhibit moderate changes.

The trends in carbon emissions from electricity consumption for data centers and communication networks exhibit a consistent upward trajectory from 2007 to 2020 as pictured in figure 15. For data centers, emissions have grown substantially from 113.4 $MtCO_2e$ in 2007 to 494.9 $MtCO_2e$ in 2020, reflecting a more than fourfold increase over the 13-year period. This steady rise underscores the expanding energy demands and associated emissions of the data center sector as digital infrastructure and online services proliferate. Similarly, communication networks have experienced a significant rise in emissions, growing from 101.5 $MtCO_2e$ in 2007 to 269.1 $MtCO_2e$ in 2020, marking an increase of over 160%. While the rate of increase in network emissions is slightly less steep compared to data centers, it still

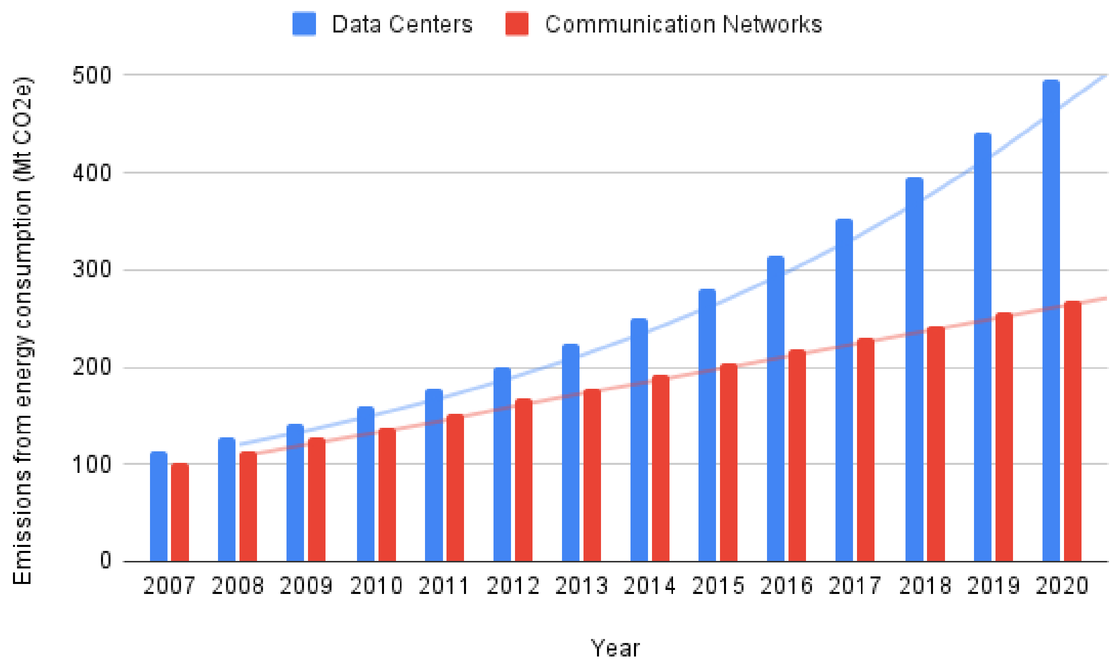



Figure 15: Annual energy consumption of data centers and communication networks in units of Mte$CO_2$-e from 2007 to 2020 (Belkhir & Elmeligi, 2018).

indicates substantial growth driven by the escalating use of mobile devices, data traffic, and global connectivity. These trends highlight the critical need for both sectors to adopt more sustainable energy practices to mitigate their growing carbon footprints.

### 3.3.2 Measuring scope emissions in the ICT sector

The data on carbon emissions, specifically Scope 1 and Scope 2 emissions measured in millions of tonnes of $CO_2$ equivalent, reveal notable trends over the period from 2020 to 2022 across three different sectors: telecom operators, colocation data centers, and cloud and content data centers. This is shown in figure 16.

For telecom operators, emissions have remained relatively stable over the three years. In 2020, emissions were recorded at 128 million tonnes $CO_2$e. This figure saw a slight increase to 129 million tonnes of $CO_2$e in 2021, marking a marginal rise of approximately 0.8%. By 2022, emissions decreased slightly to 126 million tonnes of $CO_2$e, reflecting a small reduction of about 2.3% from the previous year.

In the colocation data centers sector, emissions have shown a consistent upward trend. Starting at 35 million tonnes $CO_2$e in 2020, emissions increased to 39 million tonnes $CO_2$e in 2021, which represents an increase of around 11.4%. This upward trajectory continued in 2022, with emissions reaching 42 million tonnes $CO_2$e, indicating an additional rise of about

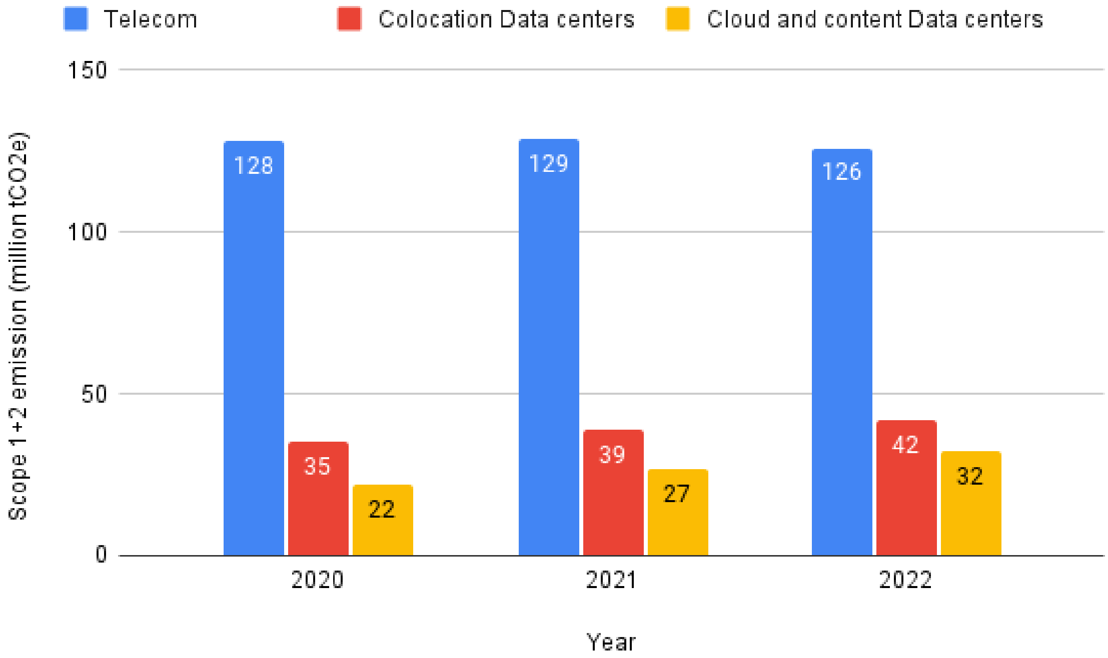



Figure 16: Scope 1 and 2 emissions of telecom operators, colocation, and cloud, content data centers from 2020 to 2022 (Ayers et al., 2023).

7.7% compared to the previous year. The cloud and content data centers sector has also experienced a steady increase in emissions over the same period. Emissions were at 22 million tonnes $CO_2e$ in 2020, which rose to 27 million tonnes $CO_2e$ in 2021, showing a significant increase of approximately 22.7%. This trend persisted into 2022, with emissions climbing to 32 million tonnes of $CO_2e$, marking a further substantial rise of about 18.5% from the previous year.

Overall, while telecom operators saw a slight fluctuation in emissions, both colocation data centers and cloud and content data centers experienced significant increases in their carbon emissions over the three-year period, highlighting the growing environmental impact of these sectors.

### 3.3.3 Embodied and use phase emission

The provided figure 17 showcases estimations of life-cycle greenhouse gas emissions ($MtCO_2e$) associated with Information and Communication Technology (ICT) equipment. Here's a breakdown of the findings, focusing on embodied emissions (during manufacturing and disposal) and use phase emissions (during operation):

Studies show a wide range of estimates for embodied emissions, even when excluding the supply chain. Embodied emissions, though significant, contribute less than the use phase.

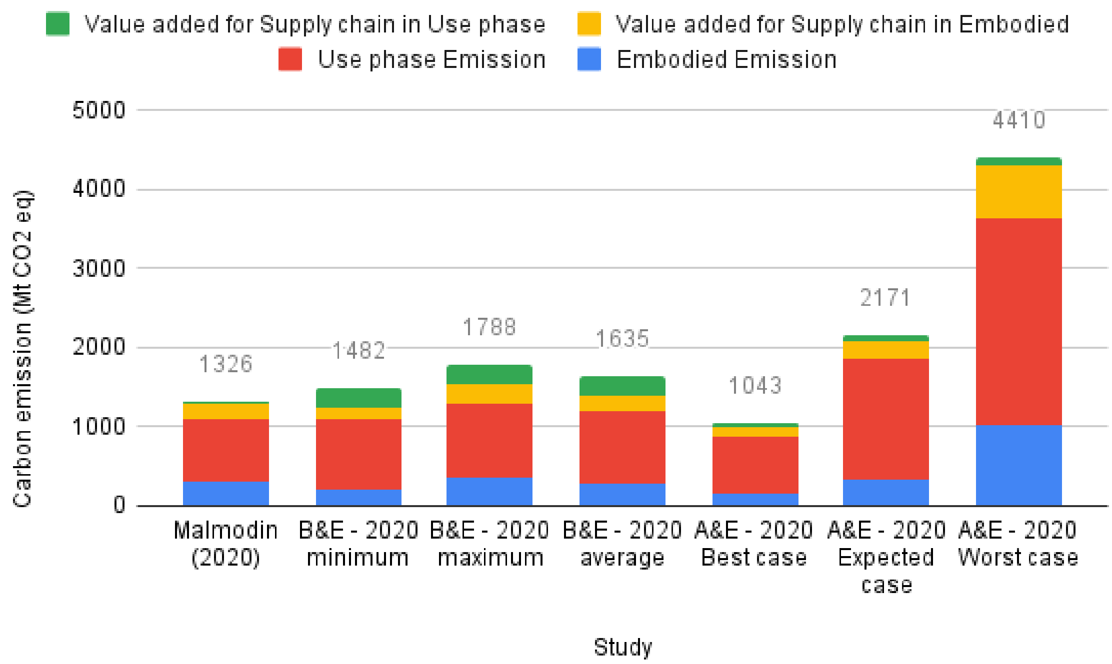



Figure 17: Estimates for 2020 adjusted to include all supply chain pathways (Freitag et al., 2021).

Estimates range from 100 $MtCO_2e/TWh$ to 680 $MtCO_2e/TWh$, with the supply chain playing a less prominent role in these emissions compared to the use phase. Malmodin's 2020 study suggests an embodied emission of 300 $MtCO_2e$, while the Belkhir & Elmeligi, 2018 team's 2020 range spans from 213 $MtCO_2e$ to 349 $MtCO_2e$. Interestingly, including the supply chain seems to have a lesser impact on embodied emissions compared to use phase emissions (around a 33% to 67% increase).

There's a significant difference in use phase emissions depending on the methodology used. The use phase appears to be the dominant contributor to ICT equipment's lifecycle emissions, with estimates ranging from 730 $MtCO_2e$ to 2610 $MtCO_2e$. Malmodin, Lövehagen, et al., 2024 study estimates use phase emissions to be 787 $MtCO_2e/TWh$, whereas the Belkhir & Elmeligi, 2018 mentions the average for 2020 is 926 $MtCO_2e$. The Andrae & Edler, 2015 study's 2020 estimates show a wider range, with a best-case scenario of 730 $MtCO_2e$ and a worst-case scenario of 2610 $MtCO_2e$. Including the supply chain in the use phase emissions seems to have a smaller impact compared to embodied emissions (around a 5% to 10% increase).

It has also been noticed that every study has considered different emission factors. Malmodin & Lundén, 2018 study has considered 0.5 $MtCO_2e/TWh$ as the emission factor, while Belkhir & Elmeligi, 2018 uses 0.6 $MtCO_2e/TWh$, and the Andrae & Edler, 2015 study's range is from 0.59 to 0.61 $MtCO_2e/TWh$. Thus, the wide range in these estimates highlights the need for more standardized methodologies for measuring ICT equipment's lifecycle emissions.

### 3.3.4 Total carbon emission of ICT calculated

While mentioning the ICT's carbon footprint, all the studies and estimations are made from three main categories such as ICT devices, data centers, and network systems. Although there are differences in defining the categories, the numbers are compared despite minor differences in considering what the categories include for the analysis of the previous studies. Especially, some of the studies include the Entertainment and Media (E&M) sectors as part of the ICT sector, but this chapter tries to consider the numbers without E&M sectors if the authors mention the estimates and calculation for this sector particularly.

The Global e-Sustainability Initiative (GeSI) estimates are essential for understanding the carbon emissions connected with the ICT sector because they provide a comprehensive, industry-wide approach to calculating the carbon footprint of ICT products and services. This technique provides uniformity, accounts for both direct and indirect emissions, and evaluates the enabling impacts of ICT solutions, making it a critical instrument for the sector's transition to a low-carbon economy. Table 5 compares the projected and recorded carbon emissions in megatons of $CO_2$ equivalent (Mt $CO_2e$) across different study years by GeSI.

| **Study** | **Year** | **Carbon emission (Mt $CO_2e$)** |
|---|---|---|
| Global e-Sustainability Initiative (GeSI), 2008 | 2002 | 530 |
| | 2007 | 830 |
| | 2020 | 1430 |
| Global e-Sustainability Initiative (GeSI), 2012 | 2011 | 910 |
| | 2020 | 1270 |
| Global e-Sustainability Initiative (GeSI), 2015 | 2030 | 1250 |

Table 5: Global e-Sustainability Initiative (GeSI) estimated ICT Sector emissions over the years

In 2008, GeSI reported that carbon emissions were 530 Mt $CO_2e$ in 2002 and increased by approximately 57% to 830 Mt $CO_2e$ by 2007. They projected emissions to reach 1430 Mt $CO_2e$ by 2020, which would be a 72% increase from 2007 levels. In 2012, GeSI recorded emissions of 910 Mt $CO_2e$ for 2011, representing a 9.6% increase from 2007. For 2020, their projection was adjusted downward to 1270 Mt $CO_2e$, indicating a 40% increase from 2011. In 2015, GeSI forecasted emissions for 2030 to be 1250 Mt $CO_2e$, showing a decrease of 1.6% from the 2020 projection made in 2012. Overall, the data from GeSI reveals a significant rise in carbon emissions over the years with a slight downward adjustment in long-term projections between the 2012 and 2015 reports.

The three papers Andrae & Edler, 2015 (indicated as A&E), Belkhir & Elmeligi, 2018 (indicated as B&E), and Malmodin & Lundén, 2018 (indicated as M&L), which discuss GHG emissions in 2015 and estimate emissions for 2020, are addressed and contrasted in subsequent studies Jha et al., 2022 and Freitag et al., 2021. Figure 14 presents GHG emissions from the ICT sector, including TVs, for the years 2015 and 2020 of these studies.

