Sensitivity Analysis on Rainbow's Refurbishing of Electronic Devices Methodology

Master Thesis Report - Erasmus Mundus Joint Master's Degree (EMJMD) in Decentralised Smart Energy Systems (DENSYS)

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DENSYS 2023-2025

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Acknowledgment

The author would like to sincerely thank Rainbow, where this work was conducted during the author's internship, for providing access to verified refurbishment project data and for their continuous support throughout the study. Special thanks are extended to Samara Vantil, Certifications Operations Lead, and Erica Dorr, Science Lead, for their guidance, insights, and valuable feedback on the methodology and analysis. The author also expresses deep gratitude to Matteo Prussi, academic adviser at Politecnico di Torino, for his expert guidance, encouragement, and support throughout the research process. Their combined contributions were instrumental in shaping the study, ensuring the accuracy of the analysis, and enhancing the overall quality of this work.

Abstract

This study conducted a sensitivity analysis on key parameters within the life cycle assessment (LCA) model of Rainbow's *Refurbishing of Electronic Devices* methodology. Using verified data from twelve refurbishment projects covering six device types (smartphones, gaming consoles, laptops, PCs, tablets, and screens), the analysis identified which parameters most strongly influence greenhouse gas (GHG) emissions in baseline and project scenarios. Results showed that in the baseline scenario, the lifetime ratio between refurbished and new devices was the most influential parameter, with an average importance of 4,857,903 kg CO_2 eq, followed by market share of refurbished devices (mean μ_i^* of 302,318 kg CO_2 eq), while recycling shares were negligible (mean μ_i^* of 4,268 kg CO_2 eq). In the project scenario, residual value dominated for most devices, obtaining an average importance of 1,139,103 kg CO_2 eq for all device types. Full and light refurbishment shares also had strong influence (mean μ_i^* of 71,504 and 37,351 kg CO_2 eq, on average, respectively), with their ranges amplifying sensitivity, particularly for monitors. Transport parameters had device-specific effects: truck distance averaged 27,339 kg CO_2 eq in importance, whereas air distance reached 59,995 kg CO_2 eq, largely due to the wide range of distances and the high number of devices collected where it dominated. Finally, recycling shares were consistently the least influential project parameter (average μ_i^* of 10,910 kg CO_2 eq), reflecting their lower environmental footprint and narrower range. These results highlight the importance of accurate data on lifetimes, residual values, and refurbishment shares, while market shares, transport, and recycling parameters contribute comparatively lower uncertainty and therefore do not require the same level of precision.

Nomenclature

For clarity and ease of reference, the following table lists the acronyms, symbols, and key terms used throughout this study, along with their definitions. This section is intended to help readers quickly understand the terminology and ensure consistent interpretation of the methodology and results.

Acronym	Definition
$E_{avoided}$	Avoided Emissions
$E_{baseline}$	Baseline Emissions
$E_{project}$	Project Emissions
GHG	Greenhouse Gas
LCA	Life Cycle Assessment
PC	Portable Computer
RCC	Rainbow Carbon Credits

I. Introduction

A. Company Description

Rainbow is a French mission-driven company (*société par actions simplifiée à mission*) founded in 2021 and develops and operates a voluntary carbon crediting standard for industrial green projects. Headquartered in Paris with branches in Lyon and Berlin, the company combines environmental responsibility with technological innovation to support the transition toward a low-carbon economy. Its core mission is to create measurable climate impact by certifying sustainability-centric projects that reduce or remove greenhouse gas emissions, while ensuring transparency, scientific rigor, and integrity throughout the process [1].

At the heart of its work, Rainbow operates the Rainbow Standard, a voluntary European carbon crediting program designed for industrial decarbonization and removal projects. The program issues RCCs, which represent verified reductions or removals of greenhouse gas emissions. By focusing on industrial applications, the Rainbow Standard provides project developers with a credible pathway to certification and gives credit buyers confidence in the integrity and environmental value of the units they purchase [2].

Rainbow also manages a digital infrastructure that underpins the credibility of the standard. The Rainbow Registry serves as a public platform where every project and carbon credit can be traced throughout its entire lifecycle, from issuance to retirement, ensuring transparency and preventing risks such as double counting. Complementing this, the Impact Certification Platform provides project developers and accredited third-party validators with tools to conduct assessments, validations, and certifications in a consistent and reliable way. A crucial part of this infrastructure is the Monitoring, Reporting, and Verification (MRV) system, where the LCA of the projects are implemented that ensure accurate, independently verified, and transparently reported carbon credit calculations. This system provides the scientific backbone of the Rainbow Standard, guaranteeing that each credit issued is based on rigorous and verifiable data [3].

The credibility of Rainbow's approach is strengthened by its recognized accreditations. In May 2024, it became the first program focused on circular economy projects to receive full endorsement from the International Carbon Reduction and Offset Accreditation (ICROA). This recognition places Rainbow among a very limited group of only twelve endorsed programs worldwide, demonstrating its alignment with international best practices. Furthermore, its methodologies are consistent with ISO standards for greenhouse gas accounting and monitoring, which highlights its commitment to scientific rigor and methodological robustness [1].

Rainbow aims to continually broaden the reach of its standard and infrastructure, developing new methodologies and strengthening monitoring systems to accelerate industrial decarbonization. By scaling across Europe and beyond, the company seeks to build trust in carbon markets and contribute meaningfully to global net-zero goals.

B. Context of the Study

To operationalize its framework, Rainbow has developed a set of methodologies that project developers can use to quantify emission reductions. As of 2025, the program offers five methodologies spanning different sectors as shown in Figure 1.

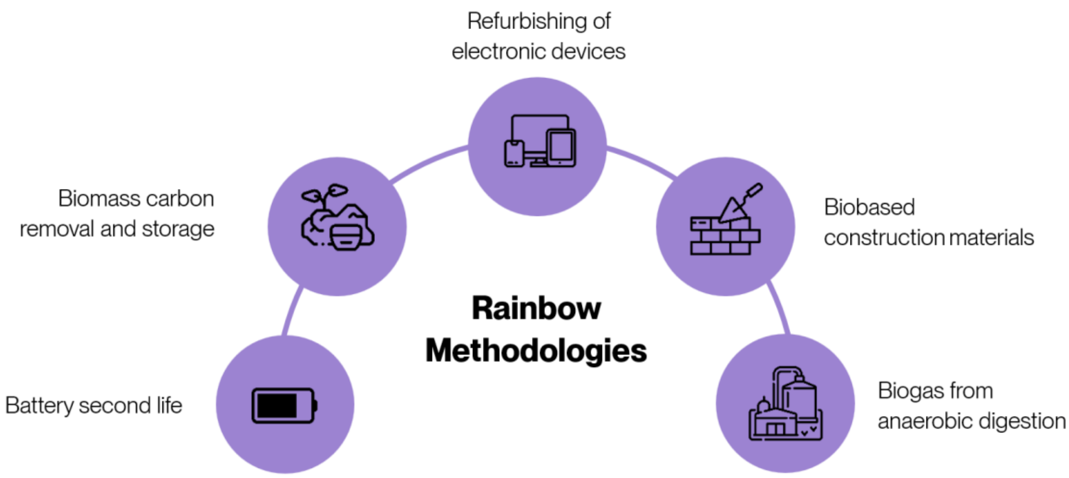


Figure 1. List of Rainbow's methodologies as of 2025 [4].

Each of these methodologies is aligned with ISO standards for greenhouse gas accounting and undergoes regular updates to maintain consistency with scientific and policy developments.

Among Rainbow's methodologies, the *Refurbishing of Electronic Devices* methodology is the most widely applied, with the largest number of validated projects (12°. It targets the extension of the lifetime of consumer electronics, such as smartphones, laptops, and tablets, that would otherwise enter waste streams or require energy-intensive recycling and disposal processes. In practice, the methodology involves restoring previously owned devices to a fully functional state through a sequence of steps including diagnosis, cleaning, repairs, replacement of parts, and performance testing [5].

The urgency of such an approach is underscored by the environmental footprint of small IT and telecommunication equipment, which accounts for roughly 2% of global GHG emissions [6] and is among the fastest growing sectors in emissions [7]. Beyond climate impacts, these devices depend on the extraction of rare minerals and critical materials, while also contributing to one of the most rapidly expanding streams of hazardous waste.

Furthermore, the majority of environmental impacts attributed to electronic devices occur during the manufacturing stage [8], making this phase a primary driver of emissions. Extending device lifetimes therefore represents a major lever for reducing GHG emissions, since fewer new devices need to be produced. Repair and refurbishing directly address this challenge by postponing end-of-life treatment and reducing demand for new manufacturing. Extending the lifespan of devices not only avoids production-related emissions but also mitigates the generation of electronic waste. While refurbishment is increasingly gaining mainstream acceptance among consumers, it still faces barriers such as high repair costs, market fragmentation, and limited consumer trust.

Despite these challenges, refurbishing remains a particularly impactful approach. By tackling both the climate and resource dimensions of electronics, it plays a central role in Rainbow's contribution to the circular economy and to broader efforts in industrial decarbonization.

The quantification of RCCs under the refurbishing methodology is based on an LCA framework that compares a baseline scenario with the project scenario. Typically, the baseline scenario reflects emissions from electronic devices in the current market without the project in place. Two main functions are considered: (1) the end-of-life treatment of the original device (Device A), and (2) the provisioning of a replacement device (Device B) [9].

The system boundary, illustrated in Figure 2, encompasses three life cycle stages:

1. Device A collection — e-waste collection from the municipality or separate programs
2. Device A e-waste treatment — landfilling, incineration, and default recycling.
3. Device B production — either as a new device or as a refurbished one, according to the current market practices.

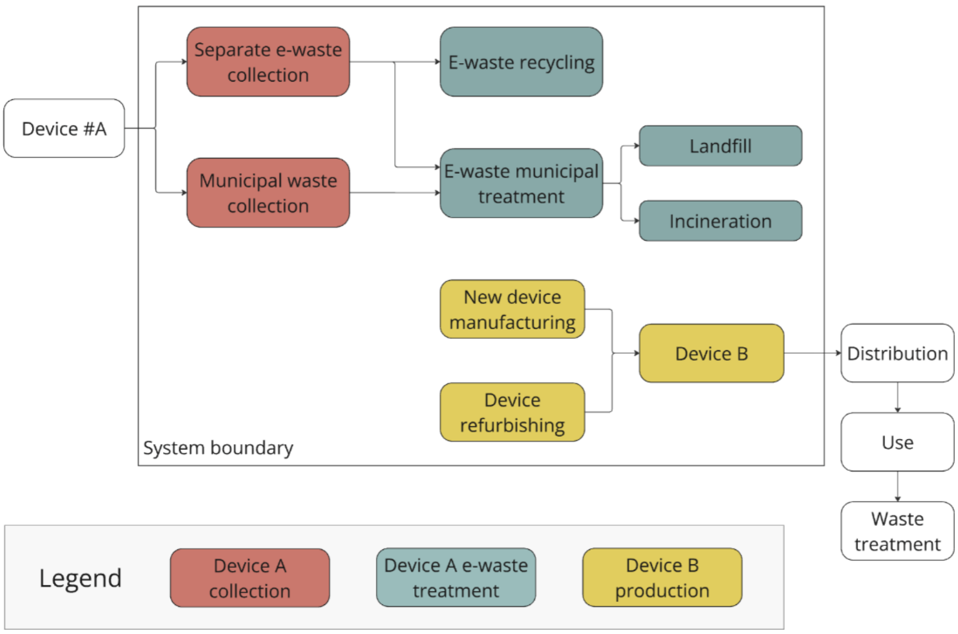


Figure 2. System boundary of the baseline scenario for the electronic refurbishing methodology [9].

By contrast, the project scenario consists of the refurbishment activity of discarded electronic devices (collectively referred to as e-waste in the methodology) of the company in focus, thereby displacing the need for new production. It also serves two functionalities as the baseline scenario: (1) the waste treatment of e-waste after its first lifetime (Device A), and (2) the refurbishment of e-waste to resell to the market (Device B) [9].

The system boundary also encompasses an equivalent of three life cycle stages:

1. Collection of Device A — collection of e-waste directly from bulk or individual suppliers
2. Device A e-waste treatment — all discarded devices in the refurbishment facility are assumed to be recycled due to limited project data
3. Device B production — either via light refurbishment or full refurbishment. Light refurbishment involves cosmetic and software improvements and does not require the replacement of parts. Full refurbishment includes light refurbishment plus repair and replacement of non-functional pieces.

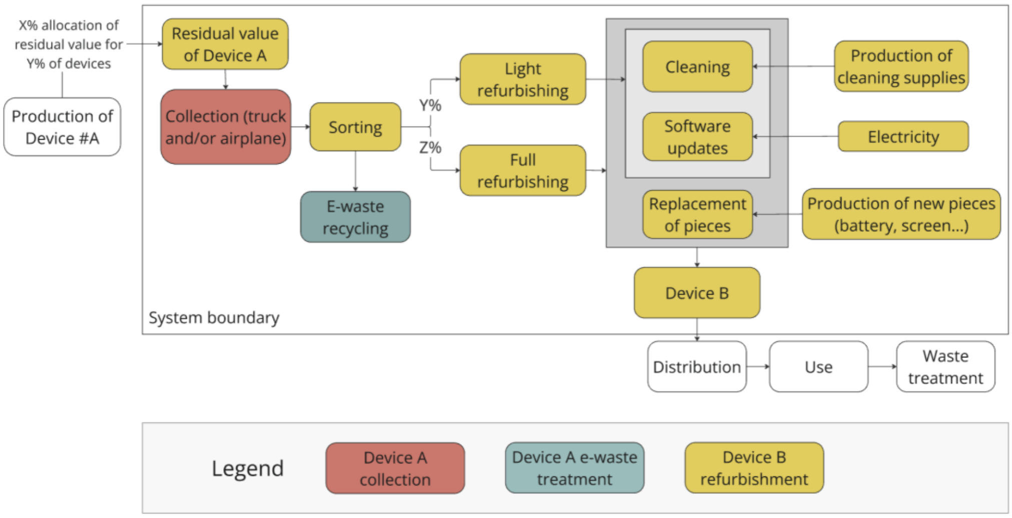


Figure 3. System boundary of the project scenario for the electronic refurbishing methodology [9].

The net emission is then obtained by calculating the difference between total baseline and total project emissions. In simplified form, this relationship can be expressed as:

$$E_{avoided} = E_{baseline} - E_{project} \qquad \text{(Equation 1)}$$

The complete and detailed discussion of the methodology calculations for the baseline and project scenarios are stated in Appendix VI.A.