While considering the ICT sector includes the entertainment and media sector (E&M), the highest and lowest estimates vary a lot. The lowest projected GHG emissions in 2015 were 775 Mt$CO_2$eq B&E, while the highest estimate was 2,257 Mt$CO_2$eq in the worst-case scenario, mentioned by A&E. The average estimated GHG emissions for the year 2015 are around 1,250 Mt$CO_2$eq (Jha et al., 2022). The lowest predicted GHG emissions in 2020 were 887 Mt$CO_2$eq in the best-case scenario, as shown in A&E, while the highest estimate was 3,634 Mt$CO_2$eq in the worst-case scenario, mentioned in A&E. The average predicted GHG emissions for the year 2020 are roughly 1,620 Mt$CO_2$eq, representing a 400 Mt$CO_2$eq increase in five years (Jha et al., 2022).

However, the exclusion of the entertainment and media sector (E&M) gives a different perspective and result for the two years as shown in figure 18. The M&L Study shows a decrease in emissions from 733 Mt$CO_2$e in 2015 to 690 Mt$CO_2$e in 2020, a reduction of 43 Mt$CO_2$e (approximately 5.9%). Conversely, the B&E Study reports increases across all scenarios: minimum emissions rose by 332 Mt$CO_2$e (42.8%), maximum emissions by 335 Mt$CO_2$e (34.5%), and average emissions by 333 Mt$CO_2$e (38.2%). The A&E Study presents a mixed outlook, with the best-case scenario showing a slight increase of 34 Mt$CO_2$e (5.8%), the expected case rising significantly by 396 Mt$CO_2$e (37.6%), and the worst-case scenario nearly doubling with an increase of 1,492 Mt$CO_2$e (96.3%). These variations highlight different methodologies and assumptions about the ICT sector's future emissions.

In summary, while the M&L study projects a decrease in emissions, both the B&E and A&E studies suggest significant increases, with the A&E worst-case scenario highlighting the potential for dramatic rises in GHG emissions. These differences underscore the importance of considering various scenarios and the potential impact of policy measures and technological advancements on future emissions.

Figure 19 presents projected $CO_2$e emissions across different scenarios from 2010 to 2030, showing substantial variability in future emission estimates according to the study of Andrae & Edler, 2015. In 2010, the best-case estimated emissions at 1 Gt, which slightly decreased to 0.9 Gt by 2015 and remained stable until 2020. However, it is projected to rise to 1 Gt in 2025 and further increase significantly to 1.5 Gt by 2030. The expected scenario shows a more consistent upward trend, starting at 1.3 Gt in 2010, increasing to 1.4 Gt in 2015, then

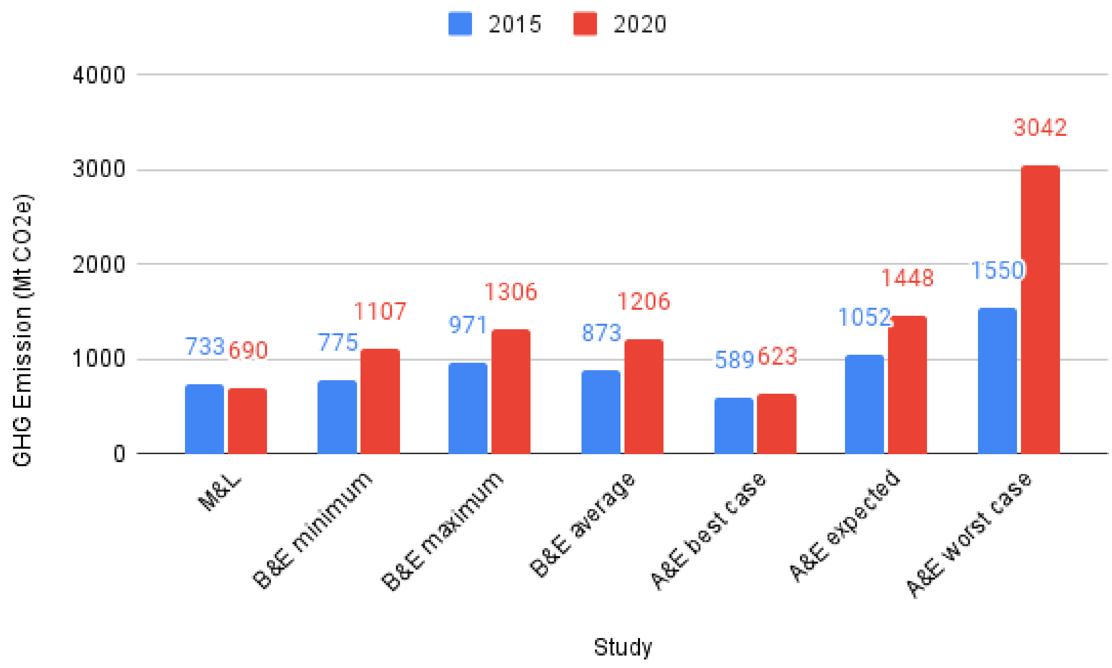



Figure 18: GHG emission (Mt $CO_2e$) of ICT without TVs.

rising more sharply to 1.7 Gt in 2020. This trend continues with a substantial jump to 2.5 Gt in 2025, reaching 4.8 Gt by 2030. The worst-case scenario depicts a dramatic increase, beginning at 1.7 Gt in 2010 and escalating to 2.3 Gt by 2015. Emissions then surge to 3.6 Gt in 2020, nearly double to 7.6 Gt by 2025, and skyrocket to 19.9 Gt by 2030. These forecasts emphasize the need for strong emission-reduction actions to avert the worst-case scenario.

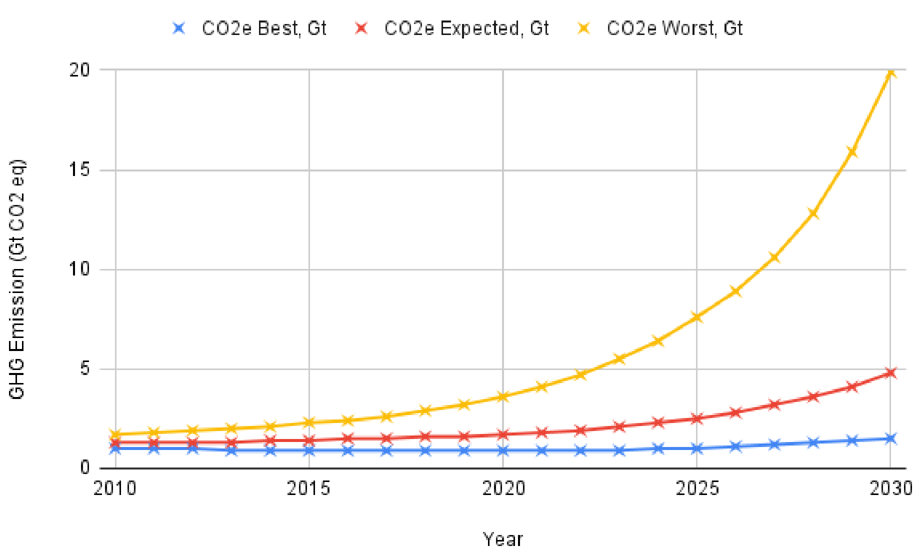



Figure 19: GHG footprint of ICT 2010-2030 (Andrae & Edler, 2015).

# 4 Methodology

This chapter provides the systematic approach used to determine the carbon footprint of the information and communication technology (ICT) sector. The study applies various statistical analyses of the data to answer earlier research on the carbon impact of ICT. A thorough explanation is also provided, along with an estimate of the carbon emissions and contributing variables over the next few years.

## 4.1 Research method

This research employs a mixed-methods approach to provide a comprehensive understanding of the factors affecting carbon emissions of Information and Communication Technologies (ICT) as well as estimating future values based on the important features. The study will be conducted in a total of three phases: systematic literature review, data processing, and data analysis. Each phase involves distinct methods and techniques to address the research questions effectively.

A comprehensive research method is employed to answer the main research question, including a systematic literature review (SLR), quantitative and qualitative data collection, data analysis, and validation. The SLR identifies existing research and previously identified significant factors affecting ICT's carbon emissions. Quantitative data on emissions and energy consumption, along with qualitative insights from industry experts, provide a basis for detailed calculations and scenario analysis. To address the sub-research questions, a methodological framework integrating time series analysis and regression analysis is to be utilized The methodology is designed to systematically investigate the significant factors influencing ICT's carbon emissions, estimate the carbon emissions of ICT, and evaluate the impact of electricity usage on the carbon footprint of the ICT sector.

To enable a thorough time series analysis, data will be gathered from reliable sources during the previous 10–20 years, such as government databases, industry publications, and international organizations. Electricity use, carbon emissions, energy efficiency measurements, and statistics on ICT hardware manufacture will be important factors. To find trends and patterns in the data, the time series analysis will include stationarity tests, smoothing methods, and decomposition.

With an emphasis on electrical consumption specifically, regression analysis will quantify the association between carbon emissions and the determined important features. Reliability tests and residual analysis will be used as diagnostics to validate the time series and multiple linear regression models, which will be used. The Greenhouse Gas Protocol and other standard emission factors and procedures will be used to estimate carbon emissions. Scenario analysis and adaptability calculations will be used to evaluate the effects of power use. Statistical analysis, which looks at the impact of important assumptions and factors, will guarantee the validity of the results.

## 4.2 Systematic literature review

A literature review is a research method that systematically searches and analyzes existing studies on a specific topic to provide a comprehensive understanding (Syrjälä, 2021). This involves gathering and critically evaluating evidence from various scientific sources, comparing and contrasting findings to identify broader themes and knowledge gaps, and ensuring depth and quality through precise methodology and effective synthesis (Aveyard, 2023). Conducting a literature review helps build a broad understanding of the research area and pinpoint areas where further investigation is needed.

There are several types of literature reviews. The Systematic Literature Review (SLR) is the most rigorous, using a defined protocol and strict search strategy to find, evaluate, and synthesize all relevant research on a specific topic (Kitchenham et al., 2009). Within an SLR, a meta-analysis quantitatively combines data from multiple studies to draw stronger conclusions (Rosenthal & DiMatteo, 2001). In contrast, a Descriptive Literature Review offers a general overview of the existing literature on a topic without the strict methodology of an SLR.

The steps of a Systematic Literature Review (SLR) involve several detailed phases (Syrjälä, 2021):

- **Formulate Research Question:** Begin by defining a clear, concise, and focused research question that will guide the entire review process. Ensure this question can be answered through existing literature and is significant within the relevant field.
- **Develop Study Plan and Background:** Outline a detailed research plan specifying methods and a timeline for the SLR. Provide a comprehensive background of the research topic, including its historical context and current knowledge base, justifying the need for the review and stating how it will contribute to existing research.
- **Establish Inclusion/Exclusion Criteria:** Define transparent and objective criteria for selecting relevant studies to ensure a systematic and unbiased review process. Examples of inclusion criteria might include publication date, study type, or specific population. Exclusion criteria could involve studies not published in peer-reviewed journals, non-English language studies, or those with irrelevant methodologies.


Figure 20: The steps of conducting a SLR (Syrjälä, 2021; Fink, 2019; Bettany-Saltikov, 2016).

- **Select Databases and Search Terms:** Choose relevant academic databases that cover the specific research field, combining general and specialized databases. Develop a comprehensive search strategy using keywords and Boolean operators, including synonyms and related terms to capture a wide range of relevant studies.

- **Conduct Literature Search and Screen Studies:** Conduct searches in chosen databases using the developed strategy. Utilize features like title and abstract filters to refine search results. Screen the retrieved studies based on predefined inclusion/exclusion criteria, initially through titles and abstracts, followed by a detailed review of full texts.

- **Analyze and Synthesize Results:** Critically appraise the quality of selected studies using established criteria. Extract relevant data using a pre-defined data extraction form that captures key information such as study design, findings, and limitations. Analyze and synthesize the findings to identify recurring themes, patterns, and contradictions across the research.

- **Summarize and Report Findings:** Present the current state of knowledge on the research topic based on synthesized findings. Highlight key findings, discuss similarities and differences in the data, identify potential research gaps, summarize the limitations of the SLR, and suggest areas for future research.

A thorough review of existing literature will be conducted to identify significant factors influencing ICT's carbon emissions. This includes reviewing peer-reviewed articles, industry reports, and governmental publications on energy consumption, material use, efficiency gains, and potential rebound effects within the ICT sector. This process ensures a rigorous and systematic approach to gathering and analyzing existing research.

## 4.3 Data processing

Since the goal of the thesis is to use time series analysis to identify factors and estimate future values, a solid data set is necessary. There have not been any previous studies with open datasets that provide a full view or calculation of the carbon emission of ICT. However, some studies focus on electricity use only, some focus on data center emissions, and so on. Thus, integrating and connecting all the data from the studies is required to create the dataset. The step begins with the features that contribute to the total carbon emission of ICT, then the available data are included in the dataset, and finally, the non-provided data is filled in using the appropriate methods.

### 4.3.1 Feature selection

There have been a lot of studies conducted and various studies use quite different assumptions and calculation methods. The most recent studies published by Malmodin, Lövehagen, et al., 2024 and the calculation method used by Global e-Sustainability Initiative (GeSI), 2012, are followed mostly to create the dataset. These two studies gave comprehensive details about the carbon emission calculation of the ICT sector. Based on these studies, some important and unavoidable features have been identified. But in the dataset, some of the constant values such as emission factor are ignored as those are not going to affect the training of different machine learning models. A total of 61 columns as features are selected for the dataset and a range for the year 2000 to 2035 is selected. Therefore, the prediction until 2035 is made through the study.

### 4.3.2 Data collection

To accurately measure carbon emissions in the ICT sector, the study gathers secondary quantitative data from various reliable sources, including environmental impact reports from major ICT companies such as telecommunication operators and data centers, government databases on energy consumption, and renewable energy adoption rates in the sector. Additionally, qualitative data is obtained through previous insights gained from industry experts, ICT professionals, and environmental scientists. The first detailed data are found in the year 2002 and the latest data are found in 2020. In between these years, there have been several studies, but not all of the year's calculations are found in detail. In some cases, there are several values for a specific data cell and the appropriate ones are chosen based on the data trend and explanation provided. Furthermore, a few columns are filled with a constant growth rate mentioned by sources. The initial dataset is created with the present data mentioned in the previous studies and found online.

### 4.3.3 Data prediction

After creating the primary dataset, there is a lot of missing data from the mentioned 35 years. In this stage, the data prediction is done with various strategies. After looking at the 61 data columns, these can be separated with different characteristics. Some columns have continuous values, others contain values with intervals, and some also have very few data points. To predict these wide ranges of data, there are different models need to be used. The predictions are made in three ways. Firstly, the previous values are filled up, and then if values are missing in the middle years, those are predicted based on the present year's value. Finally, the future values are estimated based on the previous trends analyzed by the models trained. In most cases, the Linear Regression, Ridge Regression, Lasso Regression, Support Vector Regression (SVR), and Auto Regression (AR) are used. These are discussed further in the following subsection.

## 4.4 Data analysis

This section is not limited to only applying algorithms for creating models and applying them for testing. Analysis is also done to check if the data is good enough for the algorithm to be implemented.

### 4.4.1 Statistical analysis

Statistical analysis is indispensable in time series regression analysis as it ensures the selection of appropriate models, accurate parameter estimation, significance testing, and model validation. These processes are vital for making reliable forecasts and informed decisions based on time series data.

The stationarity of a time series is vital for accurate forecasting. Stationary data allows for consistent statistical properties, reliable model assumptions, and effective identification of patterns, all of which contribute to improved prediction accuracy. A stationary time series is one whose statistical properties, such as mean, variance, and autocorrelation, do not change over time. Addressing non-stationarity through appropriate transformations is a critical step in the time series analysis process.

While stationarity is a desirable property for many time series forecasting methods, there are instances where retaining non-stationary characteristics is beneficial. This includes focusing on trends, using models designed for non-stationarity, preserving important information, dealing with small sample sizes, and addressing complex behaviors in the data.

### 4.4.2 Machine learning regression

The following models are fundamental statistical techniques used for modeling relationships between variables. All the models are used based on the efficiency in every estimation and prediction.

#### A. Linear Regression

Linear regression is a statistical method that models the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. The simplest form, simple linear regression, involves one independent variable, while multiple linear regression incorporates multiple independent variables (Yeturu, 2020). The general form of a linear regression model can be expressed as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i$$

where, $y_i$ is the dependent variable,
$x_{ij}$ are the independent variables,
$\beta_j$ are the coefficients to be estimated,
$\varepsilon_i$ is the error term.

Linear regression is widely used due to its simplicity and interpretability, making it suitable for various applications in fields such as economics, biology, and engineering.

#### B. Ridge Regression

Ridge regression, also known as L2 regularization, is a technique used to address multicollinearity in linear regression models. It introduces a penalty term to the loss function, which helps stabilize the coefficients' estimates when independent variables are highly correlated (Theodoridis & Koutroumbas, 2009). The ridge regression estimator is given by:

$$\hat{\beta}_R = (X^T X + \lambda I)^{-1} X^T y$$

where, $\lambda$ is the regularization parameter, and $I$ is the identity matrix

Adding the $\lambda$ term helps reduce the variance of the coefficient estimates at the cost of introducing some bias, which can improve overall model performance.

C. Lasso Regression

Lasso regression, short for Least Absolute Shrinkage and Selection Operator, is another regularization technique that applies an L1 penalty to the regression coefficients. This method not only helps to prevent overfitting but also performs variable selection by shrinking some coefficients exactly to zero (van Erp, Oberski & Mulder, 2019). The lasso regression objective function is expressed as:

$$\hat{w} = \arg\min_{w} \left(\mathrm{MSE}(w) + \lambda \|w\|_1\right)$$

where, $\|w\|_1$ is the L1 norm of the coefficients, and $\lambda$ controls the amount of regularization. This property of producing sparse models makes lasso regression particularly useful in high-dimensional datasets.

D. Support Vector Regression (SVR)

Support Vector Regression (SVR) is an extension of Support Vector Machines (SVM) used for regression tasks. The primary goal of SVR is to find a function that approximates the relationship between input variables and a continuous output variable while maintaining a margin of tolerance (epsilon) around the predicted values (Comito & Pizzuti, 2022). SVR aims to minimize the prediction error while keeping the model as simple as possible.

The mathematical formulation of SVR involves: Defining a loss function that penalizes errors exceeding a specified threshold (epsilon). Using kernel functions (linear or non-linear) to transform the input space into a higher-dimensional space, allows for more complex relationships to be modeled. The SVR model can be expressed as:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$$

subject to:

$$y_i - (w \cdot \phi(x_i) + b) \leq \varepsilon + \xi_i$$

$$(w \cdot \phi(x_i) + b) - y_i \leq \varepsilon + \xi_i$$

where, w is the weight vector,
$\phi(x_i)$ is the kernel function,
b is the bias term,
$\xi_i$ are the slack variables,
C is the regularization parameter.

E. Auto Regression (AR)

An Autoregressive (AR) model is a type of statistical model used to analyze and predict future values based on past values of the same variable. The AR model is defined by its order, denoted as AR(p), where p indicates the number of lagged observations included in the model (Kotu & Deshpande, 2019). The general form of an AR(p) model is:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t$$

where: $X_t$ is the current value,
$\phi_1$ are the coefficients,
$\varepsilon_t$ is a white noise error term

The AR model assumes that the current value of the series is a linear combination of its previous values.

F. Decision Tree Regression

The Decision Tree Regression model is a non-parametric, supervised learning method used for predicting continuous output variables. It operates by recursively partitioning the input space $X$ into distinct, non-overlapping regions based on the input features, and then fitting a simple model, such as a constant, within each region (Theodoridis & Koutroumbas, 2009). Given a training set $S = \{X_m, Y_m\}_m$, where $X$ is the input feature space and $Y$ is the continuous output space, the decision tree algorithm selects the optimal split at each node of the tree by minimizing a certain criterion, such as the mean squared error (MSE).

At each node $N$, the model evaluates all possible splits and chooses the one that minimizes the impurity function $f(S_l)$, where $S_l$ and $S_r$ are the resulting subsets after the split:

$$f(S_l, S_r) = \frac{|S_l|}{|S|}\text{MSE}(S_l) + \frac{|S_r|}{|S|}\text{MSE}(S_r)$$

Here, $|S|$ is the number of samples in the parent node, $|S_l|$ and $|S_r|$ are the numbers of samples in the left and right child nodes, respectively, and MSE is the mean squared error:

$$\mathrm{MSE}(S) = \frac{1}{|S|}\sum_{i\in S}(y_i - \bar{y})^2$$

where $y_i$ is the actual output and $\bar{y}$ is the mean of the outputs in subset $S$. This splitting process continues recursively until a stopping criterion is met, such as a maximum tree depth or a minimum number of samples in a node.

Once the tree is built, predictions for new input instances $x$ are made by traversing the tree according to the input feature values until a leaf node is reached, where the output $\hat{Y}$ is given by the mean value of the samples in that leaf node (Hastie et al., 2005).

G. Random Forest Regression

The Random Forest Regressor (RFR) is an ensemble learning method that combines multiple independent and uncorrelated decision trees to achieve accurate predictions. This approach relies on bagging, a technique that merges bootstrapping and aggregation. For a given training set $S = \{X_m, Y_m\}_m$, where $X$ represents the input features and $Y$ the output variables, bootstrapped subsets $S_t$ are generated to train individual trees. The predictions of these trees are then averaged to produce a final aggregated output (El Mrabet et al., 2022).

Mathematically, assuming that output variables follow a multivariate Gaussian distribution with mean $\mu$ and covariance $\Sigma$, the posterior distribution for a given tree $t$ is modeled as:

$$P(y|x, P_t) = N_t(y|\mu_t, \Sigma_t)$$

where $P_t$ is the partition created by tree $t$, and $N_t$ represents the multivariate Gaussian distribution. During training, the trees are optimized to reduce prediction uncertainty, with an entropy-based splitting function $f$ guiding the partitioning of subsets at each node (El Mrabet et al., 2022). The final prediction for a new instance is derived by averaging the posteriors across all trees:

$$P(y|x) = \frac{1}{T}\sum_{t=1}^{T} P(y|x, P_t)$$

where $T$ is the total number of trees in the forest. The model predicts the output $\hat{Y}$ by maximizing the posterior probability:

$$\hat{Y} = \arg\max_{y\in Y} P(y|x)$$

H. Polynomial Regression

Polynomial Regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modeled as an nth-degree polynomial (Coker, 1995).

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \varepsilon$$

where: y is the dependent variable,
x is the independent variable,
$\beta_i$ are the coefficients,
$\varepsilon$ is the error term.

Polynomial Regression is useful when the relationship between the variables is curvilinear, allowing for a better fit than linear regression in such cases. It can model complex relationships by increasing the degree of the polynomial.

### 4.4.3 eXplainable Artificial Intelligence (XAI)

eXplainable Artificial Intelligence (XAI) encompasses methods and techniques aimed at making the outputs of AI systems understandable to humans. As AI technologies advance and become increasingly complex, the need for clarity and transparency in their decision-making processes grows. Key aspects of XAI involve providing explanations that users can comprehend, ensuring these explanations accurately reflect the AI system's reasoning, operating within the designed parameters with adequate confidence, and fostering transparency and interoperability (Dieber & Kirrane, 2020). This is particularly vital in high-stakes fields like healthcare and finance, where human oversight is necessary to verify and trust AI decisions.

Local Interpretable Model-agnostic Explanations (LIME) is an open-source XAI framework that can provide interpretability to the decision-making steps of black-box ML models (Ribeiro, Singh & Guestrin, 2016). LIME is a widely used algorithm that explains predictions made by any machine learning classifier. LIME operates by perturbing the input data and observing changes in the predictions to identify which input features are most influential. The process involves generating predictions for perturbed inputs, weighting these inputs based on their proximity to the original, training a simple interpretable model on these weighted inputs to approximate the original model, and then using the resulting weights to determine feature importance (Salih et al., 2024). LIME's model-agnostic nature allows it to be applied to various machine learning models, from linear regressions to complex neural networks. Applications of LIME include debugging models, enhancing performance by identifying key features and ensuring model reliability in critical domains (Salih et al., 2024). Overall, XAI and algorithms like LIME are essential for maintaining trust and accountability in AI systems, especially as they become more prevalent and powerful.

# 5 Evaluating the Carbon Emissions of the ICT Industry

This chapter focuses on the work done in this research work. In the methodology chapter, the techniques used are mentioned. Now this part of the paper explains how the methods are used to create data, make predictions, and conduct an extensive analysis. In short, this chapter begins with the feature selection part derived from the background of this study. Then it mentions the calculation process followed by the data-gathering approach and initial dataset-creation method mentioned in the calculation process. After that, the important factors are identified by using explainable AI's analytical library. Finally, a future prediction is made using the process mentioned previously, which concludes the technical work of this thesis.

## 5.1 Feature selection

Feature selection involves identifying and choosing the most relevant variables (features) that contribute significantly to the target outcome of interest. This process is crucial in building efficient and effective predictive models, as it helps in reducing the dimensionality of the data, improving model performance, and making the results more interpretable.

### 5.1.1 Defining ICT sector

The first step of this section is to identify what the ICT sector contains. In this research, the ICT sector is defined in four main categories. They are ICT devices, data centers, network connectivity, and enterprise networks. An overview of what features are selected within these categories is found in table 6.

| **Category** | **Details** |
|---|---|
| **End Use Devices** | PCs (Desktop, Laptop), Mobile devices (Smartphone, other mobile devices), tablets |
| **Data Centers** | Servers, Data traffic, Computations |
| **Network infrastructure** | Fixed lines, Wireless, Mobile data |
| **Enterprise networks** | switches, routers, WLAN access points, and small cells |

Table 6: ICT sector defined by this study

A. ICT devices

Only four types of devices are considered within the range of ICT devices as they have been the major contributor to carbon emissions. The selected types are smartphones, tablets, desktop PCs, and laptops. Various product reports are used as a yearly product value for the total devices. Also, company reports are analyzed to gain insights into yearly shipment values as well as installed base values.

B. Data center

For the data centers, the previous studies mostly analyzed various industries' sustainability reports worldwide and came to some estimates. In this study no such techniques are used, rather taking the estimations from the previous studies as the contributing feature for the total carbon footprint of the data center. One of the main factors is the electricity usage of data centers.

C. Network connectivity

The network's emissions are calculated with two different network systems. The emission contributors are electricity use, fixed and mobile networks, subscribers, and data usage.

D. Enterprise networks

The enterprise network includes switches, routers, WLAN access points, and small cells as the driving factors.

Not only the factors are connected to the main categories, but also they are correlated to the embodied and use stage emission of the categories. The details of these relations are not mentioned in details in this paper, rather those are found in the supplementary document.

### 5.1.2 Selecting calculation process

After categorizing the ICT sector into three parts, each of the parts is calculated separately in the beginning. From that point, the calculation process follows a bottom-up approach. A summary of the calculation method used for creating the data set is shown in table 7. This table shows the step-by-step process that has been followed after the literature review and locating the initial publicly available data sources.

Firstly, the macro features are identified and chosen for each of the categories. The ICT devices' macro features (Device users, shipments, etc.) are filled with available data. Then the missing data are filled appropriately which is mentioned in the next few sections of this chapter. After all the independent features are filled, some of the dependent and micro-level features such as device power use, and device electricity usage are filled. Then a few features are identified as a deriving factor for embodied emission and use stage emission. In this way, the two columns are filled with data trained from the available data. Finally, add the two columns to get the total carbon emission of devices. The enterprise network's carbon emission follows the same procedure as the ICT device's. However, the calculation differs a bit for data centers and network systems.

| | **Calculating carbon emission of ICT devices** |
|---|---|
| Step 1: | Gather the initially available data (Devices produced, Devices Shipments, etc.). |
| Step 2: | Identify the macro (independent) and micro (Dependent) features. |
| Step 3: | Fill up the independent feature values with previous and future values |
| Step 4: | Fill up the dependent features based on the independent features |
| Step 5: | Embodied and Usage emissions are predicted with the available data. |
| Step 6: | Add these two to get carbon emission of ICT devices |
| | **Calculating carbon emission of Data centers** |
| Step 1: | Gather the initially available data (Servers shipped, Active servers, etc.). |
| Step 2: | Identify the macro (independent) and micro (Dependent) features. |
| Step 3: | Fill up the independent feature values with previous and future values |
| Step 4: | Fill up the dependent features based on the independent features |
| Step 5: | By following step 4 the carbon emission of the Datacenter is predicted |
| Step 6: | Based on the available data, using the extracted total carbon emission values, the embodied and use stage carbon emission is calculated |
| | **Calculating carbon emission of Enterprise Networks** |
| Step 1: | Gather the initially available data (Device shipments, installed base, etc.). |
| Step 2: | Identify the macro (independent) and micro (Dependent) features. |
| Step 3: | Fill up the independent feature values with previous and future values |
| Step 4: | Fill up the dependent features based on the independent features |
| Step 5: | Embodied and Usage emissions are predicted with the available data. |
| Step 6: | Add these two to get carbon emission of Enterprise Networks |
| | **Calculating carbon emission of Network Systems** |
| Step 1: | Gather the initially available data (Fixed/WiFi data traffic, etc.). |
| Step 2: | Identify the macro (independent) and micro (Dependent) features. |
| Step 3: | Fill up the independent feature values with previous and future values |
| Step 4: | Fill up the dependent features based on the independent features |
| Step 5: | The network's embodied and use stage carbon emission is calculated with the other three category values as independent features. |
| Step 6: | Now add the two-column values summed up the total carbon emission of the Network |

Table 7: ICT carbon emission calculation method used in this study.

## 5.2 Data collection

There has been a wide range of sources used to fill up the initial data. The data are found in the paper itself as well as supplementary documents provided with them. In many cases, there are several values present for a specific data cell and in these cases, the most promising value is chosen. The review papers have been quite useful in getting all the present values in the field. Also, a few columns have too little data present throughout the target years. There the yearly values are estimated from the annual growth rates researched by various forums and online platforms.

Andrae & Edler, 2015 calculated and predicted the values of various columns from 2015 to 2030. The columns they predicted included Production of ICT hardware Electricity use, Devices produced in billions, Global Data Centre IP Traffic, Mobile Network Electricity Usage, Mobile + Voice Traffic, Fixed access wired Electricity Usage, Fixed data traffic wired, Fixed access Wi-Fi Electricity Usage, Fixed data traffic in Wi-Fi. In that study, they predicted quite sharp upward trends in almost every feature. However, in a later study conducted by Andrae, 2019, the trends were changed and the values were re-calculated to a much lower growth trend than the initial predictions. This study also added the computations and data center's electricity usage from the year 2018 to the year 2030. These columns were filled with data from 2015 to 2030 where the updated values were added from the mentioned year previously.

The most recent study conducted by Malmodin, Lövehagen, et al., 2024, had a detailed calculation method for the year 2020. They also mention the values for servers shipped/produced globally and installed, active servers from the year 2005 to 2020. Other than these values all the mentioned values for the specific year have been added to the data set. Their data contains a detailed approach from the industry executive reports with emission and electricity usage of different categories. In an earlier report by Malmodin, Moberg, et al., 2010, a detailed calculation in the year 2007 can be found. Moreover, Global e-Sustainability Initiative (GeSI), 2012 provides a detailed value for the years 2002, and 2011 and estimations for the years 2020 and 2030. They also gave details about the overestimation of their study in the Global e-Sustainability Initiative (GeSI), 2015.