Rainbow issues two types of RCCs. The first one is removal RCCs, which involves projects that actively remove carbon and transform it into chemically and biologically stable compounds that are highly resistant to environmental degradation. On the other hand, avoided RCCs represent GHG emissions that are prevented thanks to a project's intervention. These credits are typically generated by initiatives that replace fossil fuels with cleaner energy or substitute high-emission products with lower-emission alternatives. The refurbishment of electronic devices methodology, therefore, issues the latter. One ton of CO_2 equivalent removed corresponds to one RCC [10].

In addition, the implementation of this methodology requires a wide range of parameters as enumerated in the table below.

Table 1. Inputs for the *Refurbishment of Electronic Devices* methodology.

Parameter	Unit	Source proof
Amount of sold devices in a functioning state	Units of devices per type	Company sales records
Portion of collected devices that undergo light refurbishment, full refurbishment, and recycling (should total to 100%)	Percentage (%)	Refurbishing site records
Distance travelled during collection from the source to the refurbishing site including the mode of transportation and the percent of collected devices corresponding to the latter two	km, mode of transportation (air, truck, boat, personal, public), percentage (%)	Refurbishing delivery records
If applicable, secondary transport distance associated with sending collected devices from the project site to another more specialized refurbishing site, mode of transportation, and the number of devices corresponding to the latter two	km, mode of transportation (air, truck, boat, personal, public), units of devices per type	Refurbishing delivery records

As stated in Table 1, some of these parameters can be directly obtained through project-level monitoring, such as the number of devices refurbished and the percentages of devices undergoing either recycling, light refurbishment, or full refurbishment. Others, however, are difficult to obtain accurately such as the parameters associated with the distances due to lack of project data (i.e. some companies only have the locations of the suppliers without the breakdown per device type, some have a large amount of dataset of deliveries that requires paid tools to provide accurate road distances, etc.)

The calculations itself also use fixed parameters from secondary scientific literature or established databases. Parameters in this second category may require regular updating, since they are influenced by technological progress and evolving market conditions. The most significant parameters include the following:

Table 2. Influential fixed parameters used in the LCA calculations of the electronic refurbishing methodology.

Parameter	Unit	Source
Residual value, which determines the innate portion of environmental impacts of the device before refurbishment. This is calculated using the ratio of the buyback price to the price of the newly manufactured device	Percentage (%)	StatCounter Global Stats 2024 [11]
Market share of refurbished devices	Percentage (%)	Autorité de régulation des communications électroniques, des postes et de la distribution de la presse (ARCEP) 2024 [12] Deloitte Consumer Trends 2022 [12]
Lifetimes of new and refurbished devices	Years	L'Agence de l'environnement et de la maîtrise de l'énergie (ADEME) 2022 [13]

Because the methodology depends on parameters with high uncertainty and temporal variability, sensitivity analysis is essential. Implementing this measure identifies which of them exert the greatest influence on results and where improvements in data quality are most urgently needed. It also makes it possible to assess the robustness of the estimated emission reductions in both baseline and project scenarios. Consequently, sensitivity analysis strengthens methodological integrity and ensures that refurbishing projects certified under Rainbow's standard provide credible and scientifically sound RCCs.

C. Objectives of the Study

The main objective of this study is to identify the most influential parameters affecting baseline and project scenario greenhouse gas (GHG) emissions per device type, and to evaluate how variations in these parameters, which are based on real, verified data from Rainbow's validated electronic refurbishing projects, affect overall results. Specifically, the study aims to accomplish the following:

1. Assess the contribution of each life cycle stage to total GHG emissions in both baseline and project scenarios for each device type.
2. Determine which devices are processed the most by refurbishment companies in Rainbow's records of validated projects and shortlist the types to be considered in the sensitivity analysis.
3. Map the parameters associated with each life cycle stage and shortlist those most significant for sensitivity analysis.
4. Rationalize the influence of the assessed parameters both on their corresponding scenarios and device type.

D. Project Scope

This study evaluates Rainbow's *Refurbishment of Electronic Devices* methodology, with a focus on comparing baseline and project scenarios. The methodology is applied within a clearly defined scope, summarized as follows:

- The methodology version considered for Rainbow's *Refurbishment of Electronic Devices* is 2.3 and the model version is 2.5.3.
- Baseline and project scenarios are analysed separately, including their respective life cycle stages: device collection, end-of-life treatment, and manufacturing/refurbishment of replacement devices as outlined in the Rainbow methodology (see Figures 2 and 3).
- The analysis is limited to device types included in the twelve validated electronic refurbishing projects as of June 2025.
- All data for parameter shortlisting, device shortlisting, and sensitivity analysis are obtained exclusively from this project set. This includes the input parameters and the LCA results.
- The gross GHG emissions of both baseline and project scenarios are treated as the sole determinant for evaluating the impact of each parameter per device type.

II. Methodology

The methodology outlines the approach used to perform the sensitivity analysis on key parameters of Rainbow's *Refurbishment of Electronic Devices* methodology. Devices were first shortlisted based on the types most commonly used across the twelve validated projects, followed by the selection of parameters through evaluation of existing LCA results from the same set of projects. The sensitivity analysis was then conducted in two stages. First, the Morris Global method was applied to quantify the influence of each parameter for every device and scenario. This was followed by a manual sensitivity analysis on the most influential parameters identified by the Morris method, aimed at assessing their behaviour across actual data ranges.

A. Shortlisting of Devices

Twelve validated projects were identified from the Rainbow registry, and the number and types of devices processed in each project were obtained from the MRV database. The total number of sold devices per type was aggregated across all validated projects, after which the most frequently refurbished device types sold were selected for inclusion in the sensitivity analysis. This shortlisting ensures that the analysis reflects the most representative devices in Rainbow's database while maintaining computational efficiency.

Apple devices were excluded to retain methodological consistency. Although the GHG calculations applied to Apple and generic devices follow the same equations (see Appendix VI.A), the production emission factors for Apple devices are sourced from Apple Product Environmental Reports, while those for other devices are taken from *ecoinvent* version 3.11. Including both would introduce heterogeneity in data sources, which could bias the results. For this reason, only generic devices were retained in the final selection.

B. Shortlisting of Parameters

As summarized in Table 1 and Table 2, numerous parameters could be included in the sensitivity analysis. However, to ensure efficiency and focus on the most impactful drivers, only the parameters exerting the greatest influence on GHG emissions were shortlisted for both baseline and project scenarios.

The shortlisting process was conducted as follows. First, validated LCA results generated through the MRV platform were collected for each project from Rainbow's Google Drive. For each shortlisted device type (Section II.A), GHG emissions were disaggregated into the three life cycle stages for both baseline and project scenarios: (1) Device A collection, (2) Device A end-of-life treatment, and (3) Device B production. The relative contributions of each stage to total scenario emissions were then calculated. Parameters corresponding to the most significant life cycle stage(s) were subsequently identified and retained for sensitivity analysis.

Certain parameters were excluded for clarity and methodological consistency. The number of sold devices was omitted, since total GHG emissions are directly proportional to this variable and its influence is therefore self-evident. Secondary transport parameters were also excluded, as these were optional in the methodology and available for only three of the five analysed projects, which would have limited comparability.

Several assumptions were applied to harmonize project data. Although methodology versions varied slightly across projects, these were assumed to be homogeneous for the purpose of comparison. In addition, for projects covering multiple monitoring periods, only the most recent year of verified carbon credits was considered to ensure temporal consistency in the dataset.

C. Sensitivity Analysis Calculations

Following the shortlisting of devices and parameters in Sections II.A and II.B, sensitivity analysis was conducted to evaluate how uncertainties in input parameters influence the GHG emissions estimated in both baseline and project scenarios. A two-stage framework was adopted to ensure comprehensive identification of influential parameters while maintaining computational feasibility.

1. Global Sensitivity Analysis (GSA)

The first stage consisted of a global sensitivity analysis. GSAs aims to explore the full range of variation of the input parameters and quantify their importance by analysing the resulting output response surface [14]. This step is therefore important to quantify the influence of each parameter and rank them.

Among the current GSA methods, the Morris method was selected because it requires relatively low computational effort while still yielding results that are broadly comparable to more computationally demanding yet more accurate approaches, such as Sobol [14].

In practice, the method works by slightly changing one parameter at a time while keeping all other parameters fixed. The effect of this small change is then observed in the model output, which in this study is the calculated GHG emissions per scenario per device. Each of these calculated changes is called an elementary effect [14]. The formula for an elementary effect EE_i of parameter x_i within a set of N parameters is:

$$EE_i = \frac{Y(x_1, x_2, x_3, \ldots, x_i + \Delta, \ldots, x_N) - Y(x_1, x_2, x_3, \ldots, x_N)}{\Delta} \quad \text{(Equation 2)}$$

where Y is the model output (overall GHG emissions), and Δ is the size of the change applied to parameter x_i. Note that a range should be set for each parameter x_i.

To obtain reliable results, this process is repeated many times using different random starting values for the parameters. Each sequence of calculations is often called a trajectory, meaning a set of steps where each parameter is perturbed one after the other. Collecting results from multiple trajectories provides a distribution of elementary effects for each parameter [14].

Finally, the influence of each parameter is assessed by calculating the mean of its elementary effects. However, since a parameter can produce both positive and negative changes in the model output, using the mean directly may result in cancellation effects and an underestimation of its true impact. To address this, the mean of the absolute values of the elementary effects x_i is calculated instead, providing a more robust measure of parameter importance, as stated in $\mu_i^*=\frac{1}{n_R}\sum_{r=r}^{n_k}|E_k^r|$ (Equation 3 [14].

$$\mu_i^* = \frac{1}{n_R}\sum_{r=r}^{n_k}|E_k^r| \quad \text{(Equation 3)}$$

Morris also covers the nonlinearity or interaction effects of the parameter by calculating the standard deviation of EE_i. However, such information is not relevant according to the goals of the GSA for this thesis thereby it will be omitted.

a. Code Description

To implement the Morris sensitivity analysis for both the baseline and project scenarios per filtered device type, a Python script was developed using the SALib library. The script connects to Rainbow's MRV platform through a GraphQL client to interface with the *Refurbishing of Electronic Devices* model (version 2.5.3).

The workflow of the script proceeded as follows. First, the parameters associated with the most influential life cycle stages were identified, as described in Section II.A. Two categories of parameters were considered: input parameters and fixed parameters. The ranges for the input parameters were determined by collecting the minimum and maximum values from the twelve validated projects. For inputs with only a single dataset (e.g., gaming consoles), a ±50% variation around the available value was assumed (*see Section II.C.1.b for justification*). Likewise, if a parameter was missing for a given device (e.g., air transport distance for e-waste collection), the average value of that parameter from other devices was assigned to allow sensitivity analysis to proceed despite incomplete data.

For fixed parameters, the bounds were defined by applying a ±50% variation to the currently used values (*see Section II.C.1.b for rationale*). Parameter combinations were then generated using the SALib Morris sampling procedure with 50 trajectories. A literature-based guideline for the Morris method recommends using approximately 10 to 50 trajectories to obtain reliable sensitivity measures while keeping computational costs manageable. Therefore, a choice of 50 trajectories was applied in this study to ensure robust parameter screening without excessive computational burden [15].

Special treatment was required for the parameters representing the distribution among light refurbishment, full refurbishment, and recycling. Since these three shares must always sum to 100%, they are not independent of each other. To ensure this constraint was preserved, each generated sample was adjusted accordingly, regardless of which parameter was directly perturbed in a given trajectory.

Consequently, since all three are considered in the project scenario, a separate Morris run was performed for each of the three parameters to maintain independence in the analysis. The final μ_i^* of the other parameters were obtained as the average of the three separate runs.

Another modification concerned the lifetimes of new and refurbished devices in the baseline scenario. Since these parameters are used as a ratio as per Equation A.19, the code treats the two parameters as a ratio as well for convenience. This avoids infeasible values (e.g., lifetimes less than one year or refurbished lifetimes exceeding those of new devices) and reflects the assumption that lifetimes are whole numbers. The bounds for this ratio were derived consistently with other parameters: the ratio of the existing lifetimes was taken as the baseline, and a ±50% variation was applied to define the minimum and maximum values.

The summary of the ranges of the parameters are located in Appendix VI.B.

For parameters excluded from the sensitivity analysis, the mean value across all twelve validated projects was used. Secondary transport parameters were fully omitted in line with the project scope defined in Section I.D. The consolidated inputs were structured into a Python dictionary, which was passed into the *Refurbishing of Electronic Devices* GraphQL model. Finally, the SALib Morris function was applied to calculate μ^*, which was used to rank the relative influence of each parameter.

The complete Python implementation is provided in Appendix 0 and Appendix VI.D.

b. Assumptions

Several assumptions were necessary to operationalize the sensitivity analysis given data limitations and methodological consistency requirements:

- For parameters with only a single available value across the validated projects (e.g., gaming consoles), a ±50% range around the observed value was applied. This range was selected as a conservative proxy to capture potential variability in the absence of more comprehensive datasets without skewing the sensitivity results due to a relatively wide range. Similarly, fixed parameters were assigned a ±50% variation around their default values to reflect plausible deviations without overstating uncertainty.

- Regardless of the adjustments made to ensure that the combined shares of full refurbishment, light refurbishment, and recycling sum to 100% after sampling, it is assumed that these proportional rescalings do not introduce bias or distort the relative influence of each parameter in the Morris sensitivity analysis.

- In cases where device-specific data were unavailable for certain inputs (e.g., air transport distance in e-waste collection), the average minimum and maximum value across other devices was used to define its bounds. This assumption allowed the analysis to include these parameters in a balanced way while maintaining comparability across devices.

- Secondary transport parameters were excluded entirely, as only three out of five projects reported data for this category. Given the limited coverage and optional reporting status, their exclusion avoids introducing bias or uncertainty that would outweigh potential analytical benefit.

- Although methodology versions varied across the validated projects, all projects were treated as methodologically homogeneous for the purposes of sensitivity analysis. This assumption was made to ensure comparability across the dataset and is justified by the structural similarity of the methodological updates.

- For each project, only the latest year of credit verification was considered. This assumption ensures that the most recent and representative operational data are used, reducing potential distortions from earlier project phases.