Other than these studies mentioned above, a good number of data are gathered from "statistica" publishes and estimates. Some of the devices installed base and shipments worldwide are from various sources mentioned on their website (IDC, January 15, 2024; Credit Suisse, March 16, 2011). Furthermore, the energy demand of devices and the emission per device per year are two of the most important factors contributing to the carbon footprint of ICT devices. These data are mostly gathered from the product life cycle analysis report. A specific product of a category (i.e., smartphone) is considered and the year it was introduced was chosen as that year's emission for that type of product. The energy demand of a device is calculated by setting an average usage time along with the average power consumption. As mentioned before, the product release year was set to be the value for the energy demand of that year.

It is not feasible to mention all the data sources in this section of the chapter, as many sources have been used. All the sources and references are indicated in the supplementary data file of this study.

## 5.3 Estimate previous missing data

The requirement for estimation is necessary as the goal is to make future predictions. Since the years have passed, but no data has been found for those years. There are different patterns after initial data collection. In some cases, the beginning years need to be predicted, and many others need estimations for the middle years. Based on the target a proper approach is taken. These approaches are described in this section.

The first category can be mentioned as the values available until the present date. Also, they tend to be inconsistent throughout the years. These data are gathered from the company reports. One such column is the PC shipments in million units. This PC shipment feature is an independent column. This value does not depend on any other column present in the dataset. Features and target variables are extracted, with the target variable being log-transformed for better modeling. Both features and targets are scaled using MinMaxScaler. To predict the previous values there are a few algorithms that were fitted with the available data and the best one was chosen based on the mean squared error value. Table 8 shows the models and their mean squared error.

| **Algorithm** | **MSE** |
|---|---|
| Linear Regression | 0.08511294447789558 |
| Ridge Regression | 0.08548342954873117 |
| Lasso Regression | 0.08776691235989341 |
| Support Vector Regression (SVR) | 0.025133966515239133 |

Table 8: Mean Squared Error (MSE) for different models

As the table indicates, the best model is SVR in terms of lower mean squared error. The best-performing model is refitted on the scaled data. Estimations are made for the years 2000 to 2005, inverse-transformed to the original scale, and exponentiated to revert the log transformation. Finally, figure-21 shows the data estimation for the previous years using the continuous values until the present year.

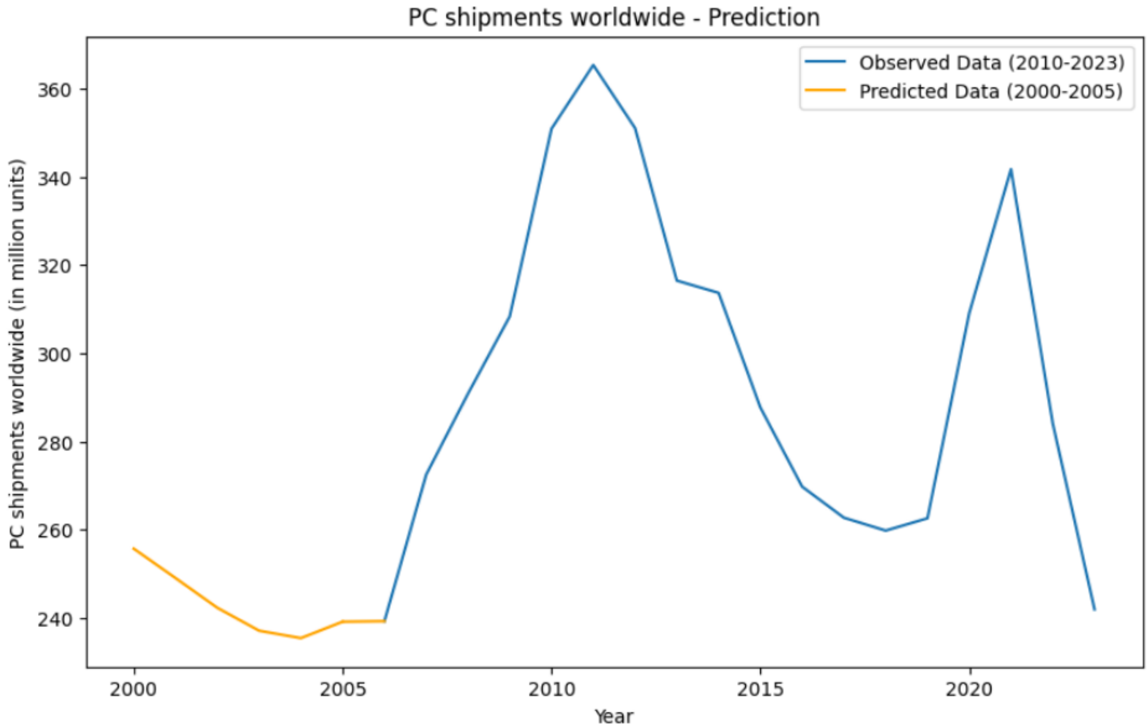



Figure 21: PC shipments worldwide.

The next type of data has a continuous trend as well and these data have been predicted for a certain time in the future. These future trends are studied and the past values are filled up. One such column is the device produced. This is also an independent column but the data from 2018 until 2030 is predicted by previous studies. The task is to estimate the number of devices produced in billions from 2000 to 2009, using data from 2010 to 2030. The data is structured into a pandas Data Frame and then reversed to facilitate the backcasting process. Features (years) and the target variable (log-transformed number of devices) are extracted. Both features and targets are scaled using MinMaxScaler. Four regression models (Linear Regression, Ridge Regression, Lasso Regression, and Support Vector Regression) are defined and evaluated by their mean squared error (MSE) on the scaled data. The model with the lowest MSE is selected as the best model. Table 9 shows the algorithms and their error values.

| **Algorithm** | **MSE** |
|---|---:|
| Linear Regression | 0.00432069409767252 |
| Ridge Regression | 0.012661274746177367 |
| Lasso Regression | 0.07567957440853651 |
| Support Vector Regression (SVR) | 0.00530454972202762 |

Table 9: Mean Squared Error (MSE) for different models (devices produced)

This best model is then refitted on the scaled data. Estimations for the years 2000 to 2009 are made using the best model, inverse-transformed to the original scale, and exponentiated to revert the log transformation. The predicted values are printed and plotted alongside the observed data, showing the backcasted predictions visually. Figure-22 shows that data estimation for the previous years using the continuous values for the future.

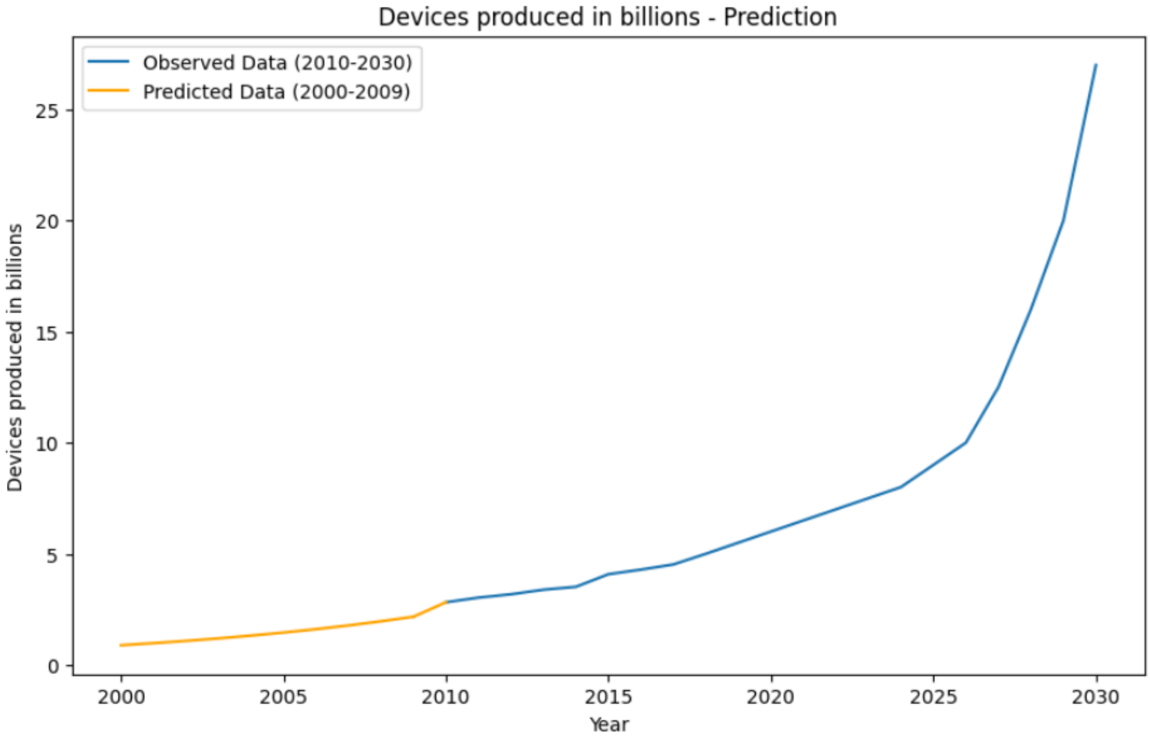



Figure 22: Devices produced in billions

Another type of data has a gap between certain years. They have some previous values and some future values. Filling up the values in the middle is the goal of this data category. For instance, the data of the desktop PC installed base shows such a trend. This is also an independent column. The data is structured into a pandas Data Frame, which contains some missing values for the years 2016 to 2018. The dataset is split into known data (without missing values) and missing data. Feature matrices (X) and target vectors (y) are prepared using the known data. Four regression models (Linear Regression, Ridge Regression, Lasso Regression, and Random Forest Regression) are defined and evaluated based on their mean squared error (MSE) using a train-test split on the known data. The model with the lowest MSE is identified as the best model. Table 11 shows the algorithms and their error values.

This best model is then trained on the entire known dataset and used to estimate the missing values. These predicted values are inserted back into the original Data Frame to fill in the missing entries. The script then plots the known data and the estimated data with different colors to visually distinguish between the original and the predicted segments. Finally, the filled data frame with both original and estimated values is printed, providing a complete

| Algorithm | MSE |
|---|---|
| Linear Regression | 30644.50662290924 |
| Ridge Regression | 30628.293082279954 |
| Lasso Regression | 30600.173216980987 |
| Random Forest Regression | 1069.724474446579 |

Table 10: Mean Squared Error (MSE) for different models (Desktop PC installed base)

series of the worldwide installed base of desktop PCs. Figure-23 shows the data prediction for the years in the places of the missing values.

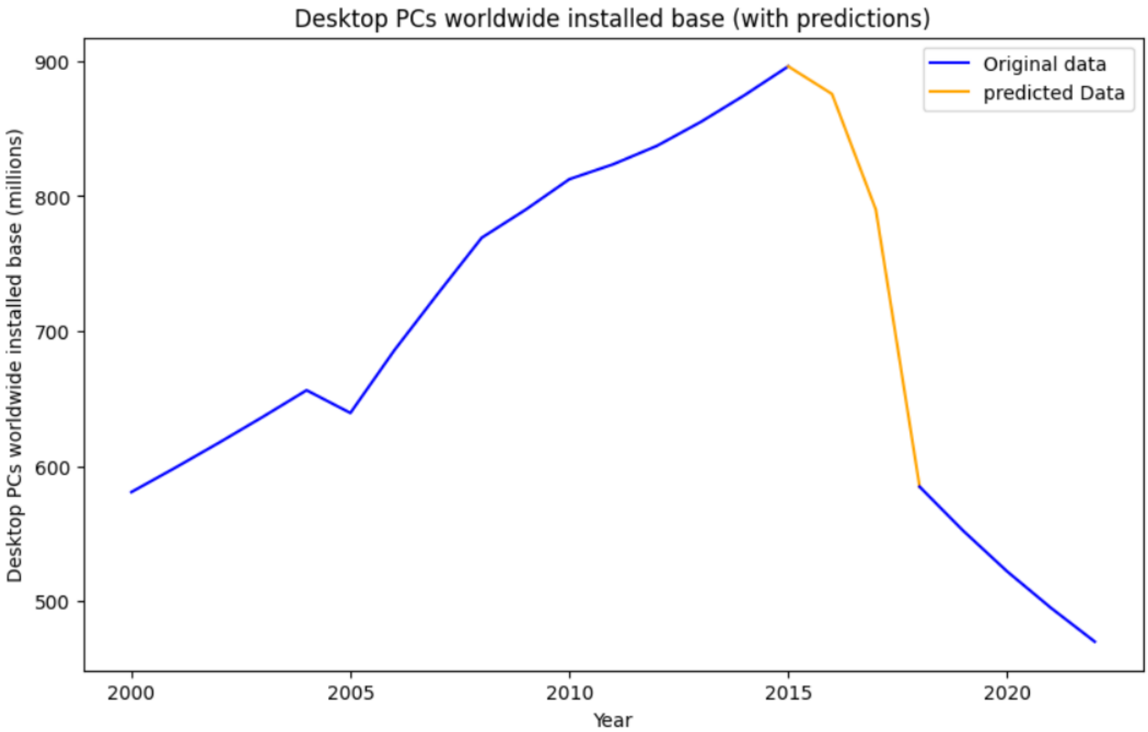



Figure 23: Desktop PC installed base in millions

The last type is a dependent column. Here the values are influenced and changed by the patterns of another data column. Production electricity of ICT hardware is such an example where the values follow the trends of the number of devices produced. The feature matrix (X) and target vector (y) are prepared, with the rows containing missing target values being dropped to form a non-NaN dataset. A Linear Regression model is trained using this non-NaN dataset. The model then predicts the missing electricity usage values based on the devices' produced data. These estimations are used to fill the missing entries in the original data frame. The model's performance is evaluated using the mean squared error (MSE) and R-squared ($R^2$) metrics on the known non-NaN dataset, providing insights into the model's accuracy. Figure-24 shows the data estimations for missing years in the middle.

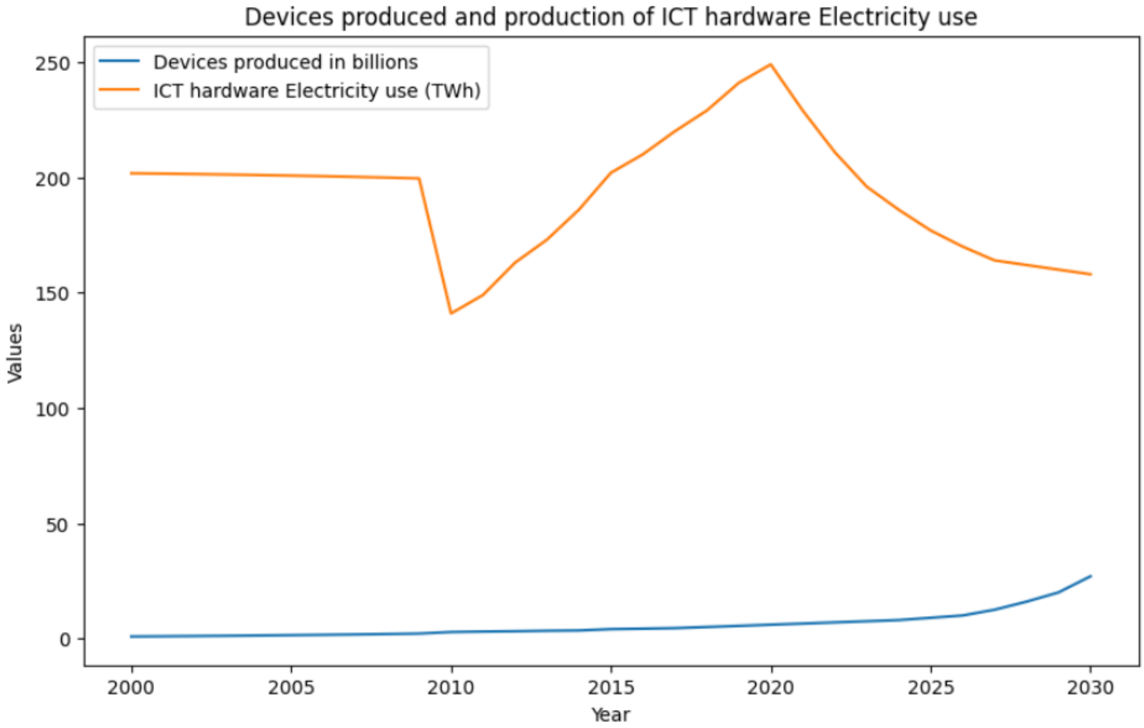



Figure 24: Production electricity usage of ICT hardware.

## 5.4 Predict future data

Predicting future data also depends on the data availability, which has been discussed in this chapter. Based on the characteristics of the data, appropriate models are chosen. However, in this part of the section, an assumption of not to include the latest models being used to predict future values.

The first example focuses on the trending models on such data of carbon emissions of ICT. Various algorithms like ARIMA, AR, and VAR are used to analyze and predict the time series data. An approach to fit the data using these models is shown in the devices produced column. To fit these models, the data needs to be stationary. To make the data stationary, the trends have to be destroyed. Since the data trend is very necessary for the dataset being used in this research. Even if the data is made stationary and then predicted with any of the models, the data does not fit. Figure-25 shows the data prediction for the future years. There can be various reasons for not fitting, but this research would not go into details about this. However, it is assumed that only a few data points as well as the need for trends and all historical data points are the main reasons for not fitting these models.

The data is split into a training set and a test set. The training set consists of the first part of the dataset, excluding the last 10 years, while the test set includes the last 10 years. This split is done to evaluate the model's performance on unseen data. An AutoRegressive (AR)

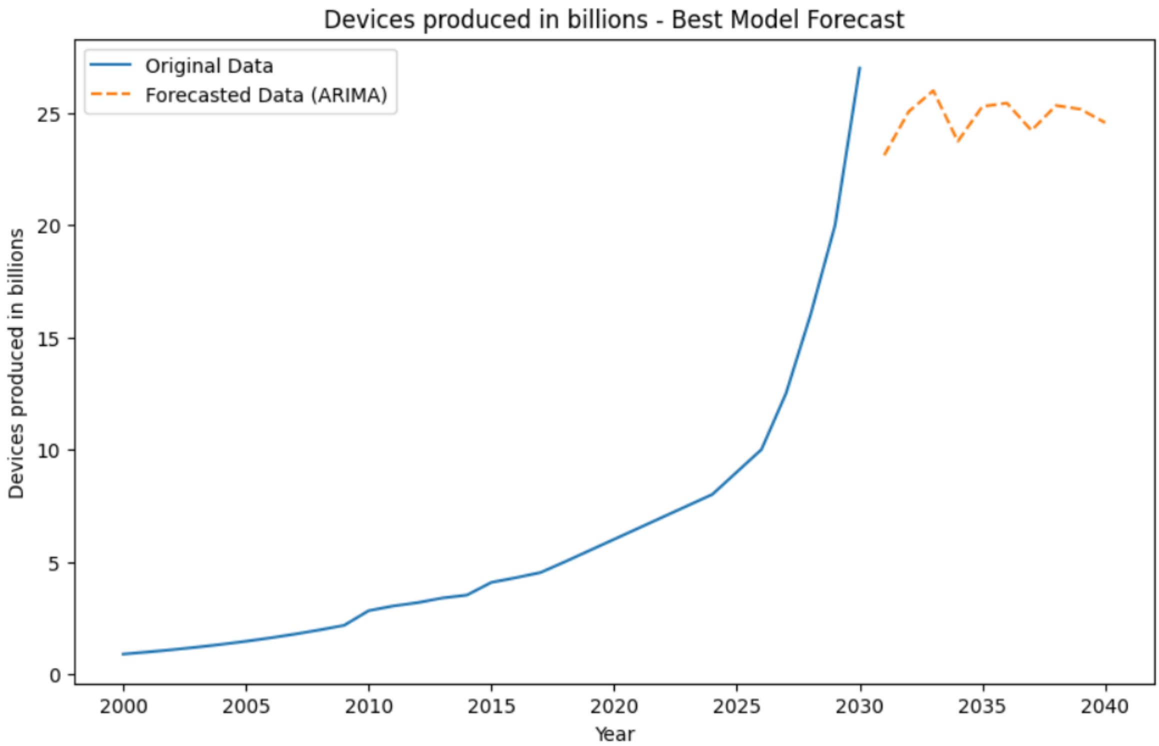



Figure 25: Devices produced future value prediction using ARIMA model.

model with 8 lags is defined and fitted on the entire dataset. The AR model uses the data to predict future values. After fitting the model, a summary of the model's parameters and statistics is printed for analysis. The model is used to predict the installed base for the test set period. These predictions are compared against the actual values in the test set. Finally, the future values are predicted. Figure-26 shows the data prediction for the future years.

The columns in the next category are heavily decreasing in order. They are critical to predict as the values might be predicted much lower than the possible values. Desktop PC installed base is an example of this category. This is also an independent column. Here the AR model predicts negative values, but it is not possible. Thus the other models are used. A possible reason for the AR model not working is the data is not stationary and the data points are too small as discussed before. Thus, the next best value for the error is taken and declared as the best model that fits this data.

| **Algorithm** | **MSE** |
|---|---|
| Linear Regression | 17150.100235008573 |
| Ridge Regression | 17149.06487591894 |
| Lasso Regression | 17143.504775481757 |
| SVR | 20820.460468846897 |
| AR | 2105.027126667138 |

Table 11: Mean Squared Error (MSE) for different models (Desktop PC installed base)

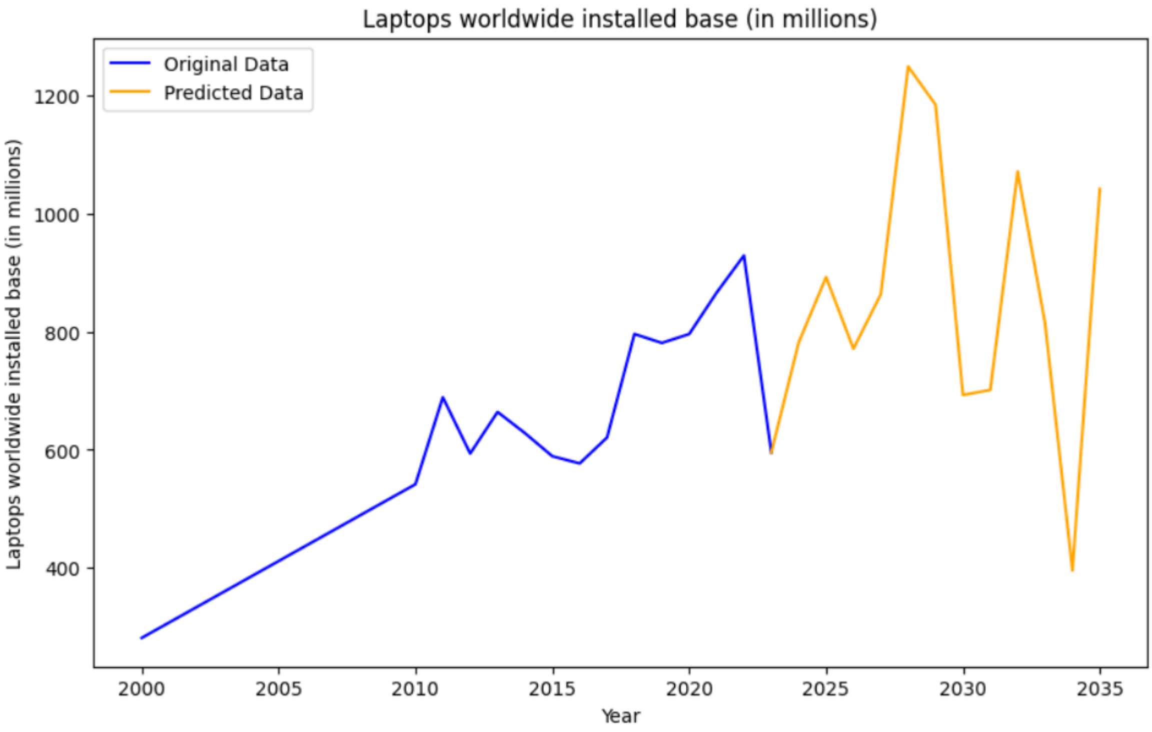



Figure 26: Laptop installed base in millions.

Figure-27 shows the data prediction for the future years. The prediction is made by following a similar approach described before, by creating train and test datasets. The best model predicts the null values based on the model trained.

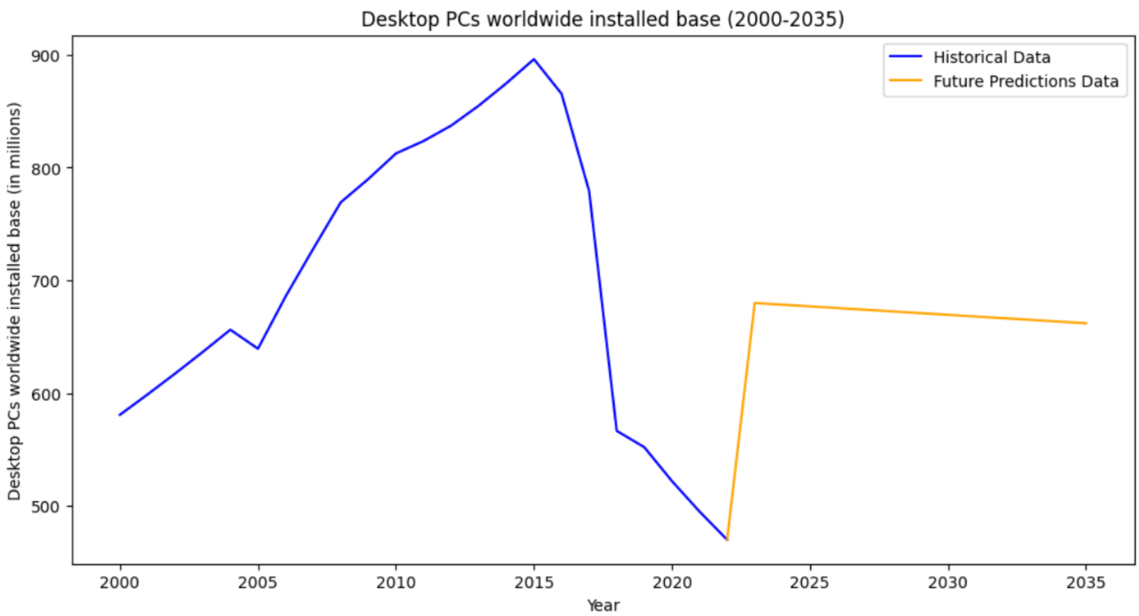



Figure 27: Desktop PC installed base in millions.

Another type of data prediction requires data from other columns. These values are dependent on other independent columns. One example of such data is calculated in use stage carbon emission of ICT, which depends on the devices installed base and energy demand of a specific device. Figure-28 shows the data prediction. To predict the missing target values, the code implements and evaluates three machine learning models: Linear Regression, Random Forest Regressor, and Support Vector Regressor. These models are trained on the training set, and their performance is assessed using the Root Mean Squared Error (RMSE) metric on a validation split. The best-performing model is selected based on the lowest RMSE value. Once the best model is identified, it is used to predict the missing values in the testing set. The predicted values are then paired with the corresponding years from the original dataset, allowing for a clear presentation of the predicted carbon emissions for the missing years. This method ensures a robust and reliable approach to imputing missing data, leveraging advanced machine learning techniques to maintain the integrity and completeness of the dataset.

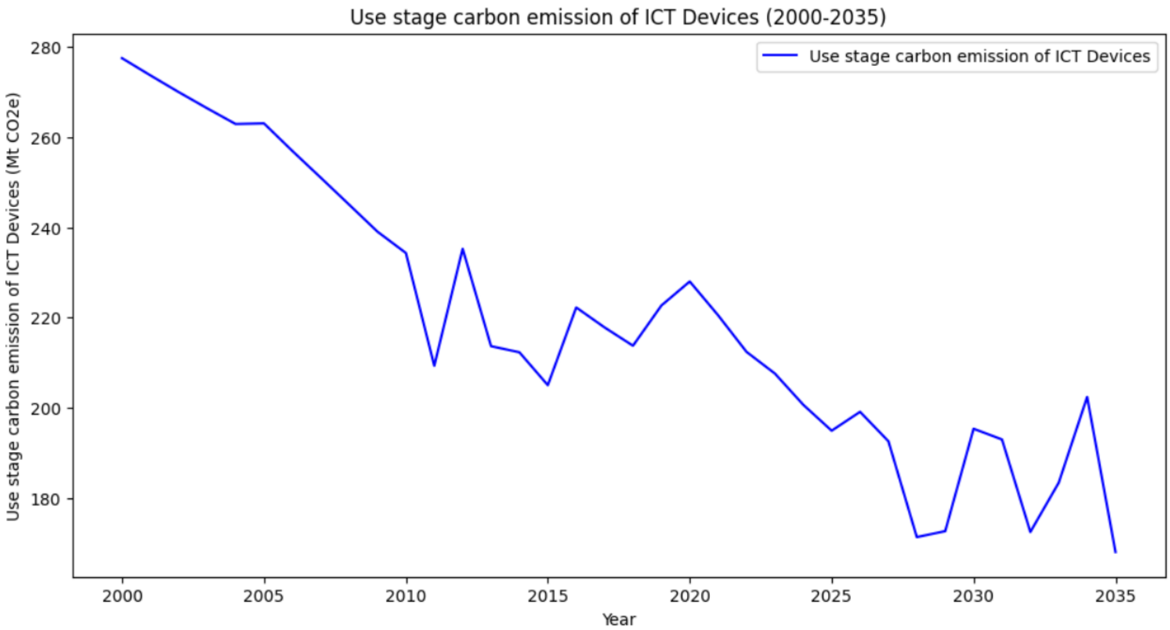



Figure 28: Use stage carbon emission of ICT devices.

## 5.5 Identify feature significance using explainable artificial intelligence (XAI)

This explanation comes after the total dataset is constructed. Here, the future prediction section is mentioned after this XAI explanation. In this section, XAI is used to analyze the whole dataset. As mentioned in the methodology, the LIME explanation is used for identifying feature importance for a year. It takes one target column and learns which of the existing columns plays a vital role in achieving the value of the target column. Here, the explanations for selected years (2011, 2022, 2030) are presented in detail. Also, the explanation is given for two target columns: electricity consumption and carbon emission.