2. Local Sensitivity Analysis

While the Morris method provides a ranking of parameter importance, it does not reveal how the model output behaves across the full range of each parameter. To address this, the GHG emissions were recalculated for each device type and scenario while systematically varying the selected parameters across the ranges defined in Section II.C.1. This procedure allowed for a more detailed quantification of how variations in each parameter propagate into the total GHG emissions, providing deeper insight into the magnitude and patterns of parameter influence that cannot be captured by the global screening alone.

a. Code Description

The local sensitivity analysis was implemented in Python to evaluate in detail the effect of the most influential parameters on baseline GHG emissions, as identified by the Morris GSA screening for both baseline and project scenarios. Each parameter was varied across 10 equally spaced points within its predefined range. For each value, a copy of the baseline input data was updated, and where necessary, related shares within the device collection (e.g., full refurbishment, light refurbishment, recycling) were proportionally rescaled to maintain a total of 100%. The updated inputs were submitted to the Rainbow MRV model via GraphQL queries, and the resulting total project and baseline emissions per device were recorded. All outputs were stored in a dataframe, with parameters as rows and sampled points as columns, and visualized using custom plotting functions to illustrate the response of GHG emissions to parameter variations.

b. Assumptions

Assumptions made for the local sensitivity analysis method are the following:

- The base inputs used for the local sensitivity analysis were identical to those used for the Morris GSA, so all assumptions described in Section II.C.1.b apply.
- Each parameter was evaluated at 10 equally spaced points across its predefined range. This number of points was assumed sufficient to capture the trends in emissions while keeping computational cost manageable.
- Each parameter was varied one at a time, assuming that interactions between parameters are negligible for the purpose of this local analysis except for the light refurbished, full refurbished, and recycling percentages, where they are always adjusted to sum up to 100%.

III. Results and Discussion

The results of this study illustrate how variations in key parameters influence GHG emissions in baseline and project scenarios across the most frequently refurbished device types in Rainbow's validated projects. By examining life cycle stage contributions, parameter sensitivities, and device-specific behaviours, the analysis identifies the most significant emission drivers and highlights where methodological assumptions matter most.

The discussion first considers the relative importance of life cycle stages, then evaluates the influence of shortlisted parameters through global and local sensitivity analyses. These findings provide insight into the comparability of results across devices, and the implications for improving Rainbow's refurbishment methodology to better capture the climate benefits of electronic device reuse.

A. Identification of Devices and Parameters for Analysis

The number of sold units per device type across the twelve validated refurbishing projects are shown in the figure below.

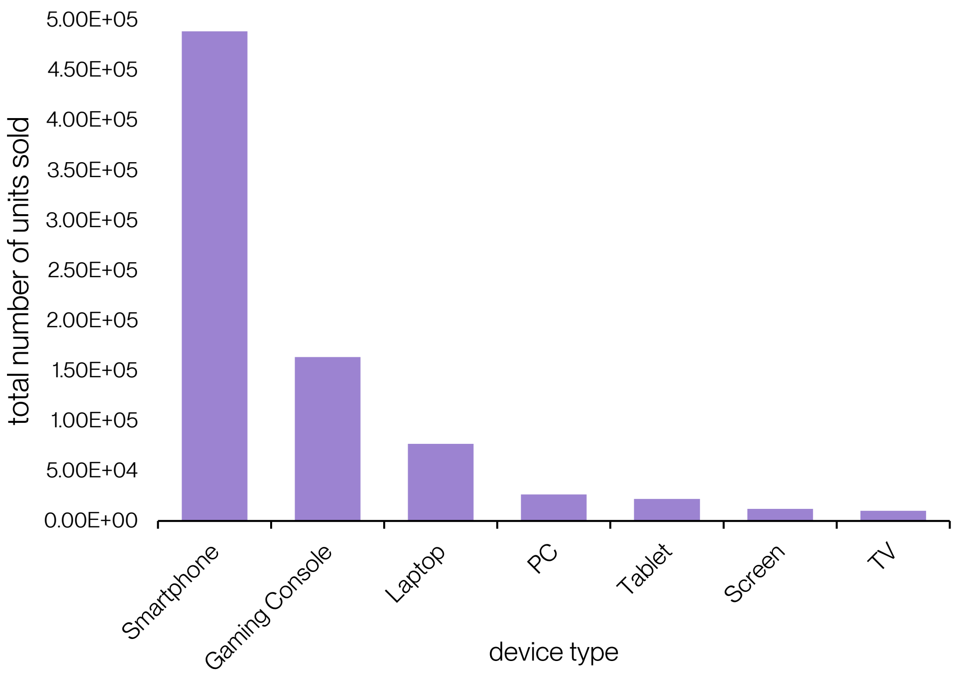


Figure 4. Total number of units sold per device type across the twelve validated refurbishment projects.

Among the seven accounted device types, the top six were considered in the sensitivity analysis: smartphone (488,782 units), gaming console (163,764 units), laptop (76,838 units), PC (26,469 units), tablet (21,885 units), and screen (11,923 units). Despite only excluding TVs, the six remaining categories were retained because they represent clearly distinct product types, each with unique use profiles, lifespans, and refurbishment value. TV was not included in the sensitivity analysis since it is functionally and structurally similar to screens, making its inclusion redundant. Furthermore, TVs and screens share comparable refurbishment pathways and market dynamics, so focusing on screens sufficiently captures the impacts associated with this device category.

Subsequently, the parameters considered in the data analysis were determined. This was first performed by assessing the contributions of each life cycle stage in the baseline and project scenarios as illustrated in Figure 5 and Figure 6.

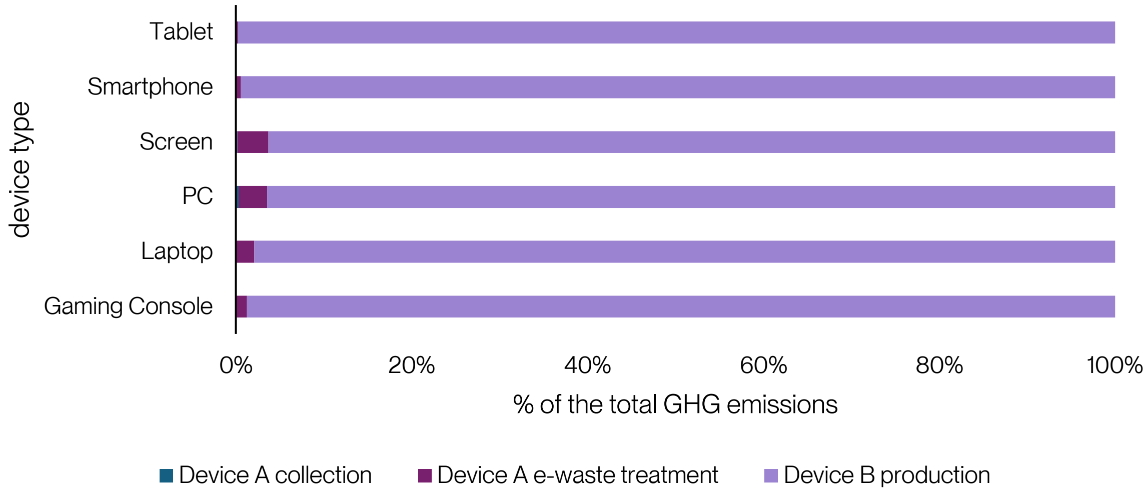


Figure 5. Average contributions of the three life cycle stages of the baseline scenario.

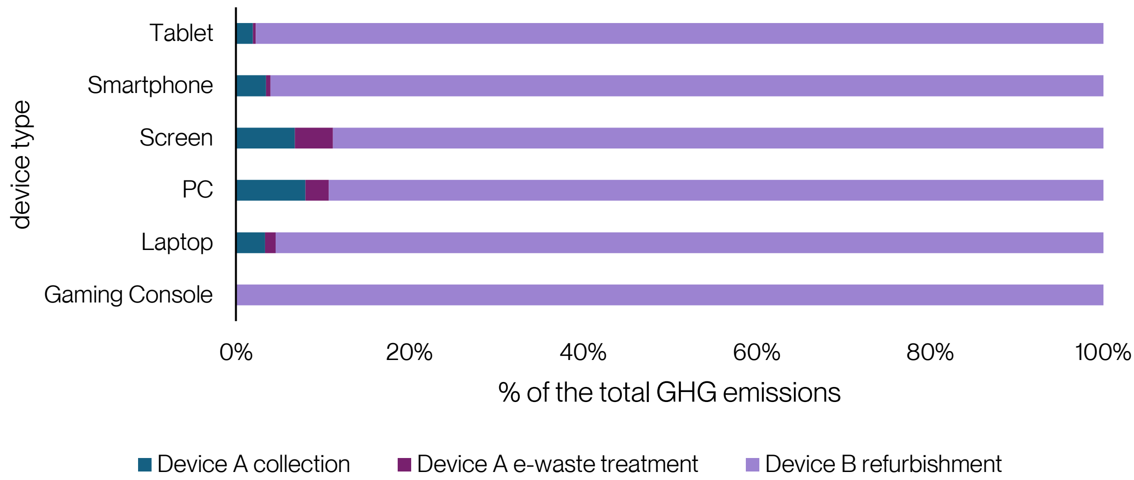


Figure 6. Average contributions of the three life cycle stages of the project scenario.

In the baseline scenario, Device B production accounted for the vast majority of overall GHG emissions, averaging 98.09% across all device types. This was followed by the Device A e-waste treatment stage, contributing an average of 1.78%, while the Device A collection stage represented the smallest share at approximately 0.13% on average.

Based on equations A.13 – A.20 in Appendix VI.A, the parameters shortlisted for this scenario among those in Table 1 and Table 2 were therefore:

- the percentage of collected device that went to recycling
- market share of refurbished devices, and
- the lifetimes of new and refurbished devices

As noted in Section II.C.1.a, the latter two parameters were treated as a ratio in the succeeding sensitivity analysis.

On the other hand, Device B production comprised majority of the overall GHG emissions for the project scenario as well. However, the Device A collection stage contributed more than the Device A e-waste treatment stage. This leaves the following parameters for the sensitivity analysis according to Equations A1 – A12:

- percentage of collected device that went to recycling
- percentage of collected device that went under full refurbishment
- percentage of collected device that went under light refurbishment
- distance travelled to the refurbishment facility per mode of transportation
- percentage of devices that were delivered to the refurbishment facility per mode of transportation

Based on the breakdown of Device A collection emissions across the 12 projects, an average of 85.1% of devices were collected via truck and the remaining 14.9% via air travel. Therefore, only these two transport modes were considered in the sensitivity analysis.

Among the two transportation-related parameters, only distance travelled was retained. This decision was based on two factors. First, project data indicated that distances to refurbishment facilities were highly variable and often more difficult to obtain accurately, introducing significant uncertainty that warranted explicit sensitivity testing. Second, the influence of transportation mode share was considered more predictable: since air transport has an emission factor approximately three times higher than truck transport (per ton-km) [16][17], any increase in the percentage of devices transported by air would consistently and linearly increase emissions. As such, the effect of mode share was judged to be qualitatively clear and redundant, whereas variability in transport distances represented a more meaningful source of uncertainty for the analysis.

B. Sensitivity Analysis

Finally, a combination of global and local sensitivity analyses was conducted to evaluate the influence of the shortlisted parameters from the previous section in both the baseline and project scenarios, for each device type considered. The results are presented and discussed below.

1. Baseline Scenario

a. Morris GSA

The Morris GSA was performed to quantify the influence of each parameter and rank them. The influence of each considered baseline parameter, μ_i^*, per device is illustrated in Figure 7.

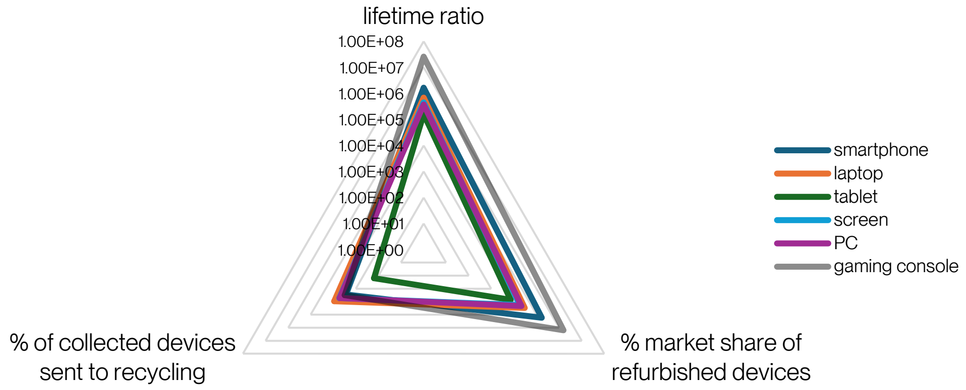


Figure 7. Calculated μ*values from Morris GSA for the baseline scenario (logarithmic scale).

The rationale of the results from this assessment is further discussed in the next section.

b. Local SA

Local sensitivity analysis was performed to visualize the trend of each parameter across the ranges in Appendix VI.B. The plots are shown in the Figure 8a-8b.

The lifetime ratio had the strongest influence in the baseline scenario with an average μ_i^* of 4,857,903 kg CO_2 eq as shown in Figure 7. This parameter accounts for the fact that refurbished devices are expected to have shorter lifetimes than new ones. As a result, the avoided production of new devices is scaled down in proportion to this ratio (Equation A.19). For instance, if a refurbished device lasts only half as long as a new device, it is credited with avoiding only half of the emissions from producing a new device [18].

This finding aligns with the overall emissions profile of the baseline scenario. According to Figure 5, emissions from producing new devices (through both refurbishment and manufacturing) contribute the most to the overall baseline emissions. This is consistent with Table B.2, which shows that over 87% of devices originate from new manufacturing in the current market. Consequently, emissions from new device production are the dominant source of baseline GHG emissions. The lifetime ratio acts as a direct multiplier in Equation A.19, explaining why it is the most influential parameter and why baseline emissions increase proportionally with it, as illustrated in Figure 8a-8b. The effect is further evident in these figures, where the lifetime ratio exhibits the steepest slope across its range for all device types.