### 5.5.1 Factors influencing electricity consumption

This part of the chapter mentions the factors influencing electricity consumption over the years. Once the dataset is created, it is divided into train test sets and then fitted into various models. The results of these models are shown in table 12.

| **Algorithm** | **MAE** | **MSE** | **$R^2$** |
|---|---|---|---|
| Linear Regression | 100.24 | 13952.85 | 0.99 |
| Ridge Regression | 58.74 | 6181.48 | 0.9975 |
| Lasso Regression | 97.87 | 13421.38 | 0.99 |
| Polynomial Regression | 97.40 | 15855.41 | 0.99 |
| Decision Tree Regression | 501.38 | 440169.48 | 0.82 |
| Random Forest Regression | 341.58 | 416670.68 | 0.83 |

Table 12: Performance metrics for various regression algorithms

The best model is chosen and this model is then used to explain the importance of the feature for a specific year. The following parts show such analysis in brief.

Explanation of 2011 electricity consumption of ICT:

Figure-29 shows the important factors for the 2011 ICT electricity consumption. The LIME explanation for the regression model prediction provides a detailed breakdown of the features contributing to the predicted value of -5592.45. The explanation reveals that the prediction range extends from -5592.45 to 9507.96, indicating a broad scope of potential outcomes based on feature variations. The visualization categorizes the contributions into negative and positive influences, with each feature's impact represented by bar lengths that indicate the magnitude of their effect on the predicted value.

Key negative contributors include Feature 2, Feature 7, and Feature 37, which significantly decrease the predicted value by 456.08, 800.66, and 270.20 units, respectively. These features' high values (589.82 for Feature 2 and 220.00 for Feature 7) are associated with a substantial reduction in the target variable. Additionally, features like Feature 31, Feature 18, and Feature 15 contribute smaller but notable negative impacts.

On the positive side, Feature 5 and Feature 14 are the most significant contributors, increasing the predicted value by 1144.73 and 373.43 units, respectively. Higher values of these features (107.87 for Feature 5 and 446.00 for Feature 14) correlate with an increase in the target variable. Feature 28 also contributes positively, albeit to a lesser extent.

Overall, the LIME explanation offers transparency into the regression model's prediction process by clearly delineating the contributions of individual features. This breakdown aids in understanding how specific feature values influence the model's output, thereby enhancing the interpretability and trustworthiness of the prediction. The significant negative contributions from certain features highlight areas where the model is particularly sensitive, while the positive contributions emphasize factors that drive the prediction upwards.

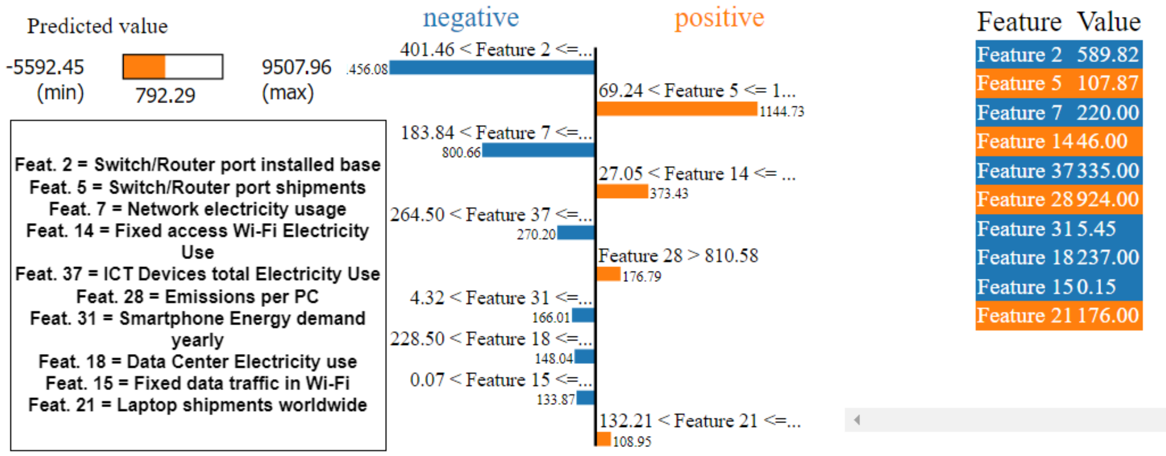



Figure 29: XAi explanation for the electricity consumption of ICT for the year 2011.

Explanation of 2020 electricity consumption of ICT:

Figure-30 shows the important factors for the 2020 ICT electricity consumption. The LIME explanation for the regression model prediction details the contributions of various features to a predicted value of -5505.28. The prediction range is wide, from -5505.28 to 9426.93, indicating significant potential variability based on the input features. This visualization separates the contributions into negative and positive influences, with each feature's impact represented by the length of the bars, indicating the magnitude of their effect on the predicted value.

Key negative contributors include Feature 2 and Feature 7, which significantly reduce the predicted value by 416.01 and 924.81 units, respectively. The high values of these features (847.79 for Feature 2 and 247.00 for Feature 7) are associated with a substantial decrease in the target variable. Other features such as Feature 18, Feature 37, and Feature 30 also contribute to the negative impact, albeit to a lesser extent.

On the positive side, Feature 5 has the largest positive contribution, increasing the predicted value by 1375.75 units. This suggests that a higher value of Feature 5 (142.94) is strongly associated with an increase in the target variable. Features like Feature 26 and Feature 25 also contribute positively, indicating their values are linked to an increase in the predicted outcome, though their impact is smaller compared to Feature 5.

Overall, the LIME explanation provides a transparent view of how individual features influence the regression model's prediction. The significant negative impacts from features like Feature 7 and Feature 2 highlight the model's sensitivity to these variables, while the positive contributions from Feature 5 and Feature 26 underscore factors that drive the prediction upwards. This detailed breakdown enhances the interpretability of the model, ensuring greater transparency and trust in its predictions.

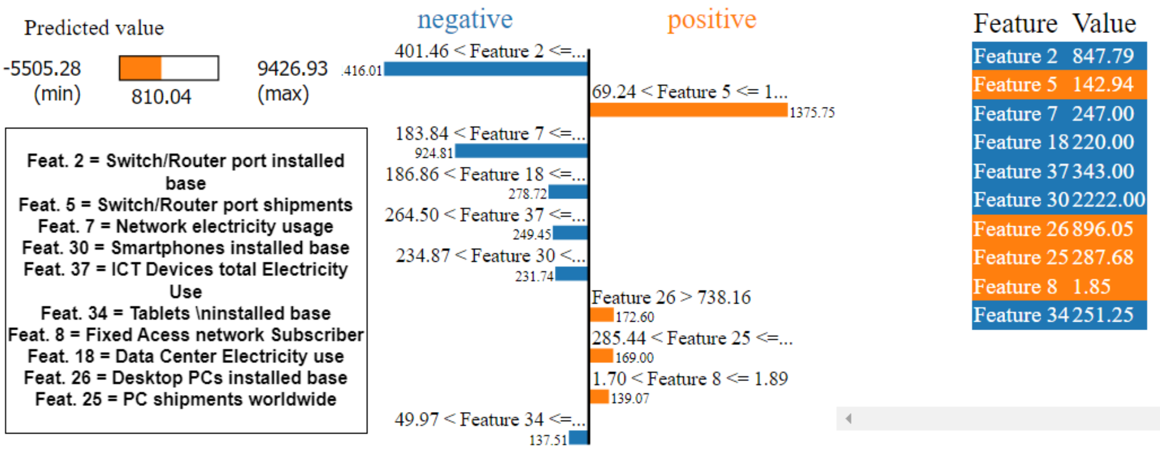



Figure 30: XAi explanation for the electricity consumption of ICT for the year 2020.

Explanation of 2030 electricity consumption of ICT:

Figure-31 shows the important factors for the 2030 ICT electricity consumption. The image represents a LIME explanation for a regression model, specifically focusing on a single prediction. In this context, the regression model predicts a value of 5625.96, with the potential range of predictions spanning from -6039.20 to 10010.11.

On the left side of the image, there is a visual scale indicating the predicted value in the context of its minimum and maximum possible values. The horizontal bar, which is partially orange and extends to the right, indicates the actual prediction of 5625.96 within this range. The contributions of individual features to the prediction are illustrated in the center of the image, where they are split into negative (blue) and positive (orange) influences.

The features with negative contributions are listed on the left, indicating how much they reduce the predicted value. Feature 5, which has a value of 677.07, contributes significantly to reducing the prediction by 2994.59 units. Other features with negative impacts include Feature 14, with a value of 51.00, contributing -778.62 units, Feature 21 with a value of 753.70, contributing -385.25 units, Feature 10 with a value of 1300.00, contributing -329.87 units, and Feature 12 with a value of 1291.05, contributing -140.21 units. These negative contributions collectively lead to a substantial decrease in the predicted value.

Conversely, the positive contributions to the prediction are depicted on the right side of the central column. Feature 2, with a value of 3319.47, is the most significant positive contributor, adding 3239.84 units to the prediction. Other notable positive influences include Feature 7, with a value of 2716.00, contributing 2082.45 units, Feature 18 with a value of 1929.00, contributing 689.39 units, and Feature 37 with a value of 889.00, contributing 336.47 units. These features counterbalance the negative contributions, leading to the final predicted value.

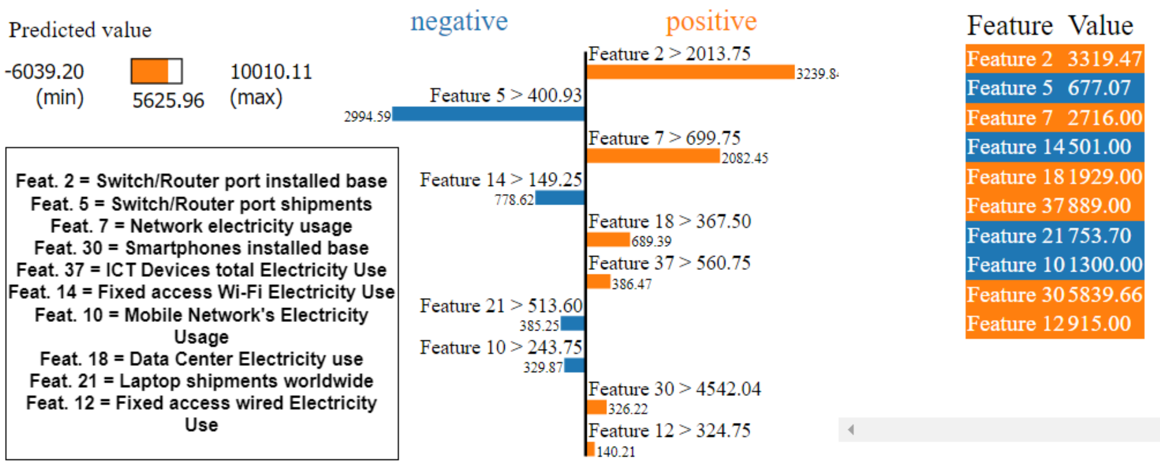



Figure 31: XAi explanation for the electricity consumption of ICT for the year 2030.

### 5.5.2 Factors influencing carbon emission

Similarly, as mentioned before for the electricity consumption analysis, this part of the chapter mentions the factors influencing carbon emission over the years. Once the dataset is created, it is divided into train test sets and then fitted into various models. The results of these models are shown in table 13.

| **Algorithm** | **MAE** | **MSE** | **$R^2$** |
|---|---|---|---|
| Linear Regression | 19.17 | 636.28 | 0.93 |
| Ridge Regression | 15.96 | 361.09 | 0.96 |
| Lasso Regression | 14.44 | 252.48 | 0.97 |
| Polynomial Regression | 18.24 | 682.70 | 0.93 |
| Decision Tree Regression | 38.31 | 2894.93 | 0.70 |
| Random Forest Regression | 19.72 | 536.44 | 0.94 |

Table 13: Performance metrics for various regression algorithms

The best model is chosen and this model is then used to explain the importance of the feature for a specific year. The following parts show such analysis in brief.

Explanation of 2011 carbon emission of ICT:

Figure-32 shows the important factors for the 2011 ICT carbon emission. The image showcases a LIME (Local Interpretable Model-agnostic Explanations) explanation for a regression model, specifically detailing the factors influencing carbon emissions of ICT (Information and Communication Technology) for the year 2011. In this context, the regression model predicts a value of 731.10 for carbon emissions, within a possible range of 272.37 (minimum) to 1249.82 (maximum). The leftmost section of the image presents this predicted value on a horizontal scale, with the orange bar representing the predicted carbon emission value within its defined range.

The image's central part breaks down individual features' contributions to the predicted carbon emission value, categorizing them into negative (blue) and positive (orange) influences. Features with negative contributions are illustrated on the left side of the vertical axis. Notably, Feature 0, with a value of 792.00, reduces the predicted emission by 61.28 units, reflecting its significant negative impact. Other features contributing negatively include Feature 53 with a value of 186.00, reducing the prediction by 38.68 units, and Feature 17 with a value of 79.98, contributing a reduction of 19.09 units. These features collectively act to lower the predicted carbon emissions.

Conversely, the right side of the central column displays the features with positive contributions to the predicted value. Feature 1, with a value of 208.00, increases the predicted carbon emissions by 47.59 units, representing a major positive influence. Additional positive contributors include Feature 48 with a value of 76.00, which increases the prediction by 43.19 units, Feature 52 with a value of 335.00, adding 34.83 units, and Feature 3 with a value of 3.50, contributing 12.13 units. These features cumulatively work to increase the overall predicted emissions.

The rightmost section lists the values of all the features involved in the prediction, offering a comprehensive view of the input data utilized by the regression model. By evaluating the contributions of these individual features, one can discern the factors that most significantly influenced the carbon emissions of ICT in 2011. This granular breakdown is instrumental in understanding the model's internal mechanics, enabling stakeholders to identify key areas where interventions can be made to manage and potentially reduce carbon emissions.

Explanation of 2020 carbon emission of ICT:

Figure-33 shows the important factors for the 2020 ICT carbon emission. The displayed image represents a LIME explanation for a regression model, elucidating the significant factors contributing to the carbon emissions of ICT (Information and Communication Technology) for the year 2020. In this instance, the regression model predicts a carbon emission value of

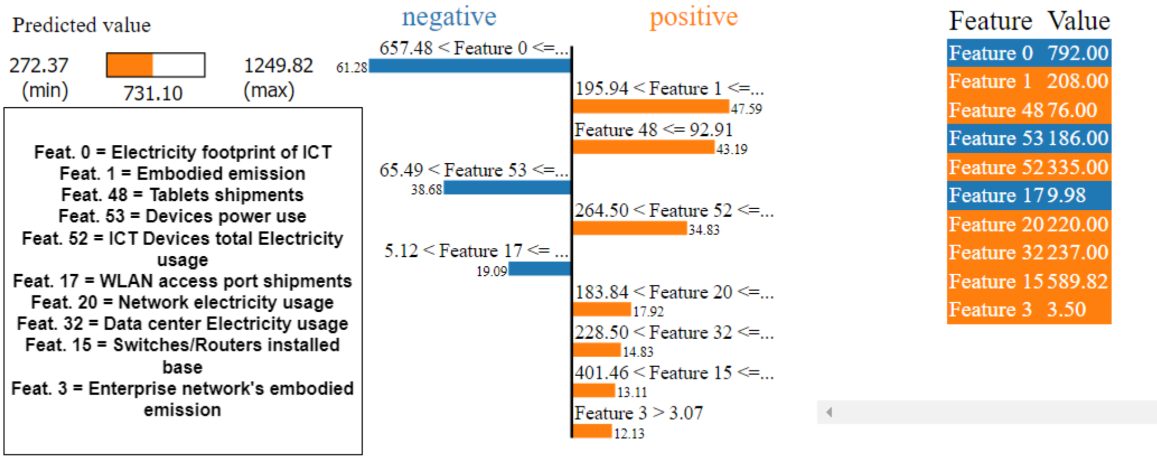



Figure 32: XAi explanation for carbon emission of ICT for the year 2011.