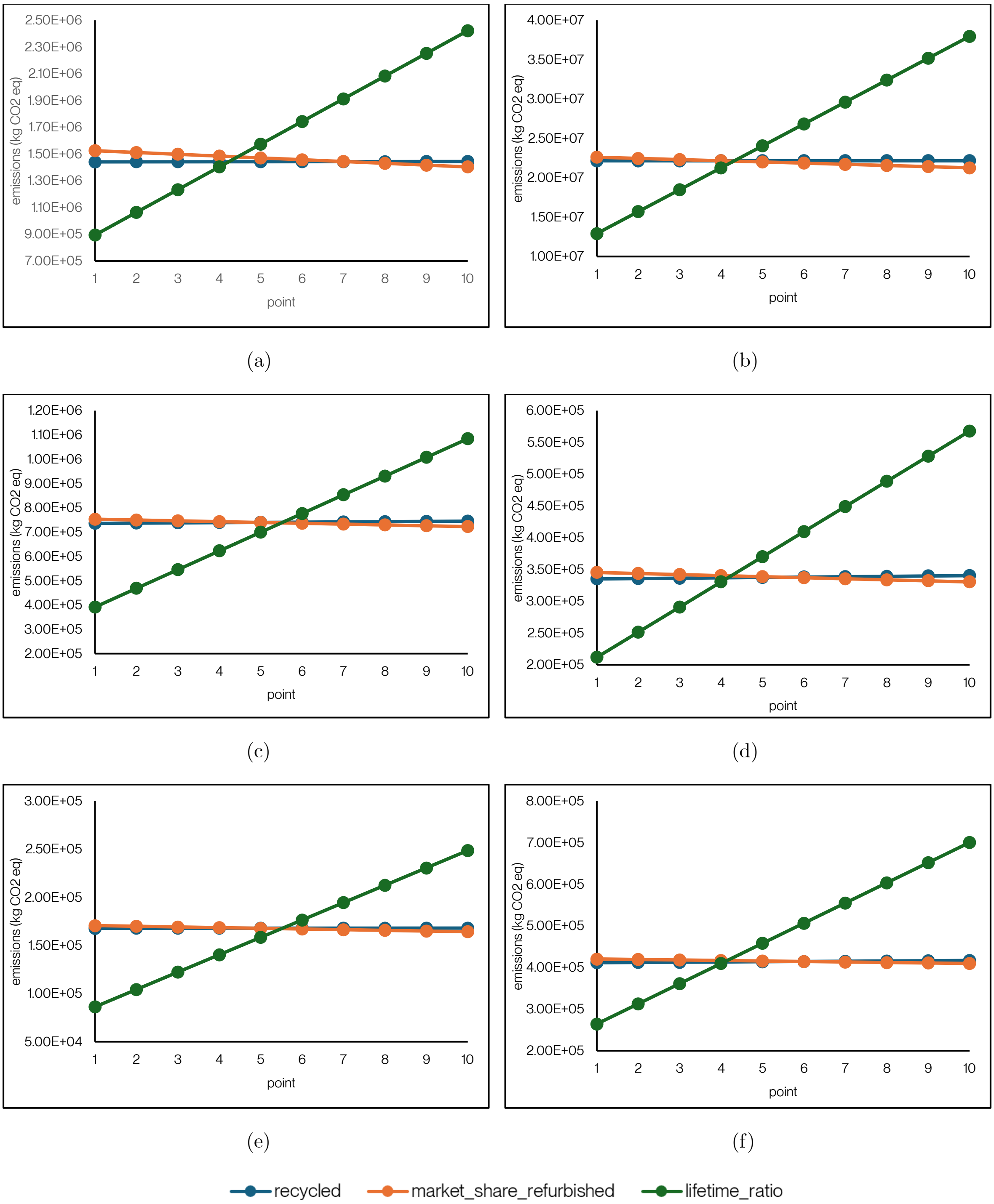


Figure 8. Local sensitivity analysis for the baseline scenario of (a) smartphone, (b) gaming console, (c) laptop, (d) PC, (e) tablet, and (f) screen.

On the other hand, the market share of refurbished devices is the second most influential parameter, having an mean μ_i^* of 302,319 kg CO_2 eq. This is because it governs the distribution of emissions between refurbished and new devices in the Device B production life cycle stage, as defined in Equations A.17 and A.18. However, its overall impact is relatively modest, since the parameter varies only within ±50% of its baseline value (for context, the average refurbished market share is 8%). Intuitively, the effect is inversely proportional to total baseline emissions: a higher market share of refurbished devices reduces emissions, because the emission factors for producing new devices are consistently higher than those for refurbishment (Appendix E).

Finally, the parameter to which the baseline emissions are least sensitive to is the percentage of collected devices sent to recycling (average μ_i^* of 4,268 kg CO_2 eq). This is because this parameter defines the amount of collected devices sent to recycling, and thus only factors into the device e-waste treatment emissions (Equation A.14), which account for an average of just 1.78% of total baseline emissions across all devices (Figure 5). Moreover, the baseline emissions increase as the recycling percentage rises, since the emission factor (EF) associated with recycling is higher than that of municipal waste disposal methods such as incineration and landfilling, as shown in the ecoinvent EF values (Appendix E).

c. Implication of Results

In the baseline scenario, the lifetime ratio is the most influential parameter among the three assessed factors. Practically, this means that maintaining up-to-date lifetime values is critical for reliable baseline GHG estimates. As Appendix VI.B indicates, the current lifetimes for new and refurbished devices are based on 2022 data. These values should therefore be regularly updated to reflect technological advances, changes in consumer usage patterns, and improvements in device durability. Without such updates, the baseline scenario may underestimate or overestimate emissions, limiting the accuracy of the results.

It was also found that the second key parameter is the market share of refurbished devices. At present, the methodology applies 2024 market share values for France (taken from *Autorité de Régulation des Communications Électroniques, des Postes et de la Distribution de la Presse*) and 2022 for other European countries (taken from *Deloitte Scandinavia*) as detailed in Appendix B). Given that changes in this parameter lead to only minor variations in total baseline emissions, updating it is of lower priority compared to parameters such as device lifetime.

Finally, the portion of collected devices sent to recycling was the least influential parameter in the baseline scenario, implying that estimations for this parameter would be acceptable. This is also supported by its resulting influence in the project scenario, as discussed in the following section.

2. Project Scenario

a. Morris GSA

Similar to the baseline scenario, Morris GSA was used to quantify the influence of the parameters considered to the project GHG emissions and rank them accordingly. The results are plotted in Figure *9*.

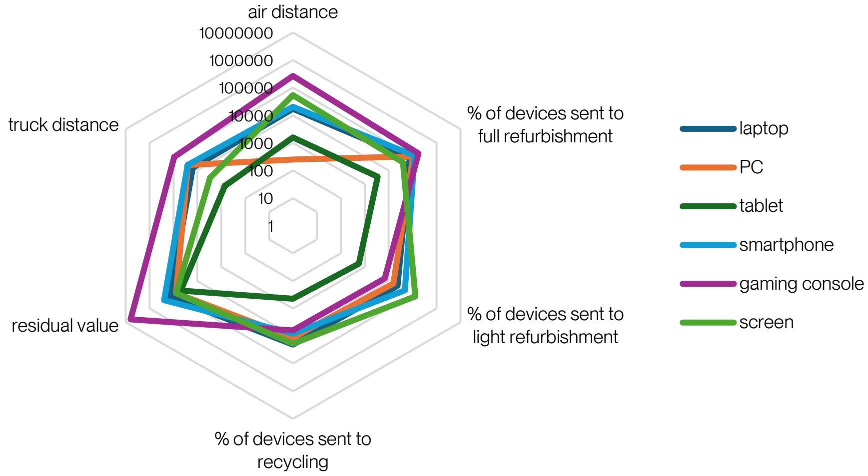
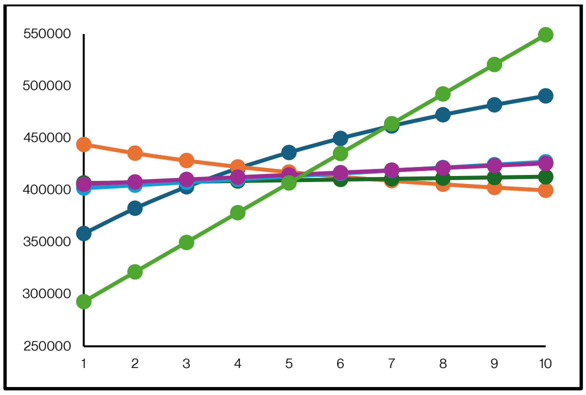


Figure 9. Calculated μ*values from Morris GSA for the project scenario (logarithmic scale).

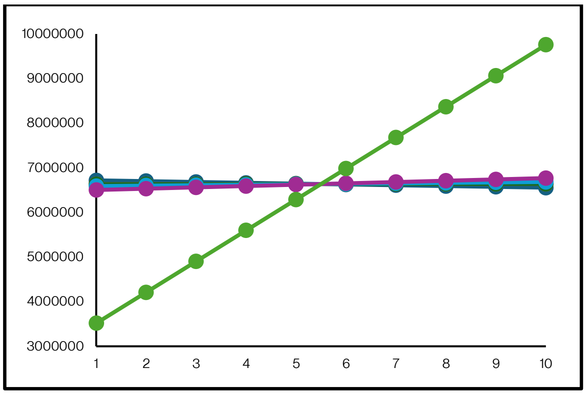
Unlike the baseline scenario, however the parameters have varying rankings of influence depending on the device. The rationale for the parameter's behaviour are discussed more thoroughly in the next section as the trend of the parameters across their respective ranges are taken into consideration.

b. Local SA

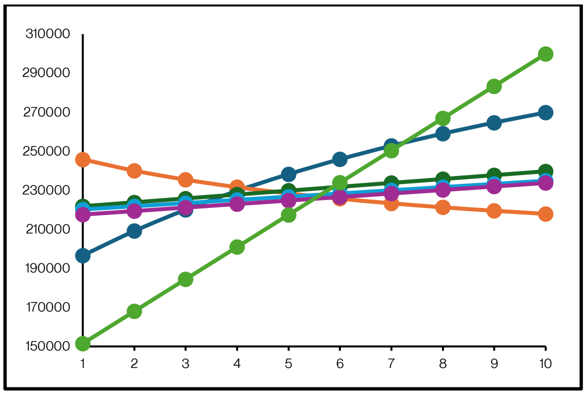
Local sensitivity analysis was also performed for the baseline scenario to illustrate the trend of each parameter across the ranges in Appendix VI.B. The plots are shown in the Figure 10a-f.

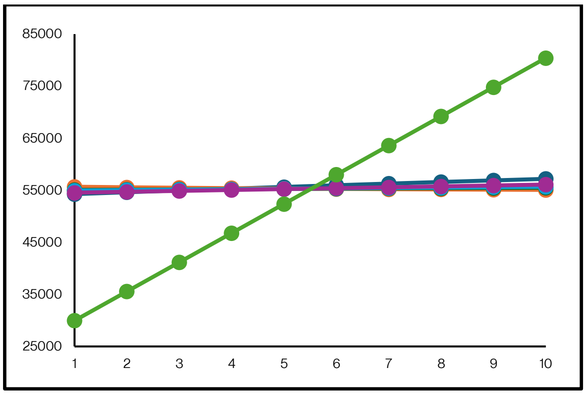


(a)



(b)





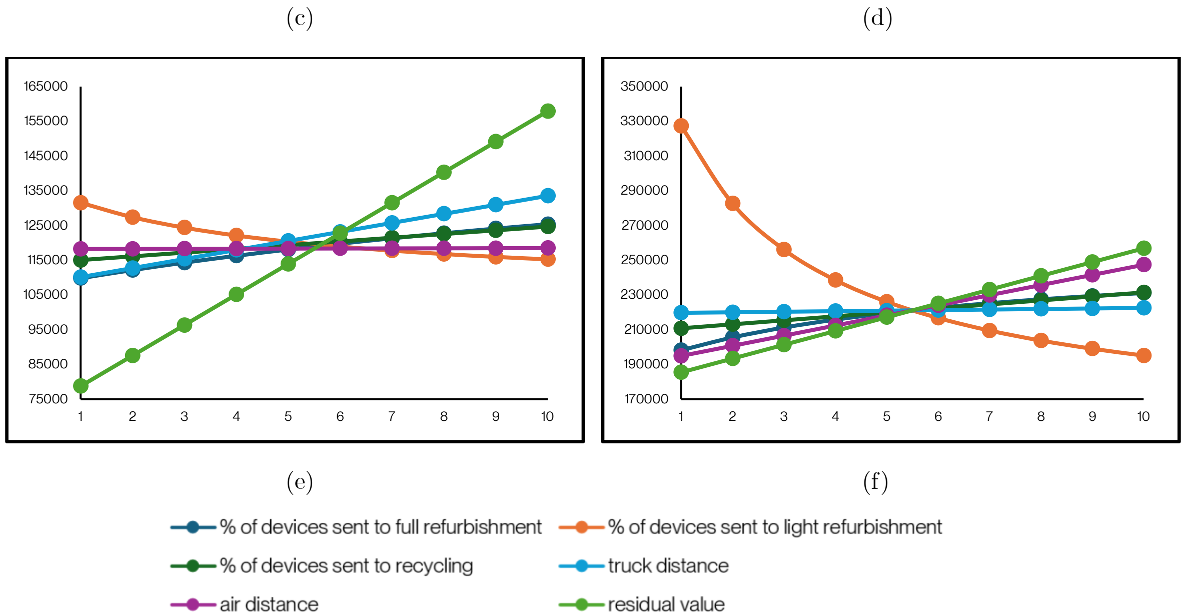


Figure 10. Local sensitivity analysis for the project scenario of (a) smartphone, (b) gaming console, (c) laptop, (d) PC, (e) tablet, and (f) screen.

The plots show that there is considerable variation in influence of the parameters per device type in the project scenario. As such, the behaviour of the parameters per device type is discussed individually.

Smartphone

For the smartphone (Figure 10a), residual value has the most influence among the parameters, with a μ_i^* of 245,345 kg CO_2 eq. Residual value is the remaining economic worth of a used device that is still functional and can be resold or refurbished. As shown in Equation A.10, only lightly refurbished devices are assumed to have residual value, so some environmental impacts from their first life are allocated to them, while fully refurbished devices are treated as non-functional waste [19]. The device's residual emissions are proportional to their residual value, calculated as the ratio of the buyback price to the selling price of a new device as summarized in Appendix VI.B. Because lightly refurbished devices make up the majority of collected smartphones (an average of 73% as of Appendix VI.B), this parameter heavily influences the Device B refurbishment stage. Moreover, it incorporates the EF of producing new devices, which is considerably higher than that of either full or light refurbishment (Appendix VI.E). Together, these factors explain why residual value dominates the sensitivity analysis for smartphones.

The next most important parameters are the percentages of fully refurbished and lightly refurbished as seen in Figures 9 and 10a (μ_i^* of 119,813 kg CO_2 eq and 47,845 kg CO_2 eq, respectively). These percentages determine how many devices are allocated to each end-of-life pathway, directly affecting the overall environmental footprint. The percentage of fully refurbished devices is the second key driver overall because full refurbishment is resource- and energy-intensive, involving extensive repairs, component replacement, and testing, resulting in the highest environmental footprint. Its wide range of 0 to 60% (Appendix VI.B) also makes project emissions highly sensitive to this parameter, since larger ranges allow greater variation in total emissions during sensitivity analysis. Lightly refurbished devices are next, as this process only involves cleaning and software updates, giving it a lower EF, but it constitutes the largest portion of collected devices (40–90.86%, Appendix VI.B), so changes in this parameter can still noticeably affect project emissions.

Transport parameters come next in influence, namely the air and truck distances associated with Device A collection. As shown in Equation A.13, they determine the emissions from transporting second-hand devices or e-waste to refurbishment facilities. Despite their very wide ranges (0–17,271 km for air and 483–4,195 km for truck), their influence is relatively small (μ_i^* of 20,310 kg CO_2 eq for air and 25,719 kg CO_2 eq) because transport-related impacts are much lower than those of refurbishment and production (Appendix VI.E). This is supported by the fact that Device A collection accounts for only about 3.5% of total project GHG emissions for smartphones (Figure 6).

Finally, the percentage of recycled devices has the least influence, having a μ_i^* of only 8,144 kg CO_2 eq. Recycling primarily involves material recovery with relatively low energy and resource inputs, resulting in the lowest EF among the processes (Appendix VI.E). Its impact is further constrained by its narrow range (0–24%) and by the fact that e-waste treatment of Device B, where this parameter applies, contributes only 0.5% of total project GHG emissions for smartphones (Figure 6).

Gaming Console

The residual value is also the dominant parameter in the project scenario for gaming consoles (μ_i^*=6,239,358 kg CO_2 eq). The rationale is consistent with that of smartphones, as the majority of collected devices are lightly refurbished (an average of 96.3%) and the EF of producing new gaming consoles is considerably higher than that of either full or light refurbishment (Appendix VI.E).

The rest of the parameter rankings are governed by the imposed range of values. In contrast with smartphones, the second dominant parameter for this device type is air distance (μ_i^*=266,606 kg CO_2 eq). Although the environmental footprint of air transport is relatively small as shown in Appendix VI.E and Figure *6*, its wide range of 2,191–6,575 km makes it more influential than the percentages of fully refurbished (μ_i^*=174,990 kg CO_2 eq) and lightly refurbished (μ_i^*=6,716 kg CO_2 eq). In sensitivity analysis, parameters with larger variation ranges exhibit higher influence because the output response is evaluated across the entire span of possible values. Thus, even parameters with lower unit impacts can appear more sensitive if the magnitude of their variation is sufficiently large.

The percentage of fully refurbished comes next due to its limited range of values (1.4–2.8%) despite the relatively higher environmental footprint than air distance. However, it still dominates truck distance (μ_i^*=94,570 kg CO_2 eq) whose range is only 202 – 606 km as per Appendix VI.B with an even smaller EF. Finally, the project emissions of gaming consoles are least sensitive to the percentages of light refurbishment and recycling, as both parameters vary within very restricted ranges, as noted previously.

Laptop

For laptops, the sensitivity of project emissions is primarily governed by the magnitude of the environmental footprints (EFs) rather than the range of parameter values. Residual value is the dominant parameter (μ_i^*=143,375 kg CO_2 eq), consistent with other device types, due to the allocation of impacts from the production stage and the high EF associated with new device manufacturing. The percentage of devices sent to full refurbishment follows (μ_i^*=75,296 kg CO_2 eq), reflecting the process's intensive material and energy requirements. Light refurbishment (μ_i^*=23,001 kg CO_2 eq) and recycling (μ_i^*=20,410 kg CO_2 eq) come next in the ranking; although their EFs are lower, they still influence results through their relative shares of collected devices. Transport-related parameters (air and truck distance) have the least influence, as their impacts are small compared to refurbishment and production, and the parameter ranges are not wide enough to outweigh these differences (μ_i^*=17,214 kg CO_2 eq for air and μ_i^*=15,598 kg CO_2 eq for truck).

PC

From Figure *9* and Figure *10*d, residual value remains the most influential parameter for PCs, consistent with other device types (μ_i^*=78,079 kg CO_2 eq). Truck distance is the second most influential parameter (μ_i^*=24,498 kg CO_2 eq) because PCs have the highest weight per unit (5.4 kg), and truck transport accounts for 85% of device collection, whereas air transport represents only 15%. As a result, the emissions from truck-based collection are the largest among all devices according to Equation A.2, contributing 8% of total project emissions for PCs (Figure 6). This higher magnitude makes truck distance more influential than the percentages of devices sent to full refurbishment (μ_i^*=16,390 kg CO_2 eq), light refurbishment (μ_i^*=15,822 kg CO_2 eq), and recycling (μ_i^*=11,323 kg CO_2 eq), which are ordered according to their environmental footprints, as observed for smartphones, gaming consoles, laptops, and tablets. These three refurbishment-related parameters still dominate air distance despite the latter parameter having the widest range (0–8,548.84 km), because the ranges of the refurbishment parameters — 0–30% for full refurbishment, 27.64–100% for light refurbishment, and 0–42.35% for recycling — combined with their higher EFs and collection shares, result in greater influence on total project emissions.

Tablet

The project emissions for tablets are most sensitive to residual value as shown in Figure *9* and Figure *10*e (μ_i^*=49,781 kg CO_2 eq). The percentage of fully refurbished devices is the second most influential parameter (μ_i^*=3,457 kg CO_2 eq), reflecting its relatively high environmental footprint and moderate range (0-10% from Appendix VI.B) and the associated high emissions involved in this process listed in Appendix VI.E. Air distance and truck distance follow in influence (1,577 kg CO_2 eq and 727 kg CO_2 eq of μ_i^* values, respectively). Although transport processes have lower environmental footprints (average contribution of 1.97%, Figure *6*), the wide ranges for air (0–17,293 km) and truck (0–2,217 km) amplify their effect on total emissions. The percentage of devices sent to light refurbishment (range 59–100%) and recycling (range 0–31%) are the least sensitive parameters, reflecting both lower environmental footprints and narrower ranges (μ_i^* of 568 kg CO_2 eq for the percentage of devices sent to light refurbishing and 444 kg CO_2 eq for the percentage of devices sent to recycling).

Monitor

In contrast with other devices, the most influential parameter for monitor project emissions is the percentage of lightly refurbished devices, having a μ_i^* of 130,153 kg CO_2 eq. Although light refurbishment has a relatively low EF, its range for monitors (0–77%, Appendix VI.B) is the widest among all device types, and this high variability makes it more dominant than residual value, which is typically the most influential parameter for other devices (μ_i^*=77,678 kg CO_2 eq). Air transport ranks third, driven by its wide range (2,191–6,575 km) despite a lower EF (μ_i^*=53,771 kg CO_2 eq). The percentage of fully refurbished devices follows, as its narrower range (0–49.9%) limits its influence relative to air transport (μ_i^*=39,083 kg CO_2 eq). Recycling comes next; while its range (23–50.1%) is narrower than that of other devices, the values are skewed toward the higher end, increasing its contribution to project emissions and placing it above truck distance (μ_i^*=18,900 kg CO_2 eq). Truck transport distance (196.77–2,206 km), although comparable to other devices in range, has the lowest influence due to its relatively small EF (μ_i^*=2,923 kg CO_2 eq).

c. Implication of Results

In the project scenario, residual value consistently emerges as the dominant parameter for smartphones, gaming consoles, laptops, PCs, and tablets, obtaining an average μ_i^* of 1,274,562 kg CO_2 eq specifically across these devices. This reflects the allocation of a portion of production-related environmental impacts to lightly refurbished devices, which constitute the majority of collected units, as well as the high environmental footprint associated with manufacturing new devices. Monitors are an exception, where the wide range in the percentage of lightly refurbished devices causes light refurbishment to dominate sensitivity. Currently, Rainbow calculates residual values per device using prices for 2023 as listed in Appendix VI.B. New prices were taken from the manufacturer's website where available, or from the manufacturer's store on Amazon. In both cases, French sources were used. Average buyback prices were shared with Rainbow by Project Developers [20].

Practically, residual values should then be updated regularly from reliable sources, as market prices fluctuate with product release cycles and regional dynamics. Outdated values risk misrepresenting the emissions allocated to refurbished devices. A systematic approach, such as annual collection of buyback and retail prices from manufacturer websites, online retailers, or resale platforms, would help maintain accuracy. Since residual value strongly governs the allocation of production-related emissions, keeping it up to date is essential for ensuring robust and credible project results.

Refurbishment shares, including the percentages of devices sent to full and light refurbishment, are also key determinants of project emissions, although their influence varies by device. Full refurbishment generally exhibits higher environmental footprints due to the resource and energy-intensive nature of the process (mean μ_i^* of 71,504 kg CO_2 eq for all devices), whereas light refurbishment contributes less per unit but can dominate sensitivity when its range is wide, as observed for monitors (mean μ_i^* of 37,351 kg CO_2 eq for all devices). Given the influence of these parameters, it is essential that project developers provide accurate and up-to-date data on refurbishment shares, as uncertainties or assumptions in these values can significantly affect the robustness of the results. This step is also supported by the fact that the refurbishment of devices contributes the most emissions across all devices in the project scenario as seen in Figure 6.

Furthermore, transport distances influence project emissions when depending on device characteristics. Truck distance, on average, has a μ_i^* of 27,339 kg CO_2 eq across all devices. However, it is particularly significant for PCs, which are heavier (5.4 kg), and given the assumption that 85% of devices are collected via truck, while air transport accounts for 15%. Air distance was also deemed to be more influential gaming consoles and monitors, where the wide ranges of distances considered (up to 17,293 km) and the large number of units sold (175,687 in total) amplified its impact. As a result, air distance had a mean μ_i^* of 59,995 kg CO_2 eq for all devices, ranking second among transport-related parameters overall.

Emissions from device collection only account for 3.9% of total project emissions on average, however, so it is not critical to obtain highly precise transport data from project developers. The high sensitivity of air and truck distances observed for some devices is mainly a result of the wide parameter ranges rather than the magnitude of their environmental footprints. In practice, distances are also difficult to determine accurately, as refurbishing companies often source devices from thousands of suppliers with numerous deliveries throughout the year. Thus, estimates such as geodesic distances are considered valid, as they introduce only low to moderate uncertainty given the relatively minor contribution of transport processes to overall project emissions.

Lastly, the percentage of devices sent to recycling consistently exhibits lower sensitivity across device types (mean μ_i^* of 10,910 kg CO_2 eq), reflecting both its relatively low environmental footprint and the narrower range of variation. This holds true in both the baseline and project scenarios. Consequently, precise data for this parameter is less critical compared to the percentages of full and light refurbishment. Since these three pathways are co-dependent and must sum to 100%, prioritizing accuracy in the refurbishment shares inherently constrains the recycling percentage within reasonable bounds.

IV. Conclusion and Future Work

This study set out to evaluate and improve Rainbow's *Refurbishment of Electronic Devices* methodology by identifying the most influential parameters affecting baseline and project scenario greenhouse gas (GHG) emissions across different device types. Drawing on real, verified data from twelve refurbishing projects, the analysis first assessed the relative contributions of life cycle stages, then shortlisted devices and parameters most relevant for sensitivity analysis. By separately examining baseline and project scenarios, the study was able to clarify how device production, refurbishment processes, collection, and recycling shape overall emissions, and to rationalize the influence of specific parameters in relation to both their environmental footprints and the ranges considered. In doing so, the work provides a systematic understanding of which factors most strongly drive uncertainty in emission estimates and highlights where methodological refinements or improved data collection can most effectively strengthen the robustness of results.

From the analysis of device sales across Rainbow's twelve refurbishment projects, six device categories were shortlisted for sensitivity assessment: smartphone (488,782 units), gaming console (163,764 units), laptop (76,838 units), PC (26,469 units), tablet (21,885 units), and screen (11,923 units). These represent the majority of processed units and encompass distinct product types with different use profiles, lifespans, and refurbishment values. TVs were excluded since their structural and functional similarity to screens, as well as their comparable refurbishment pathways and market dynamics, rendered separate analysis redundant.

In parallel, the parameters included in the sensitivity analysis were determined based on the contributions of each life cycle stage. In the baseline scenario, Device B production dominated total emissions, averaging 98.09% across all devices. The key parameters, which are the percentage of collected devices sent to recycling, the market share of refurbished devices, and the lifetime ratio between new and refurbished products, were selected because they directly influence this dominant stage. Meanwhile, for the project scenario, Device B production again represented the largest share of emissions with an average contribution of 94.54% across all devices. Consequently, the residual value and the end-life shares of collected devices (full refurbishment, light refurbishment, and recycled) were included. Device A collection contributed an average of 3.94% of total emissions across all devices, so transport parameters were considered in the sensitivity analysis. Only transport distance was retained due to its high variability and associated uncertainty, while transport mode share was excluded because its impact is predictable and linear. Furthermore, only air and truck were included since project data showed that 85.1% of devices were collected by truck and 14.9% by air, with other transport modes being negligible.

The sensitivity analysis demonstrated that the lifetime ratio between refurbished and new devices is the most influential parameter for the baseline scenario. For all devices, the lifetime ratio has the highest μ_i^* value, averaging 4,857,903 kg CO_2 eq. It captures the fact that refurbished devices generally have shorter lifetimes than new ones, which directly scales the avoided production of new devices. And given that Device B production dominates total baseline emissions, this makes the lifetime ratio the critical driver of baseline GHG estimates. The second most influential parameter in the baseline scenario was the market share of refurbished devices with a mean μ_i^* of 302,318 kg CO_2 eq. While this parameter shifts the balance between emissions from refurbishment and new production, its overall influence was modest due to its narrower range of variation. Finally, the recycling share was consistently the least influential parameter, having a μ_i^* of 4,268 kg CO_2 eq on average for all devices. This is because the recycling share only affects the e-waste treatment stage, which represents a very small fraction of baseline emissions as previously mentioned. Taken together, these findings highlight that reliable baseline estimates depend most strongly on accurate device lifetime data, while market share and recycling values, though still relevant, introduce comparatively lower uncertainty.

On the other hand, sensitivity analysis showed that residual value is the most influential parameter for the majority of device types in the project scenario, with μ_i^* values averaging 1,274,562 kg CO_2 eq specifically across smartphones, gaming consoles, laptops, PCs, and tablets. This strong influence arises because residual value determines how much of the emissions from manufacturing new devices are allocated to lightly refurbished devices, which represent the dominant share of collected units (mean of 74%). The only exception was monitors, for which the wide variation in the share of light refurbishment made this parameter more influential than the residual value.