744.94, within a defined range of 261.71 (minimum) to 1229.82 (maximum). The leftmost segment of the image illustrates this predicted value on a horizontal bar, with the orange section indicating the actual prediction of 744.94 within the spectrum of potential values.

The central section of the image details the contributions of individual features to the predicted carbon emission value, separated into negative (blue) and positive (orange) influences. Features that contribute negatively to the prediction are depicted on the left side of the central axis. Feature 0, with a value of 810.00, has the most substantial negative impact, reducing the predicted emission by 65.75 units. Other features with negative influences include Feature 48, with a value of 208.00, which reduces the prediction by 36.72 units, and Feature 53, with a value of 141.00, contributing to a reduction of 36.61 units. These features collectively lower the predicted carbon emissions.

On the other hand, the right side of the central axis highlights the features with positive contributions to the predicted value. Feature 1, with a value of 235.00, exerts the most significant positive influence, increasing the predicted emissions by 86.48 units. Additional features contributing positively include Feature 52, with a value of 343.00, adding 33.51 units to the prediction, and Feature 44, with a value of 1437.20, which increases the predicted value by 30.64 units. Other features such as Feature 2, Feature 32, Feature 50, and Feature 20 also positively contribute to the predicted emissions, albeit to a lesser extent.

The rightmost section of the image lists the values of all the features involved in the prediction, providing a comprehensive overview of the input data utilized by the regression model. By analyzing these individual contributions, one can discern the most influential factors driving the carbon emissions of ICT in 2020. This granular breakdown is instrumental for understanding the internal mechanics of the model, thereby enabling stakeholders to identify critical areas for intervention and mitigation strategies aimed at reducing carbon emissions within the ICT sector.

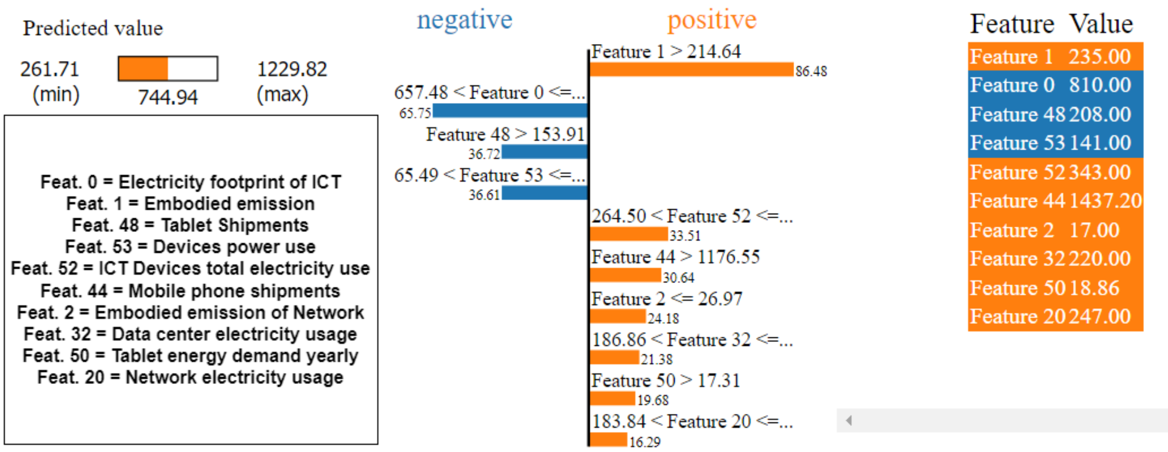



Figure 33: XAi explanation for carbon emission of ICT for the year 2020.

Explanation of 2030 carbon emission of ICT:

Figure-34 shows the important factors for the 2030 ICT carbon emission. The image presents a LIME explanation for a regression model, detailing the significant factors contributing to the carbon emissions of ICT for the year 2030. In this instance, the regression model predicts a carbon emission value of 949.71, within a potential range from 327.42 (minimum) to 1249.03 (maximum). The leftmost segment of the image depicts this predicted value on a horizontal bar, with the orange section indicating the actual prediction of 949.71 within the defined range.

The central section of the image dissects the contributions of individual features to the predicted carbon emission value, categorizing them into negative (blue) and positive (orange) influences. Features contributing negatively to the prediction are illustrated on the left side of the vertical axis. Notably, Feature 52, with a value of 889.00, reduces the predicted emission by 76.75 units, indicating a significant negative impact. Other features with negative contributions include Feature 32, with a value of 1929.00, which reduces the prediction by 75.04 units, Feature 20, with a value of 2716.00, reducing it by 42.58 units, Feature 48, with a value of 158.97, reducing the prediction by 37.98 units, and Feature 18, with a value of 677.07, contributing a reduction of 31.26 units. These features collectively act to lower the predicted carbon emissions.

Conversely, the right side of the central column highlights the features with positive contributions to the predicted value. Feature 0, with a value of 5557.22, exerts the most substantial positive influence, increasing the predicted emissions by 149.99 units. Other notable positive contributors include Feature 53, with a value of 731.27, adding 95.73 units to the prediction, Feature 29, with a value of 350.88, increasing the predicted value by 74.82 units, Feature 6, with value 739.88, contributing 53.59 units, and Feature 1, with a value of 203.61, adding 41.71 units. These features cumulatively work to elevate the overall predicted emissions.

The rightmost section of the image lists the values of all the features involved in the prediction, providing a comprehensive overview of the input data utilized by the regression model. By analyzing the contributions of these features, one can discern the factors that most significantly influence the carbon emissions of ICT in 2030. This breakdown is instrumental for understanding the internal mechanics of the model, enabling stakeholders to identify critical areas for intervention and develop strategies to mitigate carbon emissions effectively.

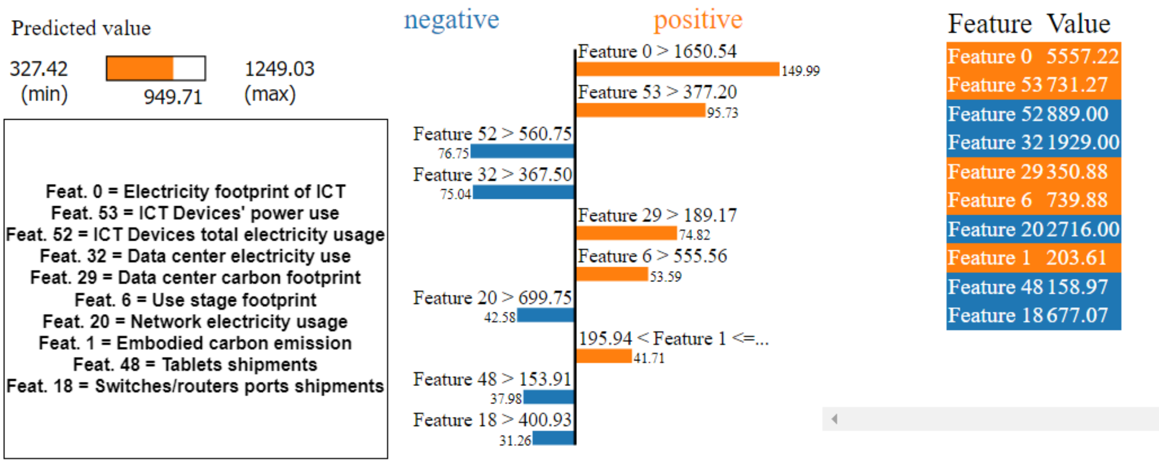



Figure 34: XAi explanation for carbon emission of ICT for the year 2030.

## 5.6 Future emission of ICT

This section shows the future prediction of electricity usage and carbon emission of the ICT sector. The study conducted a 36 years long trend visualization with detailed categorization. This pictorial representations help gain valuable insights to get the idea of the future trends.

### 5.6.1 Predicting future electricity usage of ICT

The graph (figure 35) illustrates the trends in electricity usage across four categories from the year 2000 to 2035. The data reveals significant shifts, particularly in the years from 2025 to 2035. During this period, Network Electricity Usage sees a sharp and dramatic peak, reaching its highest point before abruptly declining. This spike is the most pronounced feature on the graph. Data Center Electricity Use also experiences a rapid increase, though it is slightly more gradual than that of Network Electricity Usage, and it maintains a high level towards the end of the period. ICT Devices show a steady rise in electricity usage, surpassing both the Network and Data Center categories towards the end, though without the extreme volatility. On the other hand, Enterprise Network Electricity Usage remains relatively flat and minimal throughout the entire time span, showing little to no variation. The data from 2025 onwards indicates a period of significant transformation in electricity demand, particularly within the Network and Data Center sectors, reflecting perhaps technological advancements or increased reliance on these infrastructures.

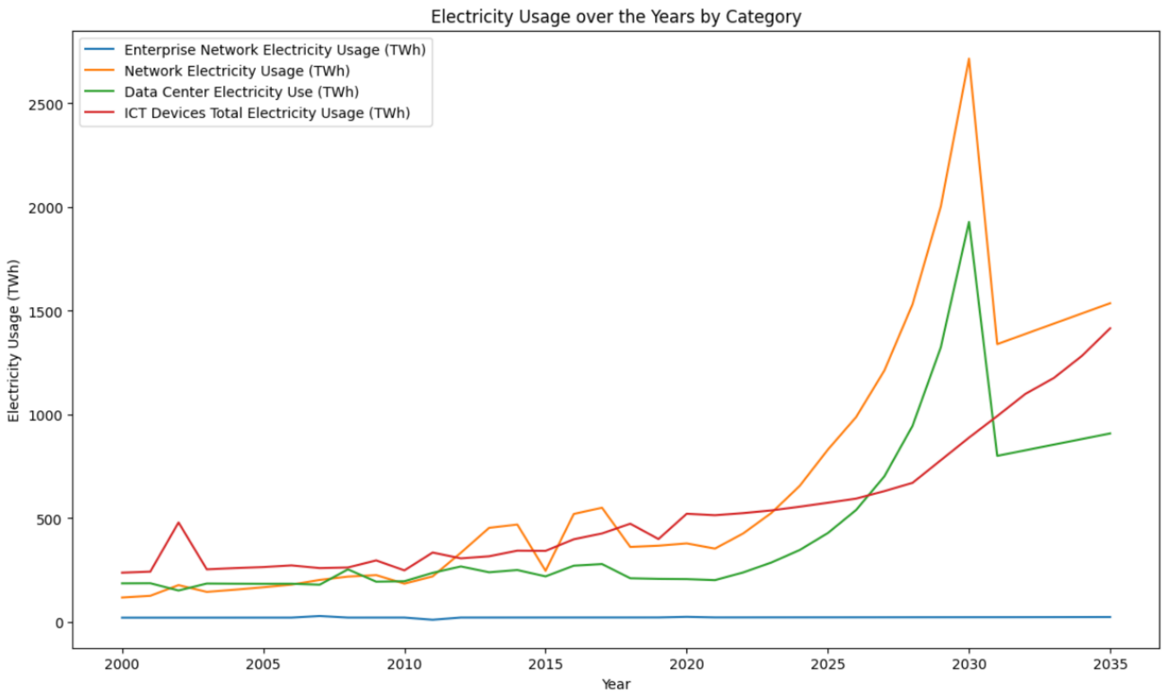



Figure 35: Electricity usage of ICT sector by category.

Figure 36 shows the trends over time and possible future values that have been calculated through this study. The analysis of the electricity footprint data for the ICT sector reveals an overall upward trend, with an average annual growth rate of 7.66%. The most dramatic increases occur in the latter part of the series, peaking at 5557.22 TWh, which is a substantial leap from the earlier figures. Despite this general increase, there is significant year-to-year variability, reflected in a standard deviation of 19.45%. The data shows periods of rapid growth, such as increases of 40.25% and 49.81%, alongside notable declines, including decreases of -25.19% and -43.19%. These fluctuations highlight the dynamic nature of the ICT sector, driven by technological advancements, increased adoption, infrastructure expansion, and varying economic factors.

In recent years, the data indicates substantial peaks and some declines, suggesting a phase of instability or adjustment within the sector. The consistent growth, despite the fluctuations, underscores the growing energy demands of the ICT industry. This trend calls for strategic measures to manage the increasing electricity consumption and mitigate the impact of these fluctuations to ensure sustainable and efficient growth in the sector.

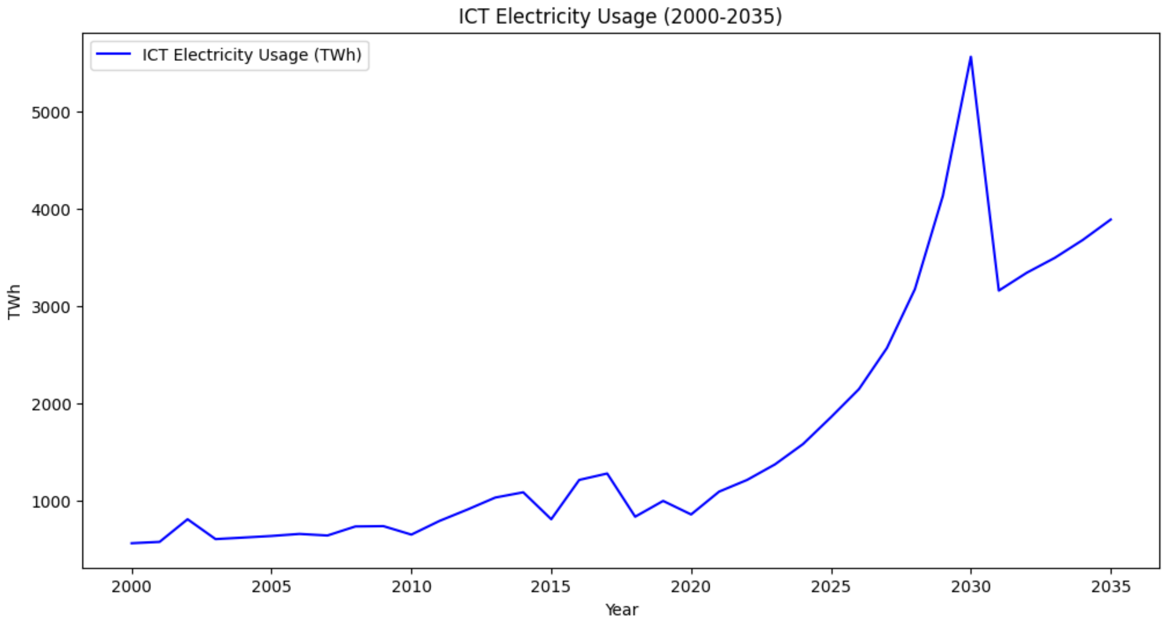



Figure 36: Electricity usage of ICT sector.

### 5.6.2 Forecasting carbon emission of the ICT sector

The line graph (figure 37) visualizes the trends in carbon emissions from four distinct categories spanning from 2000 to 2035. While earlier years show more gradual changes, the period from 2025 to 2035 exhibits significant developments. The Data Center Carbon Footprint shows a steep rise, with its trajectory sharply increasing and surpassing other categories by a substantial margin. ICT Devices Carbon Footprint, which had been fluctuating earlier, also rises but at a slower pace, showing some variability towards the end. In contrast, Network Emission, after experiencing a peak earlier, stabilizes and shows slight fluctuations in the final years. Meanwhile, Enterprise Network Emission remains relatively flat throughout, with minimal changes, indicating a more stable contribution to overall carbon emissions. This segment of the graph highlights a growing disparity in emissions contributions, particularly the rapid escalation in Data Center emissions, suggesting a significant impact on future carbon footprints from these technological infrastructures.