Moreover, across all devices, refurbishment shares emerged as key drivers of the project scenario emissions. Full refurbishment generally exerted stronger influence due to its higher environmental footprint, obtaining an average of 71,504 kg CO_2 eq in μ_i^* for all devices. Light refurbishment, on the other hand, was also shown to have the ability dominate sensitivity when its range was sufficiently large, having an average μ_i^* of 37,351 kg CO_2 eq across the device types. Meanwhile, transport parameters showed device-specific behaviour. Despite truck distance having an average μ_i^* of 27,339 kg CO_2 eq across all devices, it was particularly significant for PCs given their heavier weight and the assumption that 85% of devices are collected via truck. Air distance had greater influence in general (mean μ_i^* of 59,995 kg CO_2 eq for all devices), ranking second among transport-related parameters overall. This is because it is significant for gaming consoles and monitors, both of which has relatively wide ranges of air transport distances considered and a large number of units sold. However, since device collection processes account for only 3.9% of project emissions on average, the high sensitivity of transport distances is primarily an artefact of their ranges rather than their intrinsic impacts, meaning that approximate estimates such as geodesic distances are sufficient for robust results. Recycling shares, by contrast, consistently ranked as the least influential parameter (average μ_i^* of 10,910 kg CO_2 eq for all devices) due to their lower environmental footprint and narrower ranges, confirming that accuracy should be prioritised for refurbishment shares rather than recycling. Taken together, these findings underscore the importance of maintaining up-to-date residual values and reliable refurbishment data from project developers, while transport and recycling parameters can be treated with less precision without compromising overall accuracy.

Overall, the sensitivity of project emissions is determined by the interplay between a parameter's environmental footprint, its range of variation, and the scenario context. Parameters with high environmental impacts dominate the results even when their ranges are narrow, whereas lower-impact parameters can become significant when their ranges are wide. The analysis highlights that accurate, up-to-date data on critical parameters—particularly device lifetimes, residual values, and refurbishment shares—are essential for reliably quantifying the climate benefits of electronic device reuse. At the same time, parameters such as transport distances and recycling shares, which contribute less to overall emissions, can be estimated with lower precision without substantially affecting results. These insights provide a clear basis for prioritizing data collection and methodological refinements, ensuring that resources are focused on the factors that most strongly influence emission estimates and the robustness of the refurbishment methodology.

For future work, the robustness of the sensitivity analysis could be strengthened by incorporating the continuously expanding pool of validated Rainbow refurbishment projects. As more projects are added, the analysis would benefit from a larger and more representative dataset, improving the reliability and generalizability of the findings. Methodologically, this study applied Morris and local sensitivity analyses due to their computational efficiency and suitability for a limited dataset, but future research could explore variance-based global sensitivity methods or probabilistic uncertainty approaches as the dataset grows, to better capture parameter interactions and non-linear effects. Extending the sensitivity analysis to Rainbow's other methodologies would provide a more comprehensive view of parameter importance across different product categories and environmental contexts.

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VI. Appendix

A. *Refurbishing of Electronic Devices* GHG Quantification Calculation

1. Project Scenario

The project scenario consists of refurbishing used electronic devices, which serves two functions: 1) waste treatment of the device after its first life (Device A) and 2) refurbishing to produce a "new" device (Device B). This process is broken down into 3 life cycle stages:

- Device A e-waste collection
- Device A e-waste treatment of scrap materials
- Device B refurbishing process

a. E-waste collection

The mass of e-waste collected equals the total mass of input used devices collected at the refurbishing site annually.

Total mass of devices shall be calculated using the number of devices collected for each device type (provided by the Project Developer), multiplied by the assumed mass of each device type shown in Table 3.

For calculating transport distance, Project Developers shall provide the country and/or city where used electronic devices are transported from and provide the average distance from the collection source to the refurbishing project site.

It is assumed that transport within Europe is done 100% by truck, and overseas transport is done by long-distance air freight.

Calculations involved are:

$$N_{i,collected} = \sum N_{i,sold}/(1 - Re_{rate,i}) \quad \text{(Equation A.1)}$$

where,

- $N_{i,collected}$ represents the amount of input collected devices of type i collected by the project, in number of devices.
- $N_{i,sold}$ represents the number of devices by type ii sold in a functioning state, and shall be provided by the Project Developer for each verification.
- $Re_{rate,i}$ represents the fraction of input used devices of device type i that are recycled, saved for spare parts, or not successfully refurbished to a functioning state by the project, and shall be provided by the Project Developer for each verification.

$$E_{P,collection} = \sum(N_{i,collected} * W_i * D_{C,i} * R_{C,i}) * EF_{transport} \quad \text{(Equation A.2)}$$

where,

- $E_{P,collection}$ represents the sum of GHG emissions due to the transport of devices collected for refurbishing in the project scenario, in kg CO_2 eq.
- $N_{i,collected}$ was calculated in Equation A.1.
- W_i represents the weight in kilograms of device *i*, according to the presented in Table B.5.
- $D_{C,i}$ represents the distance travelled for device collection in km, provided by the Project Developer per sourcing country/city (C*C*) and device type *i*.
- $R_{C,i}$ represents the fraction of the devices collected per sourcing country/city (*C*) and device type *i*.
- $EF_{transport}$ represents the emission factor for transport in kg CO_2 eq/ton-km according to the ecoinvent database and includes truck or air freight.

b. E-waste collection

Devices collected by the project that cannot be refurbished undergo e-waste recycling. Refurbishing projects typically have contracts with e-waste recycling companies that collect and recycle such devices.

Project Developers shall provide the fraction of devices that are recycled, and they will be modelled as mechanical e-waste recycling with shredding and separation.

Some non-refurbished devices may be kept onsite to harvest spare parts in the future, but due to limited project data on this topic, they are assumed to be recycled.

Devices that are sold by the project in a non-functional state shall be treated in the calculations as recycled devices.

$$E_{recycling} = \sum(N_{i,collected} * W_i * Re_{rate,i} * EF_{recycling,i}) \qquad \text{(Equation A.3)}$$

where,

- $E_{recycling}$ represents the sum of GHG emissions due to the recycling process of devices/scrap not suitable for refurbishing, in kg CO_2 eq.
- $N_{i,collected}$ and $Re_{rate,i}$ were described in Equation A.1.
- W_i is described in the section e-waste collection section of the project scenario.
- $EF_{recycling,i}$ represents the emission factor of recycling each device type. Refer to Appendix E for the ecoinvent processes used.

$$E_{transport} = \sum(N_{i,collected} * Re_{rate,i} * W_i * D_{scrap} * EF_{truck\ transport}) \text{(Equation A.4)}$$

where,

- $E_{transport}$ represents the sum of GHG emissions due to the transport of devices/scrap not suitable for refurbishing that are sent to recycling, in kg CO_2 eq.

- $N_{i,collected}$ and $Re_{rate,i}$ were described in Equation A.1.
- W_i is described in the section e-waste collection section of the project scenario.
- D_{scrap} represents the distance in km until the waste treatment facility. If not known, this value is considered 100km.
- $EF_{truck\ transport}$ represents the emission factor of truck transport. Refer to Appendix E for the ecoinvent processes used.

$$E_{P,waste\ treatment} = E_{transport} + E_{recycling} \quad \text{(Equation A.5)}$$

where,

- $E_{P,waste\ treatment}$ represents the sum of GHG emissions in the project scenario e-waste treatment of non-refurbished devices, in kg CO_2 eq.

c. Refurbishing process

This life cycle stage is composed of four main processes, each described below:

- light refurbishing impacts
- full refurbishing impacts
- residual value of input devices, and
- secondary transport of devices.

Light refurbishment impacts: The refurbishing process is split into two categories: light and full refurbishment, representing the degree of intervention needed to restore the device to a functioning state. Light refurbishment involves cosmetic and software improvements and does not require the replacement of parts (e.g. new battery, new screen...). This distinction was chosen because most environmental impacts from the refurbishing process come from production of new replacement pieces.

- Light refurbishment includes inputs of cleaning alcohol, tissues, and cloth, and is modeled after the detailed LCA of electronic device refurbishing from the ADEME study [13].

Full refurbishment impacts: Full refurbishment includes light refurbishment plus repair and replacement of non-functional pieces. Detailed project data on all replacement pieces and inputs are rarely available, so full refurbishment impacts are modeled following the ADEME study [13].

- Results from this study are used to obtain the ratio of impacts of a refurbished device to the impacts of the corresponding new device. This ratio is then applied to the new device production impacts to obtain the desired amount of emissions from refurbishing. The emissions from refurbishing are modelled using the mix of ecoinvent processes used in light refurbishment described above, plus production of commonly replaced parts including screens, batteries, microphones and speakers.

Residual value of input devices: In life cycle assessments, when a project uses waste as an input, it typically enters the project system boundary with zero environmental impacts. Refurbishing projects collect and refurbish used devices that are not always at the end of their life and are not truly waste. They may still be functional and hold residual value from their first life. This is evidenced by the fact that Project Developers sometimes pay for used devices, as opposed to waste collection, where the waste generator must pay for waste treatment.

- In this case, some environmental impacts from the device's first life should be allocated to the refurbished device. It is assumed that only devices that undergo light refurbishment were in good condition and had residual value and are allocated a share of GHG emissions from the device's first life. On the other hand, devices that undergo full refurbishment are assumed to be non-functional waste and are not allocated any environmental impacts from their first life.
- The residual value and corresponding allocated emissions are based on the ratio of the buyback price to the selling price of a new manufactured device. An average ratio shall be used for each device type and is shown in Table B.3. Alternatively, project developers may provide a similar project-specific database with their own buyback data.

Secondary transport of devices: After the device is collected by the refurbishing project and sorted, it may be sent to a different refurbishment site, for example to do speciality repairs. project developers shall report such secondary transport by providing the distance transported, and the number and type of devices making this transport.

Calculations involved in this life cycle stage are listed below.

$$N_{light\ ref,i} = \sum(N_{i,collected} * Ref_{light,i}) \qquad \text{(Equation A.6)}$$

where,

- $N_{light\ ref,i}$ represents the number of devices of type i undergoing the light refurbishing process and sold in a functional state.
- $N_{i,collected}$ was described in Equation A.1.
- $Ref_{light,i}$ represents the fraction of devices of type ii undergoing the light refurbishing process and sold in a functional state.

$$E_{light\ ref} = \sum \begin{matrix} N_{light\ ref,i} * (alcohol * EF_{alcohol} \\ + paper * c + cloth * EF_{cloth}) \end{matrix} \qquad \text{(Equation A.7)}$$

where,

- c represents the sum of GHG emissions due to the light refurbishing of a device type.
- $N_{light\ ref,i}$ is calculated in Equation A.6.
- *alcohol*, *paper and cloth* represent the amount of cleaning alcohol, paper and cloth needed to clean a device. These amounts were taken per device type from the ADEME study, pages 45, 77, and 103.

- $EF_{alcohol}$ represents the emission factor, in kg CO_2 eq, for cleaning alcohol composed of 70% ethylene and 30% water. Refer to Appendix E for the ecoinvent processes used.
- EF_{paper} represents the emission factor, in kg CO_2 eq, of paper. Refer to Appendix E for the ecoinvent processes used.
- EF_{cloth} represents the emission factor, in kg CO_2 eq, of cloth used for cleaning. Refer to c for the ecoinvent processes used.

$$N_{full\ ref,i} = \sum(N_{i,collected} * Ref_{full,i}) \quad \text{(Equation A.8)}$$

where,

- $N_{full\ ref,i}$ represents the number of devices of type ii undergoing the full refurbishing process and sold in a functional state.
- $N_{i,collected}$ was described in Equation A.1.
- $Ref_{full,i}$ represents the fraction of devices of type i undergoing the full refurbishing process and sold in a functional state.

$$E_{full\ ref} = \sum(N_{full\ ref,i} * R_{full\,ref,i} * EF_{full\,ref}) \quad \text{(Equation A.9)}$$

where,

- $E_{full\ ref}$ represents the sum of GHG emissions due to the full refurbishing of a device type.
- $N_{full\ ref,i}$ is calculated in Equation 8.
- $R_{full\,ref,i}$ represents the rate of full refurbishment activities modeled per device type i. This reflects the "amount" of refurbishment used as an input for that device.
- $E_{full\ ref}$ represents the emission factor, in kg CO_2 eq, of one full refurbishment activity. This activity includes a mix of ecoinvent processes in Appendix E.

$$E_{residual} = \sum N_{light\ ref,i} * \frac{Ave.acquisition\ price_i}{Ave.selling\ price_i} * EF_{new} \quad \text{(Equation A.10)}$$

where,

- $E_{residual}$ represents the sum of residual GHG emissions from the device's first life allocated to the refurbished device, for all devices.
- $N_{light\ ref,i}$ is calculated in Equation A.6.
- $Ave.\,acquisition\,price_i$ represents the average price paid for the collected used devices of type i (also called the buyback price).
- $Ave.\,selling\,price_i$ represents the average selling price of a new device of type i.
- EF_{new} represents the emission factor in kg CO_2 eq/kg due to the production of the new device type i. The emission factors of new devices are presented in Appendix E.

$$E_{secondary\ transport} = \sum(N_{secondary\ transport} * W_i * D_{secondary\ transport} * EF_{transport})$$

(Equation A.11)

where,

- $E_{secondary\ transport}$ represents the sum of GHG emissions from secondary transport.
- $N_{secondary\ transport}$ is the number of devices of device type i that are sent for secondary transport.
- W_i and $EF_{transport}$ are described in the project e-waste treatment calculations.
- $D_{secondary\ transport}$ represents the distance traveled for secondary device transport in km per device type i.

$$E_{P,refurbishment\ process} = E_{light\ ref} + E_{full\ ref} + E_{residual} + E_{secondary\ transport}$$

(Equation A.12)

where,

- $E_{P,refurbishment\ process}$ represents the sum of GHG emissions in the project scenario refurbishing process LCA step, kg CO_2 eq.

2. Baseline Scenario

The baseline scenario consists of two main functions: 1) waste treatment of the device after its first life (Device A) and 2) provisioning of a new device (Device B). This is broken down into 3 life cycle stages, which are detailed in the following sections:

- Device A collection
- Device A e-waste treatment
- Manufacturing of Device B

The baseline scenario structure remains valid for the entire crediting period but may be significantly revised earlier if:

- The Project Developer notifies Rainbow of a substantial change in project operations or baseline conditions, and/or
- The methodology is revised, affecting the baseline scenario.

The specific values within the baseline scenario will be updated annually, using project data to accurately reflect the equivalent of the project's annual operations.

The structure of the baseline scenario is the same whether the project consists of ongoing operations or an expansion. In the former, project data from all annual site operations is considered, and the baseline scenario is defined as the functional equivalent of all annual operations. For an expansion project, only project data related to the expansion is considered, because the normal annual operations would be the same in the baseline and project scenario, and can therefore be excluded.

a. E-waste collection

It is assumed that e-waste is transported by truck 100 km to its waste treatment center.

The mass of e-waste collected in the baseline scenario equals the total mass of input used devices collected by the refurbishing project annually.

Total mass of devices shall be calculated using the number of devices collected for each device type (provided by the project developer), multiplied by the assumed mass of each device type.

$$E_{B,collection} = \sum(N_{i,collected} * W_i * D) * EF_{truck\ transport} \qquad \text{(Equation A.13)}$$

where,

- $E_{B,collection}$ represents the sum of GHG emissions in kg CO_2 eq due to the transport of devices.
- $N_{i,collected}$ is calculated in Equation A.1.
- W_i is described in Equation A.2.
- D represents the distance of the device collection in kilometres, which is assumed to be 100 km.
- $EF_{truck\ transport}$ represents the emission factor of truck transport in kg CO_2 eq/ton-km.

b. E-waste treatment

The treatment of e-waste is split between recycling, landfilling and incineration.

The proportion of e-waste recycled is based on national statistics obtained from the Eurostat database for small IT devices, as defined by the Waste from Electrical and Electronic Equipment (WEEE) directive [21]. Data for other countries where used devices are frequently sourced are taken from the UN Global E-waste Monitor [22], and extrapolated where necessary.

First, the fraction of e-waste that is not separately collected is assumed to be collected with municipal waste and incinerated or landfilled. In 2021, for example, this was an average of 31% for the countries included in Eurostat [23].

The repartition between landfilling and incineration (with and without energy recovery) was taken from Eurostat, and the total repartition for all EU countries from 2020 was used. This resulted in 52% incineration and 48% landfilling [24].

Then, the fraction of e-waste that is separately collected is considered (average of 69% in the EU in 2021) [23].

- This can be further broken down into the fraction successfully recycled/reused (average of 79% for EU countries in 2021) and the fraction that could not be recycled/reused (21%) [23].
- The separately collected e-waste that could not be recycled/reused is assumed to be incinerated and landfilled, with the same proportions described in the e-waste treatment section for the baseline scenario.

$$E_{B,waste} = \sum (N_{i,collected} * W_i * (1 - RR_{rate,i})) * (L_{rate} * EF_{landfill} + I_{rate} * EF_{incineration})$$

(Equation A.14)

where,

- $E_{B,waste}$ represents the sum of GHG emissions due to the e-waste treatment of devices not separately collected.
- $N_{i,collected}$ is calculated in Equation A.1.
- Wi is described in Equation A.2.
- $RR_{rate,i}$ represents the project's country waste reuse and recycling rate.
- L_{rate} represents the landfilling and incineration rates, respectively, described in section e-waste treatment section.
- $EF_{landfill}$ represents the emission factor of treating e-waste via landfill, in kg CO_2 eq/kg using ecoinvent database, according to the breakdown of materials on pg. 11 of the ADEME study [13].
    - treatment of waste plastic, mixture, sanitary landfill = 50%
    - treatment of waste glass, sanitary landfill = 10%
    - treatment of waste aluminum, sanitary landfill = 40%
- $EF_{incineration}$ represents the emission factor of treating e-waste via incineration, in kg CO_2 eq/kg using ecoinvent database according to the following split:
    - treatment of waste glass, municipal incineration = 10%
    - treatment of waste plastic, consumer electronics, municipal incineration = 50%
    - treatment of scrap copper, municipal incineration = 20%
    - treatment of scrap aluminum, municipal incineration = 20%

$$E_{B,separate\ waste} = \sum (N_{i,collected} * W_i * RR_{rate,i} * EF_{recycling,i}) \quad \text{(Equation A.15)}$$

where,

- $E_{B,separate\ waste}$ represents the sum of GHG emissions due to the e-waste treatment of separately collected devices.
- $N_{i,collected}$, W_i, and $RR_{rate,i}$ are describe above.
- $EF_{recycling,i}$represents the emission factor of recycling device i, in kg CO_2 eq/kg. Refer to Appendix E. for the ecoinvent process implemented.

$$E_{B,waste\ treatment} = E_{B,separate\ waste} + E_{B,waste} \quad \text{(Equation A.16)}$$

where,

- $E_{B,waste\ treatment}$ represents the sum of GHG emissions in the baseline scenario e-waste treatment life cycle stage, in kg CO_2 eq.

c. New device production

The number of new devices to consider in the baseline scenario corresponds to the number of devices successfully refurbished and sold in a functional state in the project scenario. Note that this does not necessarily equal the number of used devices collected, because a fraction of devices cannot be successfully refurbished.

To quantify avoided GHG emissions, the baseline scenario must consider the market share of the project technology already in use. Currently, new device purchases come from both new manufacturing and existing refurbishing activities. The proportions of new and refurbished devices are detailed in Table VI.B.1.

The process of manufacturing a new device is taken from the ecoinvent database: laptop, PC, tablet, and screen (See Appendix E).

The emission factor for smartphones was based on ecoinvent data and adjusted to better represent average smartphones. This was necessary because

1. smartphones are one of the most frequently refurbished devices, so special attention should be paid to them
2. smartphone emission factors are notoriously variable, and
3. it has been noted that ecoinvent smartphone emission factors are underestimated.

The difference in lifetime between refurbished and new devices is accounted for in this life cycle stage. The amount of new device production avoided in the baseline scenario is proportional to the ratio of new and refurbished device lifetimes.

Calculations involved in this life stage are detailed below.

$$E_{new\ device} = \sum(N_{i,sold} * frac_{new} * EF_{new,i}) \quad \text{(Equation A.17)}$$

where,

- $E_{new\ device}$ represents the sum of GHG emissions in kg CO_2 eq due to the production of new devices (i.e. excluding the market share of refurbished devices that are already in use).
- $N_{i,sold}$ was described in Equation A.1.
- $frac_{new}$ refers to the market share (in percentage) of new devices sold annually per device type i, as presented in Table VI.B.1.

- $EF_{new,i}$ represents the emission factor in kg CO_2 eq/kg due to the production of the new device type i.

$$E_{Ref\ B} = \sum(N_{i,sold} * frac_{refurb} * R_{full\ ref,i} * EF_{full\ ref}) \quad \text{(Equation A.18)}$$

where,

- $E_{Ref\ B}$ represents the sum of GHG emissions due to the refurbishing of used devices according to the market shares in the baseline scenario.
- $N_{i,sold}$ was described in Equation A.1.
- $frac_{refurb}$ refers to the market share (in percentage) of refurbished devices sold annually per device type i, as presented in Table VI.B.1.
- $R_{full\ ref,i}$ and $EF_{full\ ref}$ are described in Equation A.9.

Refurbished devices are assumed to have a shorter lifespan than new devices. This is accounted for in the following adjustment to avoided emissions from new device manufacturing:

$$E_{new\ device\ lifetime\ adjusted} = \sum(E_{new\ device} * Y_{refurbished,i}/Y_{new,i}) \quad \text{(Equation A.19)}$$

where,

- $Y_{refurbished,i}$ represents the expected lifespan of a refurbished device i in number of years, as presented in Table VI.B.2.
- $Y_{new,i}$ represents the expected lifespan of a new device i in number of years, as presented in Table VI.B.2.

$$E_{B,new\ device\ production} = E_{new\ device\ lifetime\ adjusted} + E_{ref} \quad \text{(Equation A.20)}$$

where,

- $E_{B,new\ device\ production}$ represents the sum of GHG emissions in the baseline scenario new device production life cycle stage, in kg CO_2 eq.

3. Avoided GHG Emissions

The total baseline GHG emissions, total project GHG emissions, and the project's avoided emissions are calculated as follows.

$$Project\ Emissions = E_{P,collection} + E_{P,waste\ treatment} + E_{P,refurbishing\ process}$$

(Equation A.21)

$$Baseline\ Emissions = E_{B,collection} + E_{B,waste\ treatment} + E_{B,new\ device\ production}$$

(Equation A.22)

$$Avoided\ Emissions = Baseline\ Emissions - Project\ Emissions \quad \text{(Equation A.23)}$$

B. Parameter Ranges

Table B.1. Ranges of values used per device in the sensitivity analysis.

Device	Value	Baseline			Project					
		Recycling Rate	Market Share of Refurbished Devices	Lifetime Ratio	Residual Value	Recycling Rate	%Light	%Full	Distance - truck (km)	Distance travelled - air (km)
Smartphone	min	0	0.065	0.333333	0.055	0	40	1	483	0
	max	24	0.195	1	0.165	24	90.86	60	4195	17271.53
	mean	10.4	0.13	0.666667	0.11	10.4	73.24833	16.35167	1588.333	3158.921
Gaming Console	min	0.45	0.03	0.3	0.07	0.45	94.45	1.4	202	2191.756
	max	1.35	0.09	0.9	0.21	1.35	98.15	4.2	606	6575.268
	mean	0.9	0.06	0.6	0.14	0.9	96.3	2.8	404	4383.512
Laptop	min	0	0.04	0.3	0.07	0	41	0	0	0
	max	59	0.12	0.9	0.21	59	100	47.665	2217	8696.331
	mean	12.62443	0.08	0.6	0.14	12.62443	73.75486	13.62071	826.5735	4362.513
Tablet	min	0	0.035	0.333333	0.1	0	59	0	0	0
	max	31	0.105	1	0.3	31	100	10	2217	17293
	mean	8.2	0.07	0.666667	0.2	8.2	88.875	2.925	680	7163
PC	min	0	0.04	0.3	0.07	0	27.64	0	441.77	0
	max	42.35	0.12	0.9	0.21	42.35	100	30.01	2552	8548.84
	mean	14.34767	0.08	0.6	0.14	14.34767	71.84533	13.807	1179.59	2849.613
Screen	min	23	0.03	0.285714	0.07	23	0	0	196.77	2191.756
	max	50.1	0.09	0.857143	0.21	50.1	77	49.9	2206	6575.268
	mean	36.55	0.06	0.571429	0.14	36.55	38.5	24.95	1201.385	4383.512

1. Market Share of Refurbished Devices

The market share of new and used devices sold annually in Europe was used to determine the repartition of avoided new and refurbished devices in the baseline scenario. Most data were available for smartphones and are taken from Deloitte Consumer Trends 2022 Report [12] and ARCEP in 2024 [25].

Similar detailed data were not available for other device types. Survey responses on the interest in buying a given refurbished device type were used to adjust the smartphone data in Table B.2 proportionally to other device types. The results from PCs were applied to laptops. Moreover, the gaming console value was chosen to have the most conservative value within the list, which is of the screen.

Table *B.2. Market percentage of new and refurbished devices used in the refurbishing methodology.*

Device type	Market share of refurbished devices	Market share of new devices
Smartphone	13%	87%
PC	8%	92%
Tablet	7%	93%
Laptop	8%	92%
Screen	6%	94%
Gaming Console	6%	94%
Average	8%	92%

2. Residual Value

The devices considered were the most popular and recent models available on the European market for smartphones and tablets. New device prices were obtained from the manufacturer's website or, where unavailable, from the manufacturer's store on Amazon, using French sources in both cases. Average buyback prices for each device category were provided by Rainbow's project developers and reflect the typical buyback price for devices from Europe in 2023. For device types lacking specific buyback data, the average value of the available device types was applied.

Table *B.3. Residual values used in the refurbishing methodology.*

Device	Percent of Residual Value
Smartphone	11%
Tablet	20%
Laptop	14%
PC	14%
Screen	14%
Gaming Console	14%

3. Lifetime of New and Refurbished Devices

The lifetime of new and refurbished devices is listed in the table below. The resulting ratio (lifetime of refurbished devices over lifetime of new devices) used in the baseline assessment is also included in the table. This data is based on the ADEME report in 2024 [13].

Table *B.4. Lifetimes of new and refurbished devices considered in the sensitivity analysis.*

Device Type	Lifetime New (years)	Lifetime Refurbished (years)	Lifetime Ratio
Smartphone	3	2	0.666666667
Laptop	5	3	0.6
PC	5	3	0.6
Tablet	3	2	0.666666667
Screen	7	4	0.571428571
Gaming Console	5	3	0.6

4. Masses of Devices

Table *B.5. Masses of devices considered in the sensitivity analysis.*

Device Type	Average Mass (kg)
Smartphone	0.2
iPhone	0.2
Laptop	1.6
MacBook	1.7
PC	5.4
iMac	4.5
Tablet	0.5
iPad	0.5
Screen	4.5
Gaming Console	2.97