The future trends are shown in figure 38. The analysis of the electricity footprint and GHG emissions data for the ICT sector reveals significant insights into the sector's energy consumption and environmental impact. The electricity footprint shows an overall upward trend with an average annual growth rate of 7.66%, characterized by substantial year-to-year fluctuations. Notable increases, such as 40.25% and 49.81%, indicate periods of rapid growth, while declines, such as -25.19% and -43.19%, reflect instability or adjustments within the sector. This trend highlights the growing energy demands of the ICT industry and the necessity for strategic measures to manage these fluctuations and ensure sustainable growth.

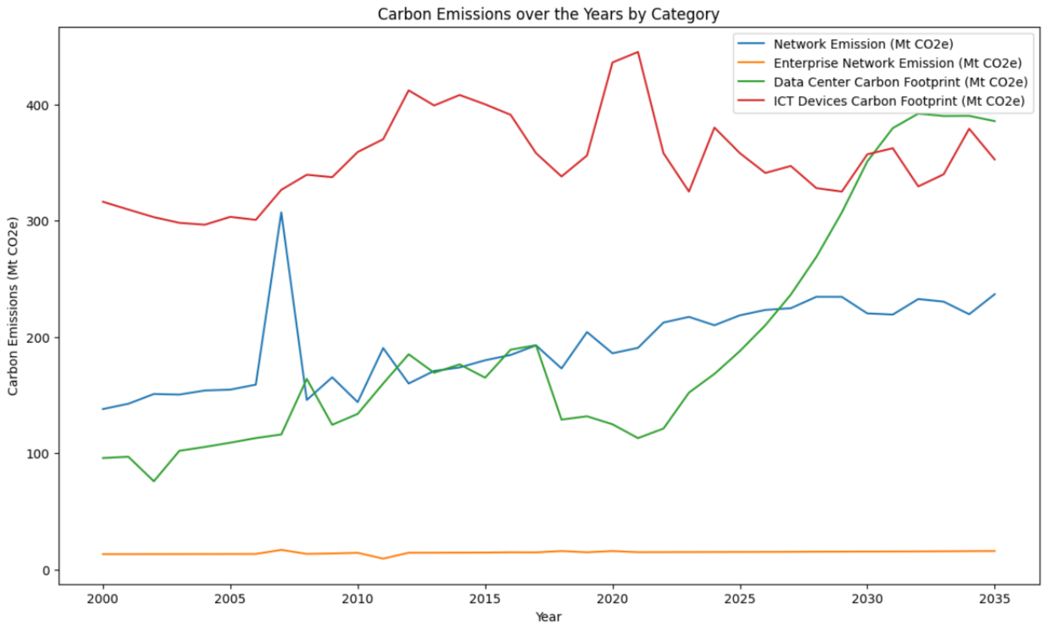



Figure 37: Carbon emission of ICT sector by category.

Similarly, the GHG emissions data presents a modest average annual growth rate of 1.72%, with a standard deviation of 4.88%, indicating a relatively stable but gradually increasing trend. Significant variability is observed, with increases up to 12.29% and decreases as large as -7.47%. These changes may result from advancements in energy efficiency, shifts in infrastructure, and operational changes. The overall rise in emissions underscores the importance of ongoing efforts in sustainability and emissions reduction to mitigate the ICT sector's environmental impact. Together, these analyses emphasize the critical need for the ICT industry to balance growth with environmental responsibility.

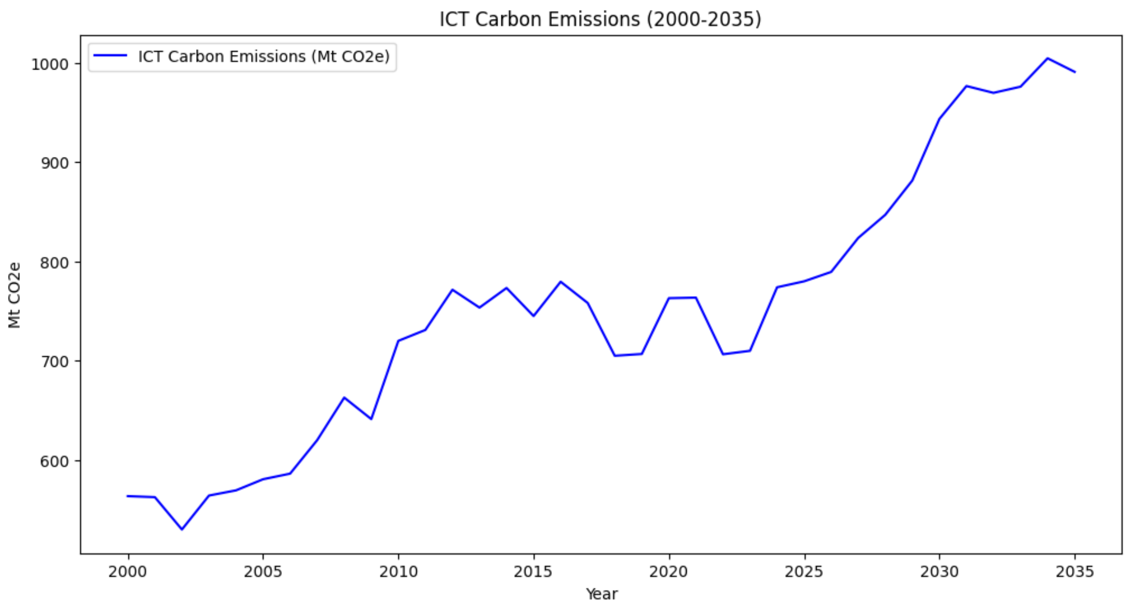



Figure 38: Carbon emission of ICT sector.

# 6 Discussion

As global warming has become a major concern around the world, greenhouse gas producers are getting a lot of focus. ICT as a field has been growing in the last decades, almost becoming one of the leading sectors in the GHG-producing industry. Thus, the need to monitor the emission levels of ICT has become inevitable. The carbon emission of the ICT sector has been a debated topic in recent years. The calculated values differ a lot, mostly because of the clearly defined scope. Also, some studies predicted the future of ICT's carbon emissions. Later on, those values were proven to be over-fitting, and a new measurement was introduced. There is a need to identify the significant factors contributing to carbon emissions and, based on those, predict future trends that are helpful for industries as well as government policies. Therefore, this research aims to identify the significant factors that employ carbon emissions calculation and gather and create detailed datasets from the beginning of this century to a future value prediction until 2035.

The dataset was created after a thorough literature review and several assumptions and predictions were made through the extensive data analysis. There has been an increasing tendency for both carbon emission and electricity usage of ICT. This study suggests that the carbon emission of ICT is expected to be around one thousand $MtCO_2e$ during the duration years of 2030 to 2035. Using the LIME framework, it is seen that electricity usage in the ICT industry is the most important feature contributing to the changes in the carbon footprint of ICT. Also, similarly, the importance of various features has been identified for some specific years, which helps address the aims of this research work.

The main aim of this research is to address the method to calculate the carbon emission of ICT as well as predicting future trends, machine learning approach is used to answer this. This approach has not been used up to the date of this research being done. There are quite a few studies done to calculate the carbon emission of ICT for a specific year or a comparison among various years, but a lack of studies using a long-term time series analysis is present in this research area. This paper tries to fit the same features every year to give a meaningful prediction. The ever-changing technology is very hard to predict. Although it is not feasible to find all the technological items for every year. These features as well as the values are changing frequently. For example, in the early 2000s, smartphones, wireless headphones, and such devices were not mostly introduced. But to get a common ground for 2000 and 2030, a common ground needs to be established. This establishment of the common ground has been done with the creation of the dataset in this research.

For the second part of the main research question, the way of predicting future trends is addressed. This part is covered in the dataset creation part. Within the dataset, some of the predictions from the previous studies are also included. After the initial data collection, the data needed to be filled to fit the algorithms to work. The main challenges were to predict past values and to estimate future ones for the independent features. Based on the columns category, the data pattern is trained with the best machine-learning model. Several models (Linear regression, Ridge regression, Lasso regression, random forest regression, Support Vector regression, polynomial regression, Auto regression, Decision Tree Regression) have been judged based on their mean squared error. The best model is used to predict past trends and after the past data are filled in, a similar approach was taken to estimate the future values. Getting all the values of the non-dependent columns allows predicting the dependent ones. Finally, through a series of dependencies and predictions in the same way, the electricity consumption and the carbon footprint of ICT columns are filled. In this way, the prediction for the future was made. It has been predicted from this research that electricity consumption will keep growing until 2030 (to be around five thousand TWh) but will see a decrease at the start of 2031 to approximately 3100 TWh and from there a slight increase to almost four thousand TWh is predicted to 2035. But the situation is different for carbon emission calculation. The values are predicted to be increasing mostly, with some minor decreases. From the last and most recent reported value of 763 $MtCO_2e$ in 2020, the values are expected to reach almost 950 $MtCO_2e$ by the year 2030 and just below 1000 $MtCO_2e$ by the year 2035.

After the dataset is created with 61 columns and 36 rows from the year 2000 to 2035. The first sub-problem focuses on the factors that predict the target column which is the carbon footprint of ICT. Local Interpretable Model-agnostic Explanations (LIME) an open-source XAI framework, is used to explain the factors that play the most significant role in predicting the target column. With LIME explanation, each year's value can be explained to get the factors that affect the total carbon footprint. It is seen that electricity consumption has been the most significant factor affecting the emission. The other factors that contribute to the predicted values are device shipments, energy demand of devices, and so on. Since it has been established that electricity is the most significant factor contributing to the emissions, LIME is also used to explain the electricity footprint. After creating the model with the most efficient algorithm tested, the switch and routers installed base as well as their shipments have been the most important factors. The details of these factors are widely discussed with the impact scores in the result analysis section.

The second sub-question emphasizes the importance of electricity consumption on the carbon emission of iCT. It is seen throughout the created dataset that electricity usage is the most looked upon feature. The three categories of ICT that are defined in this research, ICT devices, data centers, and network connectivity (including enterprise networks) have their electricity footprint calculated. Also, the use stage emission of the categories is directly linked to electricity consumption. Thus, it is impossible to distinguish electricity usage from calculating the carbon emission of the ICT sector.

The Global e-Sustainability Initiative (GeSI), 2012 reported that by 2020 the emission would be 1270 $MtCO_2e$. But the study by Malmodin, Lövehagen, et al., 2024 reported that the number was 763 $MtCO_2e$. Similarly, in the same report of Global e-Sustainability Initiative (GeSI), 2015, it is mentioned that by the year 2030, the carbon emission of ICT will be around 1250 $MtCO_2e$. However, this research shows that the values would not grow that much and keep at 944 $MtCO_2e$.

In another study, Andrae & Edler, 2015 mentions the best, worst, and expected cases of carbon emission as well as electricity usage. The expectation was a lot higher than the predicted values in this study. Their (Andrae & Edler, 2015) 2020 value was also shown as way higher by Malmodin, Lövehagen, et al., 2024 which is 763 $MtCO_2e$ compared to the 1700 $MtCO_2e$ (In the best case the value is 900 $MtCO_2e$). The 2030 value rocketed in the research of these authors, which is almost 5000 $MtCO_2e$ in the expected case and 1500 $MtCO_2e$ in the best case. The best case is also much higher than the GeSI estimates and certainly of this study. On the contrary, the trends look different in electricity consumption. Although the best case for the year 2020 was almost 1500 TWh, which was seen as overvalued by Malmodin's calculation of 859 TWh. This study also supports the claims by Malmodin and using those data the dataset was trained. The 2030 values for electricity consumption of this study are over 5557 TWh which is lower than the expected case and much higher than the best case mentioned by the authors. One of the reasons for such higher values could be the use of prediction by Andrae, 2019. In the dataset, some columns use the predicted values of that study. Although this author mentions the overestimation of the values of Andrae & Edler, 2015 study, this research gives the value higher than the best case mentioned above.

It has been discussed before that the value mismatch occurs for many reasons. However, double counting and overestimation have been proved in some cases. Therefore coming to a conclusion of selecting important features that contribute to the total emission, is necessary. This research has used a systematic literature review to primarily select the features that are used to calculate the emissions. Also, the aim of this study was not to go into the total details from a device production manufacturer to the assembler to the retail store to the customer and finally end of life situation. This circular approach was not taken to create the dataset. Thus a broader view was taken for prediction.

Another limitation of this work is to predict the past values. Since not a lot of data could be gathered, a huge number of cells had to be estimated and predicted. Often these predictions are biased based on the machine learning models used. In some cases, the model's unfitness tendency gave unrealistic values, which caused the algorithm to give the least error value to be ignored. Also, the predictions from other studies are used in several cases. These values can also be overestimated, but as for this research, these estimations are not questioned.

For the future work, there are a lot of scopes to be discovered. Coming to a standardized calculation method can be implemented. This can give a more accurate and realistic prediction for the future. Also, the lack of data is a serious drawback for the researchers working in this field. Meaningful collaboration with industry, government, and academia can be a good step to begin with. Every country can impose its laws and policies to better maintain detailed data about ICT and its carbon emissions.

# 7 Conclusion

The conclusion of this research emphasizes the development of a comprehensive methodology for accurately calculating and predicting the carbon emissions of the Information and Communication Technology (ICT) sector. This study was motivated by the sector's significant contribution to global greenhouse gas emissions and the existing ambiguities in the methodologies used to assess its carbon footprint. By employing a mixed-methods approach, the research integrated a systematic literature review, time series analysis, and regression analysis, resulting in a robust framework that identifies and quantifies key factors influencing ICT emissions. Electricity consumption emerged as the most significant contributor, alongside other factors such as device shipments and energy demand.

The findings indicate a general trend of increasing carbon emissions and electricity consumption in the ICT sector up to 2035. While electricity usage is projected to fluctuate, carbon emissions are expected to rise steadily, reaching nearly 1000 $MtCO_2e$ by 2035. This trajectory is lower than the estimates provided by previous studies, such as those from the Global e-Sustainability Initiative (GeSI), 2015 and research by Andrae & Edler, 2015. These discrepancies highlight the need for more refined and accurate predictive models, which this study aims to address through the integration of recent and comprehensive data.

The research has significant implications for policy-making and industry practices. By identifying electricity consumption as the primary driver of ICT carbon emissions, it suggests that policies aimed at improving energy efficiency and promoting renewable energy sources could effectively reduce the sector's carbon footprint. Moreover, the establishment of standardized methods for calculating ICT emissions would enhance the accuracy of future predictions, facilitating better-informed decision-making. The study also underscores the necessity for ongoing collaboration between industry, government, and academia to ensure the availability of accurate and up-to-date data.

Despite its comprehensive approach, the research acknowledges several limitations. The reliance on estimated past values due to historical data gaps introduces potential biases. Additionally, the study's broad approach, which did not account for the entire lifecycle of ICT devices, leaves room for detailed future research. Future studies should focus on more granular data collection, including detailed lifecycle assessments from production to end-of-life stages. Furthermore, the dynamic nature of technological advancements poses a challenge for long-term predictions, necessitating continuous assessment of new technologies' energy demands and associated carbon emissions. This research lays the groundwork for more accurate and informed strategies to mitigate the environmental impact of the ICT sector.

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