C. Baseline Python Code

```
from SALib.sample.morris import sample
from SALib.analyze.morris import analyze

from python_graphql_client import GraphqlClient

import numpy as np
import pandas as pd

import copy

from ..utils import (
    find_value_in_process_tree,
    load_combined_graphql,
    plot_morris,
    set_from_path,
    get_from_path,
    plot_manual,
)

from ..inputs.erefurbishment import (
    Laptop,
    Smartphone,
    Tablet,
    PC,
    Monitor,
    Gaming_console,
)

pd.set_option('display.max_rows', None)      # Show all rows
pd.set_option('display.max_columns', None)   # Show all columns

import matplotlib.pyplot as plt
import time
start = time.time()

client = GraphqlClient(endpoint="http://localhost:9000/graphql/")
query_graphql = load_combined_graphql(
    "queries/SensitivityOutput.graphql",
    "queries/ERefurbishingM2V2.graphql",
)

#------------MORRIS ANALYSIS------------#

device = Smartphone() #EDIT
device_type = device.device_type

num_trajectories=2 #EDIT

problem = device.baseline_morris_problem()

param_values = sample(problem, N=num_trajectories)
param_values = np.array([row for row in param_values])

emissions = np.array([])

variables = device.default_variables()


vars_locations = { # because they cannot be referenced directly and i dont want to declare the
variable dict twice bc it confuses me when i change variables per device ( ,,ᘮ'︿'ᘮ,,)
        "recycled":["inputs","device_collection", 0, "recycled"],
        "market_share_refurbished": ["inputs","market_share_refurbished"],
        "lifetime_ratio":["inputs","lifetime_ratio"],
}

full_refurbished = variables["inputs"]["device_collection"][0]["full_refurbished"]
light_refurbished = variables["inputs"]["device_collection"][0]["light_refurbished"]
recycled_idx = problem["names"].index("recycled")

for row_idx, row in enumerate(param_values):
    #scale the full and light refurbishment percentages
```

```python
    variables_morris = copy.deepcopy(variables)

    # recycled = row[recycled_idx]
    # scale = (100-recycled)/(full_refurbished+light_refurbished)
    # full_refurbished_new = scale*full_refurbished
    # light_refurbished_new = scale*light_refurbished

    recycled = row[recycled_idx]
    scale = 100/(recycled+full_refurbished+light_refurbished)

    row[recycled_idx] = recycled*scale
    full_refurbished_new = scale*full_refurbished
    light_refurbished_new = 100-full_refurbished_new-row[recycled_idx]

    variables_morris["inputs"]["device_collection"][0]["full_refurbished"] = full_refurbished_new
    variables_morris["inputs"]["device_collection"][0]["light_refurbished"] = light_refurbished_new

    for idx,(var,loc) in enumerate(vars_locations.items()):
        set_from_path(variables_morris,loc,row[idx])

    data = client.execute(query=query_graphql, variables=variables_morris)
    assert "errors" not in data, f"GraphQL returned errors: {data['errors']}"

    path = ["Baseline Total", f"Baseline device total: {device_type}"]
    result = find_value_in_process_tree(data=data,path=path)["value"]

    emissions=np.append(emissions,[result])

#------------PLOT------------#

morris_results = analyze(problem, param_values, emissions)
morris_result_df = plot_morris(
    morris_results=morris_results,
    problem=problem,
    device_type=device_type,
    scenario="baseline",)

print(morris_result_df)



#------------MANUAL SENSITIVITY ANALYSIS------------#

conduct_manual_sens = True #EDIT
if not conduct_manual_sens:
    end = time.time()
    print(f"Runtime: {end - start:.4f} seconds or {(end - start)/60:.4f} minutes")
    quit()

num_vars_manual_sens = 3
vars_manual_sens = problem["names"]
print(vars_manual_sens)

points = 10
cols = [f"Point {int(f)}" for f in range(10)]

manual_results_df = pd.DataFrame(index=vars_manual_sens, columns=cols)
for var in vars_manual_sens:
    idx = problem["names"].index(var)
    median = np.mean(problem["bounds"][idx])
    emissions = np.array([])

    bounds = problem["bounds"][idx]
    step = (bounds[1] - bounds[0]) / (points - 1)
    bounds_list = [bounds[0] + i * step for i in range(points)]
    for new_var_value in bounds_list:
        variables_manual = copy.deepcopy(variables)
        set_from_path(variables_manual,vars_locations[var],new_var_value)

        #scale
        if var == "recycled":
            scale = 100/(new_var_value+full_refurbished+light_refurbished)

            new_var_value *= scale
```

```
            full_refurbished_new = scale*full_refurbished
            light_refurbished_new = scale*light_refurbished

            variables_manual["inputs"]["device_collection"][0]["recycled"] = new_var_value
            variables_manual["inputs"]["device_collection"][0]["full_refurbished"] =
full_refurbished_new
            variables_manual["inputs"]["device_collection"][0]["light_refurbished"] = 100 -
new_var_value - full_refurbished_new

        data = client.execute(query=query_graphql, variables=variables_manual)
        assert "errors" not in data, f"GraphQL returned errors: {data['errors']}"

        path = ["Baseline Total", f"Baseline device total: {device_type}"]
        result = find_value_in_process_tree(data=data,path=path)["value"]

        emissions=np.append(emissions,[result])
    manual_results_df.loc[var] = emissions

print(manual_results_df)

plot_manual(
    manual_results_df=manual_results_df,
    device_type=device_type,
    scenario="baseline"
)

end = time.time()
print(f"Runtime: {end - start:.4f} seconds or {(end - start)/60:.4f} minutes")
```

D. Project Python Code

```
from SALib.sample.morris import sample
from SALib.analyze.morris import analyze

from python_graphql_client import GraphqlClient

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

import copy

from ..utils import (
    find_value_in_process_tree,
    load_combined_graphql,
    plot_morris,
    set_from_path,
    get_from_path,
    plot_manual,
    remove_others_in_group,
    remove_others_in_group_vars_locations,
)

from ..inputs.erefurbishment import (
    Laptop,
    Smartphone,
    Tablet,
    PC,
    Monitor,
    Gaming_console,
)

pd.set_option('display.max_rows', None)      # Show all rows
pd.set_option('display.max_columns', None)   # Show all columns

import time
start = time.time()

client = GraphqlClient(endpoint="http://localhost:9000/graphql/")
query_graphql = load_combined_graphql(
    "queries/SensitivityOutput.graphql",
    "queries/ERefurbishingM2V2.graphql",
)

#------------MORRIS ANALYSIS------------#

device = Tablet()  #EDIT
device_type = device.device_type

cp_param_infocus = "light_refurbished" #EDIT
problem = device.project_morris_problem()
problem_modified = remove_others_in_group(problem,cp_param_infocus)

num_trajectories = 2 #EDIT
param_values = sample(problem_modified, N=num_trajectories)

vars_locations = { # because they cannot be referenced directly and i dont want to declare the
variable dict twice bc it confuses me when i change variables per device ( ,,ʊ'︿'ʊ,,)
        "full_refurbished":["inputs","device_collection", 0, "full_refurbished"],
        "light_refurbished":["inputs","device_collection", 0, "light_refurbished"],
        "recycled":["inputs","device_collection", 0, "recycled"],
        "truck_distance": ["inputs","freight_transport", 0, "distance"],
        "air_distance":["inputs","freight_transport", 1, "distance"],
        "residual_value":["inputs","residual_value"],
}

vars_locations_modified = remove_others_in_group_vars_locations(vars_locations, [cp_param_infocus])

# default values for the particular device, the sequence of variables should be the same as the
problem declaration because morris input transforms problem into an ARRAY AHHH
variables = device.default_variables()
```

```
param_values = np.array([row for row in param_values])
emissions = np.array([])

# need to get rows where the recycled, light ref, and full ref are in
# need to adjust the other two variables

cp_param_infocus_idx = problem_modified['names'].index(cp_param_infocus)
for row_idx, row in enumerate(param_values):
    # normalize refurbishing + recycled percentages
    # Extract current values
    device_collection = variables["inputs"]["device_collection"][0]
    values = {
        "recycled": device_collection["recycled"],
        "light_refurbished": device_collection["light_refurbished"],
        "full_refurbished": device_collection["full_refurbished"],
    }

    # Override the focused parameter from row
    values[cp_param_infocus] = row[cp_param_infocus_idx]

    # Normalize so the sum = 100
    scale = 100 / sum(values.values())
    for k in values:
        values[k] *= scale

    # Ensure sum is exactly 100 (fix floating-point drift)
    others = [k for k in values if k != cp_param_infocus]
    values[others[0]] = values[others[0]]
    values[others[1]] = values[others[1]]
    values[cp_param_infocus] = 100 - values[others[0]] - values[others[1]]

    # Update param_values
    param_values[row_idx, cp_param_infocus_idx] = values[cp_param_infocus]

    # Deep copy variables and update
    variables_morris = copy.deepcopy(variables)
    variables_morris["inputs"]["device_collection"][0].update(values)

    # inject morris sample into variables
    for idx, (var, loc) in enumerate(vars_locations_modified.items()):
        set_from_path(variables_morris, loc, param_values[row_idx][idx])

    data = client.execute(query=query_graphql, variables=variables_morris)
    assert "errors" not in data, f"GraphQL returned errors: {data['errors']}"

    path = ["Project Total", f"Project device total: {device_type}"]
    result = find_value_in_process_tree(data=data, path=path)["value"]

    emissions = np.append(emissions, [result])


#------------PLOT------------#

morris_results = analyze(problem_modified, param_values, emissions)
morris_result_df = plot_morris(
    morris_results=morris_results,
    problem=problem_modified,
    device_type=device_type,
    scenario="project",)

print(morris_result_df)

#------------MANUAL SENSITIVITY ANALYSIS------------#

params_cp_idx_dict = {
        "recycled": problem['names'].index("recycled"),
        "light_refurbished": problem['names'].index("light_refurbished"),
        "full_refurbished": problem['names'].index("full_refurbished"),
    }

conduct_manual_sens = False
if not conduct_manual_sens:
    end = time.time()
```

```
    print(f"Runtime: {end - start:.4f} seconds or {(end - start)/60:.4f} minutes")
    quit()

to_remove = {} #EDIT
vars_manual_sens = [n for n in problem["names"] if n not in to_remove]

points = 10
cols = [f"Point {int(f)}" for f in range(10)]

manual_results_df = pd.DataFrame(index=vars_manual_sens, columns=cols)
for var in vars_manual_sens:
    idx = problem["names"].index(var)
    median = np.mean(problem["bounds"][idx])
    emissions = np.array([])
    bounds = problem["bounds"][idx]
    step = (bounds[1] - bounds[0]) / (points - 1)
    bounds_list = [bounds[0] + i * step for i in range(points)]

    need_scaling = var in params_cp_idx_dict.keys()

    for new_var_value in bounds_list:
        variables_manual = copy.deepcopy(variables)

        set_from_path(variables_manual,vars_locations[var],new_var_value)
        recycled =  variables_manual["inputs"]["device_collection"][0][ "recycled"]
        light_refurbished = variables_manual["inputs"]["device_collection"][0]["light_refurbished"]
        full_refurbished = variables_manual["inputs"]["device_collection"][0]["full_refurbished"]

        total = recycled+light_refurbished+full_refurbished
        scale = 100/total
        full_refurbished *= scale
        light_refurbished *= scale
        recycled = 100- full_refurbished- light_refurbished

        variables_manual["inputs"]["device_collection"][0][ "recycled"] = recycled
        variables_manual["inputs"]["device_collection"][0]["light_refurbished"] = light_refurbished
        variables_manual["inputs"]["device_collection"][0]["full_refurbished"]= full_refurbished

        data = client.execute(query=query_graphql, variables=variables_manual)
        assert "errors" not in data, f"GraphQL returned errors: {data['errors']}"

        path = ["Project Total", f"Project device total: {device_type}"]
        result = find_value_in_process_tree(data=data,path=path)["value"]

        emissions=np.append(emissions,[result])

    manual_results_df.loc[var] = emissions

print(manual_results_df)


plot_manual(
    manual_results_df=manual_results_df,
    device_type=device_type,
    scenario="project",
)


end = time.time()
print(f"Runtime: {end - start:.4f} seconds or {(end - start)/60:.4f} minutes")
```

E. Ecoinvent Processes and Values

Device type	Ecoinvent activity	Value	kg CO2 per
Smartphone*	consumer electronics production, mobile device, smartphone | consumer electronics, mobile device, smartphone | Cutoff, U, GLO	7.019982333	unit device
Tablet*	consumer electronics production, mobile device, tablet | consumer electronics, mobile device, tablet | Cutoff, U, GLO	83.35827488	unit device
PC**	computer production, desktop, without screen | computer, desktop, without screen | Cutoff, U, GLO	215.6814344	unit device
Laptop*	computer production, laptop | computer, laptop | Cutoff, U, GLO	163.3984312	unit device
Screen	display production, liquid crystal, 17 inches | display, liquid crystal, 17 inches | Cutoff, U, GLO	352.449192	unit device
Gaming Console**	computer production, desktop, without screen | computer, desktop, without screen | Cutoff, U, GLO	280.0941959	unit device
Transport, truck	market for transport, freight, lorry 7.5-16 metric ton, EURO5 | transport, freight, lorry 7.5-16 metric ton, EURO5 | Cutoff, U, RER	0.25533238	ton-km
Transport, air	market for transport, freight, aircraft, long haul | transport, freight, aircraft, long haul | Cutoff, U, GLO	0.83159729	ton-km
Smartphone recycling	treatment of used smartphone, mechanical treatment | used smartphone | Cutoff, U, GLO	0.75013477	kg device
Tablet recycling	treatment of used tablet, mechanical treatment | used tablet | Cutoff, U, GLO	0.61185203	kg device
PC recycling	treatment of used desktop computer, mechanical treatment | used desktop computer | Cutoff, U, GLO	0.42742733	kg device
Laptop recycling	treatment of used laptop computer, mechanical treatment | used laptop computer | Cutoff, U, GLO	1.1323136	kg device
Screen recycling	treatment of used liquid crystal display, mechanical treatment | used liquid crystal display | Cutoff, U, GLO	1.24942397	kg device
Gaming Console recycling	treatment of used desktop computer, mechanical treatment | used desktop computer | Cutoff, U, GLO	0.55507751	kg device
Light refurbishing***	market for ethanol, without water, in 99.7% solution state, from ethylene | ethanol, without water, in 99.7% solution state, from ethylene | Cutoff, U, RER	1.43747613	kg liquid

Device type	Ecoinvent activity	Value	kg CO2 per
Light refurbishing***	market for water, completely softened | water, completely softened | Cutoff, U, RER	0.00029925	kg liquid
Light refurbishing***	market for tissue paper | tissue paper | Cutoff, U, GLO	2.85833221	kg material
Light refurbishing***	market for textile, knit cotton | textile, knit cotton | Cutoff, U, GLO	8.40302083	kg material
Full refurbishing	market for ethanol, without water, in 99.7% solution state, from ethylene | ethanol, without water, in 99.7% solution state, from ethylene | Cutoff, U, RER (0.007 kg)	1.43747613	kg liquid
Full refurbishing	market for water, completely softened | water, completely softened | Cutoff, U, RER (0.003 kg)	0.00029925	kg liquid
Full refurbishing	market for tissue paper | tissue paper | Cutoff, U, GLO (0.005 kg)	2.85833221	kg material
Full refurbishing	market for textile, knit cotton | textile, knit cotton | Cutoff, U, GLO (0.005 kg)	8.40302083	kg material
Full refurbishing	market for battery, Li-ion, NCA, rechargeable, prismatic | Cutoff, U, GLO (0.1 kg)	21.938971	kg material
Full refurbishing	market for electronic component, passive, mobile, earpiece and speaker | Cutoff, U, GLO (0.002 kg)	55.4710502	kg material
Full refurbishing	market for liquid crystal display, unmounted, mobile device | Cutoff, U, GLO (0.1 kg)	110.279501	kg material
E-waste incineration	treatment of waste glass, municipal incineration | waste glass | Cutoff, U, GLO = 10%	0.02731586	kg material
E-waste incineration	treatment of waste plastic, consumer electronics, municipal incineration | waste plastic, consumer electronics | Cutoff, U, GLO = 50%	3.0947596	kg material
E-waste incineration	treatment of scrap copper, municipal incineration | scrap copper | Cutoff, U, Europe without Switzerland = 20%	0.02273487	kg material
E-waste incineration	treatment of scrap aluminum, municipal incineration | scrap aluminum | Cutoff, U, Europe without Switzerland= 20%	0.0255479	kg material
E-waste landfill	treatment of waste plastic, mixture, sanitary landfill | waste plastic, mixture | Cutoff, U, RoW = 50%	0.0922268	kg material
E-waste landfill	treatment of waste glass, sanitary landfill | waste glass | Cutoff, U, GLO = 10%	0.01082863	kg material
E-waste landfill	treatment of waste aluminum, sanitary landfill | waste aluminum | Cutoff, U, RoW = 40%	0.01670508	kg material

*removed the power adapter production and waste treatment, and the device waste treatment

**removed the device waste treatment

***amount of each input varies by device type